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**Authors**

Yamauchi, Takashi
Seo, Hwaryong
Choe, Yoonsuck
et al.

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# Assessing Emotions by Cursor Motions: An Affective Computing Approach

**Takashi Yamauchi[1], Hwaryong Seo[2], Yoonsuck Choe[3],**
**Casady Bowman[1], and Kunchen Xiao[1]**

[1]Department of Psychology, [2]Department of Visualization,
[3]Department of Computer Science and Engineering
Texas A&M University, TX 77843
(takashi-yamauchi@tamu.edu)

## Abstract

Choice reaching, e.g., reaching a targeted object by hand, involves a dynamic online integration of perception, action and cognition, where neural activities of prefrontal cortical regions are concurrently coordinated with sensori-motor subsystems. On the basis of this theoretical development, the authors investigate the extent to which cursor movements in a simple choice-reaching task reveal people's emotions, such as anxiety. The results show that there is a strong correlation between cursor trajectory patterns and self-reported anxiety in male participants. Because computer cursors are ubiquitous, our trajectory analysis can be augmented to existing affective computing technologies.

**Keywords:** affective computing; cursor motion; choice reaching

## Introduction

An adaptive computer system that can read users' emotions and tailor its output dynamically will transform the nature of human-computer interactions. Present affective computing methods apply facial expressions, vocal tones, gestures, and physiological signals for emotion assessment (Calvo & D'Mello, 2010; Zeng, Pantic, Roisman, & Huang, 2009); yet, these methods are not always practical for everyday applications (e.g., wearing a multi-channel EEG cap). This article investigates the possibility of analyzing cursor motion for affective computing in a choice reaching task.

To reach a target object by hand, thousands of muscles and billions of nerve cells have to coordinate. In this process, higher cortical systems (e.g., the prefrontal cortex) can only make a coarse action plan (e.g., move your hand), and local sensori-motor subsystems modulate the hand movement by dynamically processing contextual and cognitive information (Thelen, 1998). Choice-reaching behavior is dynamic in nature, where motor coordination is adjusted in real time in a continuous feedback loop (Spivey, 2007; Song & Nakayama, 2007). We hypothesize that emotions influence this process and fine-tuned analysis of cursor trajectories can help assess users' emotional states.

## Affective Computing

Two influential reviews published in 2009 and 2010 (Calvo & D'Mello, 2010; Zeng et al., 2009) suggest the following short-comings in the current Affective Computing (i.e., AC) technologies: (1) many of the visual- and audio-based methods (e.g., detecting emotions by facial expressions and speech) do not fare well in a natural setting; (2) assessment methods based on physiological signals (e.g., EEG) are still impractical for everyday application. Our independent review of the studies published in major Human Computer Interaction (HCI) conferences and journals show significant improvements in AC technologies in the last several years. Techniques developed in "wearable computers" made great progress in assessing people's physiological states in everyday settings (Hedman et al., 2009; McDuff, Karlson, Kapoor, Roseway, & Czerwinski, 2012). The scope of AC research has grown significantly, as AC technologies are now applied for public speech training (Pfister & Robinson, 2011), gaze detection in infant-parent communication (Cadavid, Mahor, Messinger, & Cohn, 2009), and intelligent tutoring/game systems (D'Mello, Graesser, & Picard, 2007; Graesser & D'Mello, 2011).

Cursor motion analysis originated in the late 1970s when researchers started to evaluate the performance of different input devices (Accot & Zhai, 1997, 1999; Card, English, & Burr, 1978). In the last 15 years, a number of research studies have employed cursor movement analysis for emotion assessment. Zimmermann (2008) employed a film-based emotion elicitation technique and investigated the impact of arousal and valence on cursor motion in an online shopping task. Kapoor et al. (Kapoor, Burleson, & Picard, 2007) adopted a pressure-sensitive mouse for their multichannel automatic affect detection system and measured mean, variance, and skewness of mouse pressure while participants (middle school students,) learned to solve a Tower of Hanoi puzzle. Azcarraga and Suarez (Azcarraga & Suarez, 2012) evaluated EEG signals and mouse activities (the number of mouse clicks, distance traveled, click duration) during algebra learning in an intelligent tutoring system (ITS) to predict participants' emotions. Prediction rates based solely on EEG were 54 to 88%. When mouse activity data were augmented to the EEG data, accuracy rates increased up to 92%. Yamauchi (2013) presents a new machine learning technique involving feature selection associated with cursor motions and emotion detection. Beyond these studies, clear evidence that links cursor activities and affects remains sparse.

