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Choice Reaching Trajectory Analysis as Essential Behavioral Measures for Psychological Science

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Abstract

Existing psychophysiological measures (e.g., fMRI, EEG, MEG) are impractical for a large scale behavioral study (N>1000) due to their exorbitant data acquisition costs. Psychological tests (e.g., Emotional Stroop task), which rely on response time and performance accuracy measures, are economical but are too coarse to inform dynamic continuous interactions among perceptual, cognitive, and affective processes. By augmenting standard cognitive tests with choice-reaching measures, the problems inherent in psychological tests can be resolved. Recent revolutionary research in cognitive science has shown that choice-reaching involves a dynamic integration of motivation, action and cognition. This complex interaction of motivation, action and cognition can be examined by analyzing the movement of the computer cursor pixel by pixel every few milliseconds. Open source software and R data analysis library “mousetrap” help researchers to collect mouse-cursor trajectory data relatively easily. With continued interest and innovation, the mouse cursor trajectory method is likely to become a standard procedure for psychological tests, especially for the study investigating individual differences underlying cognitive, affective, and perceptual processing.

Keywords

Mouse-Cursor Trajectory; Dynamic Analysis; Psychological Measurement; Choice Reaching; Social-Affective-Cognitive Processing

A large scale behavioral study is essential to establish a mechanistic foundation for psychological science, especially for the study investigating individual vulnerability to mental disorders, such as anxiety, depression, and attention-deficit/hyperactivity disorder (ADHD). However, existing psychophysiological methods (e.g., functional magnetic resonance imaging-fMRI, electroencephalography-EEG, magnetoencephalography-MEG) are impractical for a large scale behavioral study (N>500) due to their exorbitant data acquisition costs. Psychological tests-e.g., the Emotional Stroop task, the Attention Network Test, and questionnaires [1-3]-are inexpensive to implement but they are inadequate to probe *dynamic* interactions among perception, emotion, and cognition.

The following metaphor highlights this plight. Imagine flight information from Washington D.C. to Beijing, China. The information provides the duration of the flight, such as 20 hours and 20 minutes. Assume that your goal is to find the exact route and condition of the flight. Did the airplane stop over Los Angeles, San Francisco, or Tokyo? Or was the plane delayed because of the bad weather in Alaska or Colorado? From the “response time” and “accuracy” data, one could hardly infer the exact route and condition of the flight.

To clarify the inner mechanism of mental disorders (e.g., anxiety disorder, attention deficit/hyperactivity disorder), experimental psychologists and psychiatrists have scrutinized the performance for behavioral tasks, such as the Emotional Stroop task [3]. In each trial, these tasks yield two discrete data points-response time and accuracy. By probing these behavioral data under different experimental conditions, the researchers have inferred interactive mechanisms of emotion and cognition. Response time data provide the duration from the onset of a trial (e.g., stimulus presentation) to the end (e.g., key press); performance accuracy is represented by a binary value of 0 or 1 (e.g., “incorrect” / “correct”). Any processing interactions happening in-between is glossed over.

Psychophysiological measures (e.g., fMRI, EEG, MEG) can supplant the shortcomings of the response time and accuracy measures. However, these measures are also, in main, *static*, not *dynamic*, because their analyses are contingent on aggregated data (e.g., mean and SD) (Figure 1). For example, in a typical ERP (event-related potential) study, aggregated magnitudes (i.e., mean) of event-related potentials are statistically compared in two conditions (Figure 1a). In a typical EEG study, powers of wavelengths are extracted and compared [4] (Figure 1b). In an fMRI study, changes in blood flow (e.g., blood-oxygen-level dependent, BOLD) are measured over a predetermined duration and means of BOLD are compared (Figure 1c). In all cases, temporal information is discarded by aggregating the data. Note that the Fourier transform applied to EEG data also reduces temporal information to spectral information, and spectral information (i.e., wavelengths) is agnostic about timing.

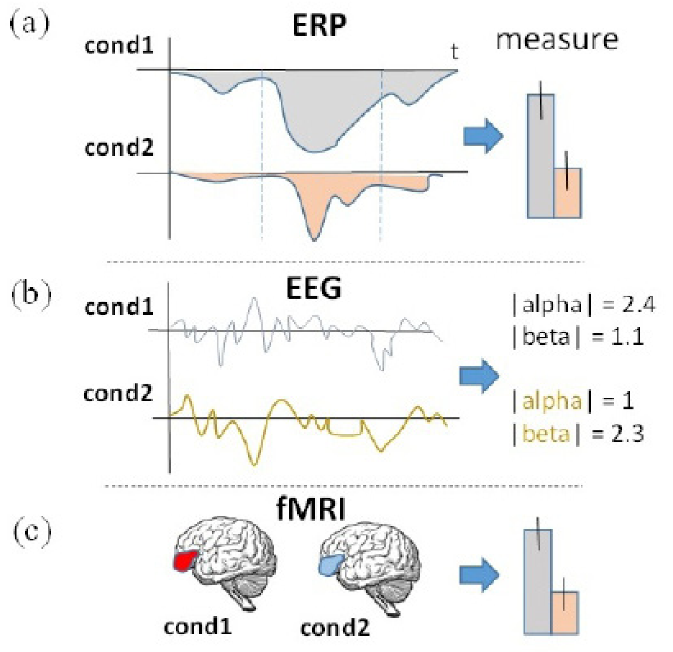

Figure 1: Illustrations of hypothetical (a) ERP, (b) EEG, and (c) fMRI data analyses. In these analyses, dynamic temporal information is often removed by aggregating the data.

