Increasingly, cognitive psychologists are using response dynamics (i.e. tracking participants’ movements while making a motor response) as a dependent measure. The purpose of this review is to provide a brief history of this technique, an introduction to its practical use, and some examples of applications relevant to cognitive psychologists. Those seeking greater detail on the technique are referred to articles in bold in the reference list.

Perhaps the best known techniques for tracking response dynamics are eye tracking and measures of brain activity (e.g. EEG, MEG) the use of which is well established in cognitive psychology. We focus here on how a simpler, cheaper, and less intrusive technology, the humble computer mouse, can be used to capture the temporal dynamics of cognition. Although other motion tracking methods are available none are as cheap, natural for participants, or readily available as the mouse. Before we look at how to use a mouse to capture movement dynamics, we provide some theoretical justification and examples illustrating that mouse trajectories may be linked to cognitive processes.

Early cognitive psychologists focused on the information processing metaphor: the idea that cognition may work like a computer which operates on discrete abstract symbols that have been transduced from static stimuli and outputs a motor response. This framework left little room to consider the interplay between mind and body. Thus motor responses were largely thought to be distinct and separate from the processes with which cognitive psychologists should concern
themselves (see Rosenbaum, 2005, for a detailed analysis of motor controls neglect). Arguably, with the notable exception of eye tracking and imaging techniques, this has led to the majority of the cognitive psychology literature relying on measuring simple discrete outcomes: the choices made and the time it took to make those choices (RT). Although invaluable, these measures are fundamentally limited: they represent the end state of the process. Modern conceptions of cognition, however, do not view the processes of encoding, storing, retrieving, and responding as discrete states, but instead as continuous graded states, in which mind, body and environment interact (e.g., Spivey & Dale, 2004). Motor responses co-exist in a complex feedback process whereby our actions are constantly interlinked with our cognitive state (Freeman, Dale, & Farmer, 2011; Spivey, Richardson, & Dale, 2009). For example, when reaching for an object which subsequently moves, the hand movement is updated and altered by feedback from the physical world (Goodale, Pélisson & Prablanc, 1986, see Song and Nakayama, 2009 for a review). Such changes of mind can be captured by mouse movements and modelled as embodied choice: a bidirectional relationship between action and decision (Lepora & Pezzulo, 2015). It should be noted that the millisecond continuous nature of mouse trajectories may be an overstatement and simplification and that the recorded trajectories might be composed of several discrete steps towards a response (see Friedman, Brown, and Finkbeiner, 2013; see also Fischer & Hartmann, 2014, for important considerations).

To illustrate the use of mouse tracking in cognitive psychology, we focus on examples from language including phonetics, sentence verification, and bilingualism. Initially, the use of computer mouse movements as an index of response indecision attempted to address differences between discrete and dynamic models of language processing. Spivey, Grojean, and Knoblich (2005) had participants identify a spoken word by selecting an object on screen. The objects displayed were phonetically similar, e.g. candle and candy. By analysing the curvature of the mouse trajectories during responses, Spivey et al. (2005) found that, consistent with dynamic models, the mouse first moved towards the incorrect response before moving towards and choosing the correct response.
Dale and Duran (2011) asked participants to verify whether simple negated statements such as “Elephants are not small” were true or false and manipulated the pre-context in which it was shown (through a simple pre-able to the sentence or enhanced pragmatics, to setup the anticipation of plausible denial for negated sentences). They concluded that whether negation affected the curvature of the mouse trajectories (i.e. whether the trajectory first moved towards the incorrect response) depended on the pragmatic implications of the context (whether or not they facilitated the parsing of a negated sentence, e.g. through plausible denial). Incera and McLennan (2016) used mouse tracking to address discrepancies in previous findings as to whether bilinguals are especially able to inhibit irrelevant information. Using a Stroop task they were able to examine the complexity of the mouse trajectories and explore the different processing style of bilinguals. Incera and McLennan found that bilinguals took longer to initially move the mouse but moved towards the correct response faster than monolinguals. Because these two differential effects would effectively cancel each other out in a mean RT, evidence for bilingual differences would not have been demonstrable using mean RT alone. Tomlinson, Bailey and Bott (2013) used mouse trajectories to provide support for a two-step derivation model of scalar implicatures (e.g. “Some elephants are mammals”), which is false insofar as it implies “Not all elephants are mammals”), in an experimental paradigm where mean RTs would be unable to distinguish a two-step process from a costly single-step process.