## Theoretical Rationale

*Embodied cognition.* Recent advances in "embodied cognition" introduce a new way of analyzing human behavior. People's cognitive, attitudinal, and affective states are expressed in their bodily actions, and their bodily actions invoke affective states (Barsalou, 1999; Barsalou, Niedenthal, Barbey, & Ruppert, 2003). These intricate interactions among cognition, emotion and action are articulated by Barsalou's (1999) perceptual symbol systems hypothesis, which states that the essence of off-line cognition involves a reenactment (simulation) of sensory and perceptual modules.

Physiological findings provide another layer of evidence that emotions can be reflected in voluntary hand motions. The dorsolateral prefrontal region—the control center of high-order cognition—is connected to all premotor areas and controls limb movements; this area receives a considerable amount of input from dopaminergic cells, which influence emotional states such as feelings of reward and pleasure (Kolb & Whishaw, 2009).

The basal ganglia, which play a pivotal role in voluntary motor control, receive excitatory input from almost all cortical areas, and transfer the information back to the same cortical areas through the thalamus. These feedback loops involve not only motor-related cortices (e.g., primary motor, supplementary motor and primary somatosensory cortices), but also other cortical and subcortical regions that control emotion, motivation and decision making (Mendoza & Foundas, 2008). It is well known that dopamine deficiency in the basal ganglia results in neurological movement disorders such as Parkinson's disease and Tourette syndrome. These motor disorders often come with emotional disorders. More than 40% of the people suffering from Tourette syndrome experience symptoms of Obsessive-compulsive disorder, which is an anxiety disorder (Mink, 2008). Apathy—"a decrease of goal-directed behavior, thinking, and mood"—occurs about in 40% of the patients suffering from Parkinson's disease (Weintraub & Stern, 2007). Those individuals with deficits in dopamine production often exhibit impairments in motor control as well as emotion and higher order cognition (Mink, 2008).

Recent behavioral research suggests that high-order cognitive judgments such as inductive reasoning and knowledge formation are affected by tacit knowledge, affects and mindsets, which in turn can be captured by the movement of a computer cursor (Dale, Kehoe, & Spivey, 2007; Freeman, Pauker, Apfelbaum, & Ambady, 2009; Spivey et al., 2005; Xiao & Yamauchi, 2014; Yamauchi, 2013; Yamauchi & Bowman, 2014; Yamauchi, Kohn, & Yu, 2007).

On the basis of these findings, we postulate that subtle emotional states can be reflected in the way people move computer cursors and fine-tuned analysis of cursor trajectories can be applied for affective computing. Below, we present an empirical study that explores this possibility.



Figure 1: A screen shot of a choice-reach trial (the dotted line was not shown in the actual experiment.)

## Experiment

Our experiment consisted of visual perception task involving judgments of similarities of simple figures (Kimchi & Palmer, 1982; Yamauchi, 2013). Participants were presented with a triad of geometric figures on a computer monitor (96 trials in total), and selected which choice figure, left or right, was more similar to the base figure shown at the bottom (Figure 1). Participants indicated their choice by pressing the "left" or "right" button placed at the top of each choice figure (Figure 1). We selected this choice-reaching task because the perception of similarity is one of the most fundamental psychological functions that mediates decision making, memory, generalization, impression formation and problem solving (Hahn & Ramscar, 2001).

In each trial, our program recorded the x-y coordinates of the cursor location every 20-30 milliseconds from the onset of a trial (participants pressing the "Next" button) until the end of the trial (participants pressing either the left- or right-choice button). From this data set, we extracted 16 features of cursor motions, and examined the extent to which cursor movement patterns of individual participants reflect their self-reported state anxiety scores (Spielberger, Gorsuch, Lushene, Vagg, & Jacobs, 1983).
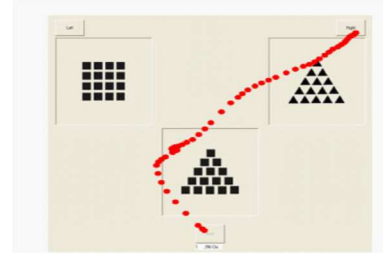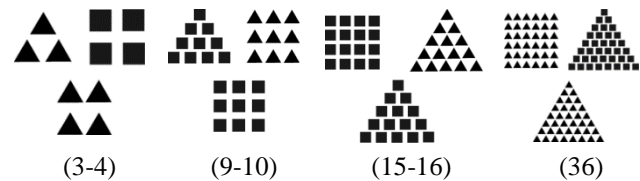


Figure 2: Sample stimuli used in the choice-reaching task.