Because of these constraints, existing neuropsychiatry research relies on a small number of subjects (N < 46) [5-7]. This is a serious problem because knowledge obtained from these studies can be easily distorted by a few outliers (Figure 2). Figure 2a simulates the influential data presented in the Hariri et al. study [7], in which the magnitude of ventral striatal activity is shown to be associated with performance for a delayed discounting task. The article is among the most cited (417 citations in Google Scholar as of June 9, 2017), and the researchers draw this conclusion on the basis of a statistically significant correlation between ventral striatal activity and performance for a delayed discounting task ($r = 0.38$, $p < 0.01$, N=45). However, as Figure 2b shows, the correlation can be easily distorted by the two outliers. By removing the two outliers, the statistically “significant” correlation disappears in Figure 2b ($r = 0.11$, $p = 0.47$).

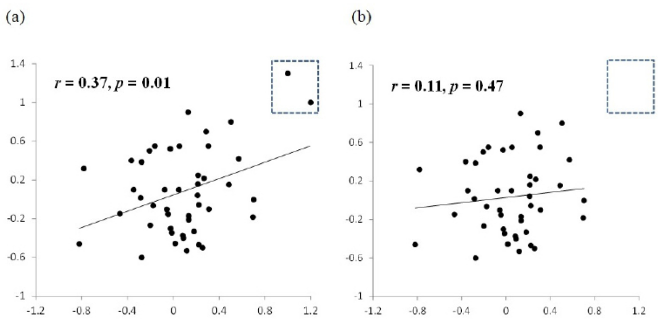

Figure 2: (a) Synthetic data simulating the data reported in the Hariri et al. 2006 (Figure 2 in their article). As in the Hariri et al. data, the significant correlation between two variables ($r = 0.37$, $p = 0.01$) are produced by two outliners (enclosed in the box). (b) By removing the outliers, the significant correlation disappears completely ($r = 0.11$, $p = 0.47$).

By augmenting standard cognitive tests (e.g., attention network tests) with choice-reaching measures (Figure 3), the problems inherent in psychological tests can be resolved. Choice-reaching, e.g., reaching a targeted object by the hand, involves a dynamic integration of motivation, action and cognition, where neural activities of prefrontal cortical regions are concurrently coordinated with sensori-motor subsystems [8,9]. This complex neural coordination results from neural circuits that bridge the prefrontal cortex, the basal ganglia, and the thalamus [10], and that the interactive nature of emotion and cognition can be studied in trajectories of the computer cursor in a choice-reaching task (Figure 3).

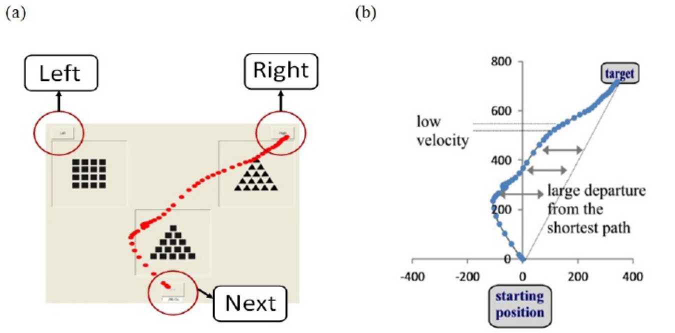

Figure 3: (a) In a choice-reaching task, participants are to make a selection (left or right) by navigating the computer cursor. The dotted line is shown to indicate a trajectory of the cursor in a choice-reach trial. (b) Dynamic trajectory measures, such as velocity, acceleration, and maximum deviation can be extracted in an individual choice-reaching trial.

The findings in support of this principle come from a broad range, including perceptual and numerical judgment tasks [8,11-13], semantic categorization [14], linguistic judgment [9,15], racial and gender judgment of morphed face pictures [16,17], attitudinal ambivalence toward certain topics (e.g., abortion) [18,19], uncertainty in economic choices [20]. In human computer interaction research, studies have shown that cursor movement analysis can be applied for emotion recognition [4,21-25] and individual differences in vulnerability to emotion disorders (anxiety) can be assessed by the trajectory of the computer cursor.

A number of studies conducted in our lab found that this complex interaction of motivation, action and cognition can be examined by analyzing the movement of the computer cursor pixel by pixel every few milliseconds, and attentional and affective interventions in conscious and unconscious processing can be adequately probed by various mouse cursor trajectory metrics [4,12,13,23,24,26].

Fortunately, a number of open source software and data analysis libraries are available to ease the data acquisition and analysis procedures. The mouse-cursor tracking plug-in “mousetrap” for OpenSesame programming environment [27,28] allows researchers to collect mouse-cursor trajectory data relatively easily; R statistical package “mousetrap” [29] also helps analyze many cursor movement features, including the velocity and acceleration of cursor motion, absolute deviation from the straight line between starting and ending points of a trajectory, hover time and many others. With continued interest and innovation, the mouse cursor trajectory method is likely to become a standard procedure for psychological tests, especially for the study investigating individual differences underlying cognitive, affective, and perceptual processing.

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