As well as language, mouse tracking has been used to study key cognitive areas such as recognition memory (Papesh & Goldinger, 2012); prospective memory (Abney, McBride, Cone & Vinson, 2015); decision making (McKinstry, Dale, & Spivey, 2008); categorization (Dale et al., 2007) and social cognition (e.g., Freeman & Ambady, 2009). In our own lab we have used mouse tracking to investigate the time course of information processing. Previously, psychologists wishing to investigate the dynamics of a process (without the associated costs of imaging or eye tracking) moved from a respond-when-ready task to signal-to-respond (STR) tasks. Such STR tasks typically involve instructing participants to respond at a randomly chosen time point after stimulus onset.
Times are selected such that responding ranges from chance level (very soon after stimulus onset) to asymptotic responding (several seconds after stimulus onset), enabling researchers to see how responses might change over the typical time course of a trial. Although STR methodologies provide an important means to model and understand the dynamics of a process (see Kent Guest, Adelman, & Lamberts, 2014), they have limitations: responding to a prompt interrupting normal processing is unnatural, which requires lots of practice (i.e. many trials); not every participant is able to respond within a strict time window (leading to a select sample); it is inefficient in that a typical STR experiment requires at least 5-7 signal times and responses that are too fast or too slow must be discarded; and, most importantly, it may add an additional cognitive load (participant must attend for a signal and potentially prepare to output a response outside of normal processing). We suggest that tracking a computer mouse trajectory may provide an alternative way to trace the time course of cognition which is more natural (our typical undergraduate population are expert mouse users, requiring no training), more efficient (each trial provides a complete trajectory from stimulus onset to response), and doesn’t require an additional cognitive load (participants need not even be aware their mouse is being tracked).

We have used mouse tracking to investigate the false memory effect in the DRM paradigm (we demonstrated that Critical, unseen lure, words produced more linear, direct movements when responding “Old” than correct recognition of Studied words, whilst correct rejections of Critical words showed an early bias towards “Old”); negation in sentence processing (increasing the episodic predictability of a critical word in a negated sentence resulted in a lower proportion of trials showing curvature towards the incorrect response, in contrast to previous findings relating to pragmatic predictability); attention allocation in visual discrimination (decreasing the number of distractors, increasing the number of cues and targets plus having the response option and target share characteristics such as location or orientation made locating a target easier, as was shown in smoother more direct response trajectories); and the time course of feature perception in object categorization (the saliency of a single feature affects the response trajectory in perceptual
matching, and the combination of features in a single object determines the trajectory in a categorization task. Thus, mouse tracking can be used to study both the time course of ambiguous decisions (over several seconds) and low level feature perception and attention allocation (in the order of several hundred milliseconds). We outline next the main steps involved in using this methodology.

Most programming languages provide a relatively simple set of commands to abstract mouse position (X Y coordinates) over time and so it is relatively straightforward to include mouse tracking in your experiments. Alternatively, Mousetracker is a freely available software package for Windows PCs (Freeman & Ambady, 2010) that allows researchers to quickly (and freely!) set up and analyse simple mouse tracking experiments. Mousetracker offers an optional interactive GUI interface for designing experiments, or you can edit a .csv file that contains the experimental parameters and trial lines; it also provides an interface to many other languages typically used to program experiments. Currently, Mousetracker allows you to import video, audio, images and letter strings as stimuli and to have up to 4 response options. As well as designing the experiment, Mousetracker allows you to explore the data collected from your experiment in its own GUI, or process the data and export it in .csv format for analysis in your software of choice. We have used Mousetracker successfully for undergraduate and postgraduate student projects, which gives students the ability to design and run their own experiments in a short amount of time. For more details see www.mousetracker.com.