## Method

*Participant.* Participants (N = 133; female = 75, male = 58) were undergraduate students participating for course credit.

*Materials and Procedure.* The stimuli for the choice-reaching task were 32 triads of geometric figures—two choice figures placed at the two top-corners of the frame and a base figure placed at the bottom-center of the stimulus frame (Figures 1&2). Each figure shows an overall shape (either a square or a triangle) with smaller squares or triangles, yielding four types of figures—a global square or triangle made of local squares or triangles.

In each triad, two choice-figures placed at the upper two corners of a stimulus frame were similar to the base figure

either in their overall shape or local shapes. In total, 16 basic triads were produced by varying the number of local shapes—figures made of 3-4, 9-10, 15-16, or 36 local shapes (Figure 2). In the experiment, 32 triads were produced from the 16 basic triads by swapping the locations of the choice figures; these 32 triads were shown 3 times, yielding 96 trials of choice reaching for each participant.

To start each trial, participants pressed the "Next" button, and a triad stimulus appeared. Participants indicated their responses by pressing the "left" or "right" button (Figure 1). After their response, the "Next" button appeared again. This cycle was repeated 96 times. Note that there are no correct/incorrect answers in this task, and participants were instructed to make a selection based on their personal preference.

Shortly after the completion of the choice-reaching experiment, participants received the state anxiety questionnaire (Spielberger et al., 1983) and rated each statement (e.g., "I feel afraid") on a four-point scale (20 questions in total). This questionnaire has been used widely to assess generalized anxiety disorder (GAD). In this study, we focused on anxiety for our analysis because anxiety is one of the key affective states that arise at the time of cognitive disequilibrium, and anxiety is also a key emotion pertinent to deep learning (D'Mello, Dale, & Graesser, 2011).
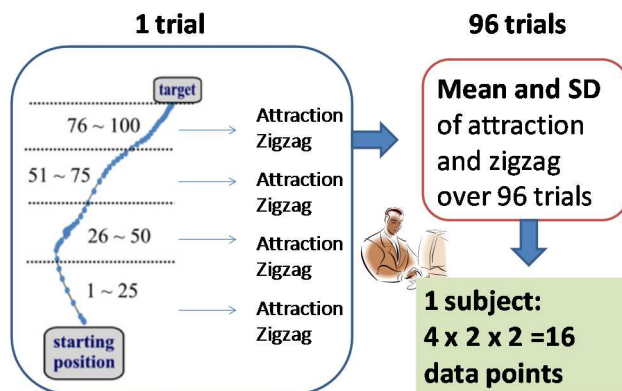


Figure 3: An illustration of cursor trajectory features. 16 features were extracted for each participant.

*Data analysis.* To pre-process the cursor movement data, we first applied a linear interpolation method and standardized cursor trajectories of all trials into 100 equally-spaced time steps starting from the onset time of the first cursor move to the time slice of the final move (at which the choice button, either left or right, was pressed (Dale et al., 2007; Freeman et al., 2009; Spivey et al., 2005; Yamauchi, 2013).

For each trajectory, we divided the 100 time-steps into four equal segments (Figure 3) and extracted two features—attraction and zigzags (Figure 4)—from the four segments. Attraction was defined as the area of departure from the shortest path and the zigzag is the number of changing directions with respect to the straight line from the starting

position to the end position (Figure 4). These cursor trajectory features were selected because these features have been shown to be significant in cognitive decision making (Dale et al., 2007; Freeman et al., 2009; Spivey et al., 2005; Xiao & Yamauchi, 2014; Yamauchi, 2013; Yamauchi & Bowman, 2014; Yamauchi et al., 2007).

For individual participants, means and standard deviations of these features were calculated over trials, yielding 16 predictors (2 features x 4 segments x 2 statistical properties (mean, SD)). D'Mello and colleagues (D'Mello et al., 2011) investigated body movements of users in an intelligent tutoring system and showed that inconsistent body motions during learning reflect high levels of anxiety. In this vein, standard deviations of cursor properties over different trials are likely to reflect participants' emotional states.
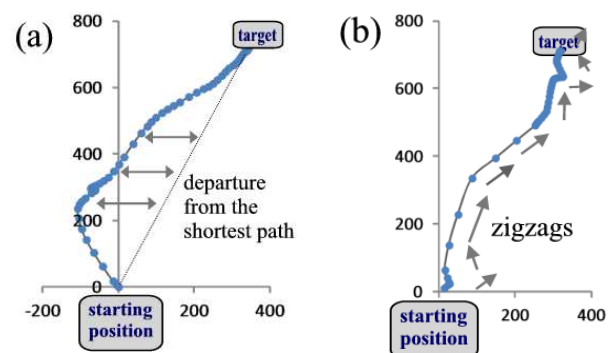


Figure 4: Illustrations of (a) attraction and (b) zigzags

*Design.* For the cursor trajectory data, we employed linear regression analysis with anxiety scores as the dependent variable and 16 cursor trajectory features as the independent variables (Figure 3). The values of independent variables (i.e., extracted cursor trajectory properties) and the dependent variable (i.e., observed anxiety scores) were normalized so that the mean and standard deviation of each variable were 0 and 1, respectively. For the cursor trajectory analysis, the trials that took more than 6 seconds were not analyzed. Thus, a total of 11,555 trials (90.1 % of the entire trials) were analyzed.

## Results and Discussion

*Anxiety questionnaire data.* The anxiety questionnaire asked participants to indicate their levels of anxiety on a 1-4 scale (20 questions). Our questionnaire results showed that female participants reported a higher level of anxiety (M = 2.0, SD = 0.56) than male participants (*M* = 1.8, *SD* = 0.46), $t(132) = 2.36$, $p = 0.02$, $d = 0.3$, 95% CI$_d$ [-0.04, 0.64].

*Linking cursor trajectories to anxiety.* To investigate the relationship between cursor trajectories and self-reported anxiety scores, we applied stepwise regression analysis separately to female (n = 75) and male (n = 58) participants. This separate analysis procedure was adopted because a large number of studies demonstrate sex differences in emotionally charged stimuli (e.g., Bradley & Lang, 2007), and our anxiety questionnaire data revealed significant sex differences. For

this analysis, a total of 16 predictors were submitted to a stepwise linear regression (Figure 3) with the Akaike Information Criterion (AIC) for the predictor selection criterion.
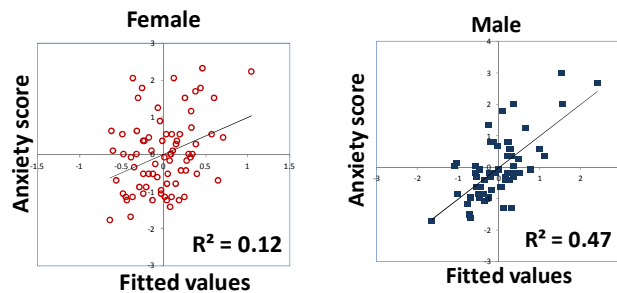


Figure 5: Graphical summaries of two regression analyses. The units of the x-y coordinates of the graphs are standardized "z-scores."

Consistent with the studies that report gender differences in emotional experience (Cahill, 2006), our results revealed a strong gender effect. Cursor trajectory patterns obtained from female participants were moderately correlated with their self-reported anxiety scores; $F(2, 72) = 4.81$, $p = 0.01$, $R^2 = 0.12$ (adjusted $R^2 = 0.09$); 12 % of the variance observed in female participants' anxiety scores was explained by two predictors identified in the stepwise regression. Given male participants, our regression analysis indicated that 47% of the variance was explained by seven predictors; $F(7, 50) = 6.22$, $p < 0.001$, $R^2 = 0.47$ (adjusted $R^2 = 0.39$) (Figure 5).

Table 1: Coefficients selected by the regression analysis

| | | Female | | Male | |
|---|---|---|---|---|---|
| | Segments | Mean | SD | Mean | SD |
| Attract | 76-100 | | | | |
| | 51-75 | .34** | | | |
| | 26-50 | | | | .51** |
| | 1-25 | | | -.29* | |
| Zigzag | 76-100 | -.16# | | -.81*** | .39* |
| | 51-75 | | | .77*** | |
| | 26-50 | | | -.23# | .24# |
| | 1-25 | | | | |

Note. p***< .001, .001 ≤ p**< .01 .01≤p*< .05, .05≤p#.

Overall, two properties, attraction and zigzag, extracted during the midsection time-steps (26-50 & 51-75) appear particularly important. For male participants, zigzags extracted from 51-75th time-steps and 76-100th time-steps were shown to be highly correlated with self-reported anxiety scores (Table 1). Given female participants, attraction taken in the middle section (51-75th time-steps) was critical.