Whatever your preferred software solution, a typical trial in a (two choice) mouse tracking experiment will involve the participant clicking a ‘Start’ button (located at the bottom centre of the screen) which will locate the mouse in the same start position at the beginning of each trial. The stimulus is then presented. Participants are usually encouraged to respond quickly by moving the mouse within a short duration of stimulus onset (thus capturing online responding, rather than the end state of processing). Response options are generally located at the top left and top right of the
screen, allowing for the longest possible response trajectory, and the trial ends when a participant clicks one of the responses. As an approximation, 20-30 trajectories per condition per participant provides a reasonable set of data, similar to using RT as a dependent variable.

The data obtained from mouse tracking is rich and extensive, open to a range of descriptive and inferential analyses (see Hehman, Stolier, & Freeman, 2014, for a detailed discussion). Due to the variability in individual trial duration, the trajectories for each trial tend to be normalised first, by linear interpolation into a fixed number of time bins (typically 101). This allows trajectories’ spatial patterns to be averaged and compared when conditions and/or trials may vary considerably in RT. Depending on your design and analysis, you may also want to transpose trajectories from the one response choice location onto the other, to allow a direct comparison between the two trajectories (for example comparing responses trajectories to ‘Words’ and ‘Non-words’). Once the data has been prepared, and any data cleansing taken place (for example removing any obviously erratic movements) you have a range of possible trajectory statistics to explore. The two most often reported are the Area Under Curve (AUC) and the Maximum Deviation (MD). Both are calculated relative to an imaginary trajectory extending from the start X,Y position to the end X,Y position in a straight line (an ‘optimal’ trajectory). AUC is the geometric area between the observed trajectory and the imaginary one. MD is the greatest distance between the observed and imaginary trajectories. These are typically highly correlated (a large MD will likely coincide with a large AUC, meaning you can usually use one or the other rather than both). In addition other measures include: initiation time (how quickly the mouse moves at the onset of the stimulus); x and y ‘flips’ (the number of reversals along the x or y axis; which can be taken as a measure of uncertainty or complexity of the trajectory); the entropy of the trajectory (the degree of irregularity and predictability of a movement); MD time (the point in time at which the trajectory reaches the MD); the x and y position over time (allowing you to plot each trajectory or the average trajectory); in addition if using raw time (non-normalised) then velocity, acceleration, and angle of heading can be plotted over time. Raw time analysis is useful when looking at specific temporal aspects of data.
A typical approach is to average the X,Y coordinates for each time bin across participants to leave you with a single averaged X,Y trajectory plot for each condition that you are interested in comparing. From this you can visually judge whether a movement appears to have any distinguishing features based on condition before moving onto any further analysis. In order to check whether overall differences exist between conditions, tests comparing the average MD or AUC (or other derived measures) can be run. One potential issue in the analysis of average response trajectories is the possibility that the data contain distinct types of trajectory patterns. For example, it is not uncommon to see trajectories that move smoothly and directly to a response, whereas others move first to one response, before changing direction mid-flight to the other response. Averaging across these two trajectory types can give the misleading perception that trajectories are drawn smoothly on an intermediate trajectory with an initial target appearing to lie between the correct and incorrect responses. Although tests of bimodality exist (for review of commonly used tests see Freeman & Dale, 2012), our own experience suggests visualization using density plots of MD (or AUC) can clearly highlight bimodality (if statistics are required to confirm bimodality, then Gaussian mixture modelling, for example, can be employed). Bimodal data can have particular implications for debates centred around single versus dual process models of cognition (see Freeman & Dale, 2012). However, analysis of bimodal data is trickier, and not so amenable to standard statistics most psychologists are familiar with. In our own experience we have found several approaches to analysing bimodal data useful ranging from classifying trajectories by eye, to using Gaussian Mixture models or K-means clustering algorithms over X coordinates or X,Y pairs to estimate the proportion of each trial type, and comparing density plots via Kolmogorov-Smirnov tests. Nonetheless, this type of data and analysis is less familiar and less well understood than typical psychological variables.

Overall, for many cognitive tasks we believe that mouse tracking can offer a finer grained insight into the decision processes at stages earlier than response termination. We have found it a useful alternative to STR tasks. Given the ready availability of computer mice and free software or
easy integration with existing code, mouse tracking may be a useful tool to add to your methodological repertoire.

References