*Assessing the validity of the regression result.* To assess the validity of our cursor trajectory analysis, we examined the

extent to which randomly generated pseudo predictors could explain the empirical anxiety scores obtained in the experiment. If the 16 cursor properties extracted from individual participants performed no better than randomly generated pseudo-predictors, our method should be judged as ineffective.

In this simulation analysis, we replaced the 16 trajectory predictors with 16 vectors of arbitrary numbers sampled randomly from the standard normal distribution. We applied the same stepwise regression analysis to the "pseudo predictors" and calculated $R^2$. This process was repeated 1000 times to estimate the distribution of $R^2$ obtained from the pseudo predictors.
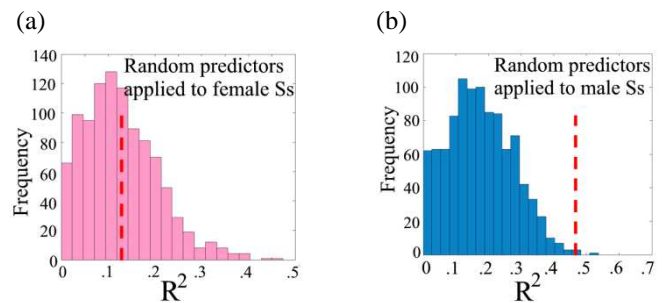


Figure 6: Results from the simulation study based on female participants (a), and male participants (b).

Figure 7 shows the results of this simulation study. The dotted red lines represented $R^2$ obtained from the actual experiment. Given the female participants, our empirical predictors outperformed random pseudo predictors slightly more than 50% of the time, suggesting that the cursor trajectory predictors extracted from female participants were barely effective compared to randomly generated predictors. Given the data from male participants, our empirical predictors outperformed the random pseudo predictors more than 99% of the time, suggesting that our cursor trajectory worked well in explaining male participants' self-reported anxiety levels.

## Discussion

The extracted cursor trajectories for male participants predicted about 47% of the variance of their self-reported anxiety scores. For female participants, the same predictors were not very effective. Although we found a statistically significant correlation between some of the identified predictors and anxiety scores, our verification analysis showed that randomly sampled pseudo predictors can achieve a comparable level of accountability in female participants. It is well known that there are considerable sex differences in male and female brains especially in the amygdala. The way that emotional states are expressed is also different between male and female (Burleson & Picard, 2007; Conati, 2002). It appears that such basic sex differences are at play in the cursor movements observed in our male and female participants as well.

The idea that emotion influences bodily motions has been investigated in HCI (Glowinski & Mancini, 2011; Thrasher, Van der Zwaag, Bianchi-Berthouze, & Westerink, 2011). Other studies suggest that emotional states are expressed through keystrokes (Epp, Lippold, & Mandryk, 2011). The present study extends these studies by showing that people's emotional states (at least for male participants) can be reflected by the subtle movements of computer cursors in a simple choice-reaching task.

Our cursor trajectory analysis provides a new method for affective computing for male participants with added advantage for the ease of implementation and computation. Computer cursors are by far among the most ubiquitous means connecting people and computers, and almost all computers, including tablets, require some form of cursor or finger movements for interaction. Because movement can be traced in time-stamped x-y coordinate points, the cost for online data processing can be miniscule.

## Limitations and Future directions

Our study is correlational and the causal link between cursor motion and emotion is unknown. The impact of emotion on cursor motion should be tested experimentally where a certain emotion is experimentally elicited. This study employed a simplified task and our procedure was effective only for male participants. Although such a controlled situation is needed for the initial investigation of a new technology, the proposed method should be vetted thoroughly in more realistic settings. The applicability of the cursor-based method should be examined further with more rigorous statistical methods (e.g., cross validation). It is possible that the cursor-based analysis is viable only in the task context that requires choice-reaching. The generalizability of our procedure should be investigated further in contexts that do not involve choice reaching. It should be also noted that the cursor-based affective computing method is limited because it requires direct interaction with computers (e.g., facial expressions can be assessed without computers). These limitations should be effectively addressed in future studies.

## Conclusion

In recent years, there has been an increasing consensus about the need to broaden our understanding of human emotion and its impact on human computer interaction. The present study combines the virtues of the integrated understanding of human physiology, emotion and motor control and shows the intricate link between the three. We suggest that cursor trajectory analysis can be integrated into existing AC technologies, providing an economical method of affective computing.

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