OBSERVATION

Do Curved Reaching Movements Emerge From Competing Perceptions? A Reply to van der Wel et al. (2009)

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Spivey, Grosjean, and Knoblich (2005) reported smoothly curved reaching movements, via computer-mouse tracking, which suggested a continuously evolving flow of distributed lexical activation patterns into motor movement during a phonological competitor task. For example, when instructed to click the "candy," participants' mouse-cursor trajectories curved conspicuously toward a picture of a candle before landing on the picture of the candy. In their commentary on this work, van der Wel, Eder, Mitchel, Walsh, and Rosenbaum (2009) describe a quantitative simulation of reaching movements that stands as an existence proof that a discrete-processing speech perception system can feed into a continuous-processing motor movement system to produce reach trajectories similar to that observed by Spivey et al. In this reply, we describe eye-tracking evidence, new mouse-tracking evidence, and a dynamic version of van der Wel et al's simulation, all of which suggest that competing perceptual representations may instigate the preparation of multiple movement plans that are merged in a dynamically weighted average, thus producing a single smoothly curved movement. Like van der Wel et al., we are optimistic that an emphasis on the computational linking hypothesis between hypothesized perceptual representations and recorded motor movements will elucidate the discrete versus continuous aspects of perceptual, cognitive, and motor processing.

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When inferring the character of underlying cognitive processing from behavioral data, it is crucial to consider alternative models that may generate those data. The semicontinuous arm movements identified by Spivey, Grosjean, and Knoblich (2005) can be modeled by a system that cascades continuously from cognition into action. However, the existence proof offered by van der Wel, Eder, Mitchel, Walsh, and Rosenbaum (2009) is an exemplary demonstration of the need to consider alternative frameworks that may generate continuous behavioral results from systems that contain some serial-processing components. We are sympathetic to these efforts, and agree that their model does indeed capture some general findings of Spivey et al. (2005). Nevertheless, in considering this alternative simulation carefully, along with further empirical data obtained since Spivey et al. (2005), we argue in this reply that our continuous model has several advantages.

A general consideration that seems to favor our continuous interaction model is that it assumes the same continuous cascading principle for perceptual, cognitive, and motor processing (cf. Spivey, 2007). In contrast, the van der Wel et al. (2009) model assumes qualitatively different processing dynamics in perception and in motor control. Perceptual or cognitive processing is modeled as discrete whereas motor processing is modeled as continuous. Unless there are strong reasons to assume an asymmetry, the principle of parsimony suggests that the explanation with fewer assumptions should be preferred. Although perceptual and motor systems do have some distinguishable functions and brain regions, they also share many of them, and thus it seems implausible that they would operate by such categorically different dynamics.

In fact, there is a growing consensus that perceptual processing is not discrete. Most current research on perception challenges traditional stage-based models that assume serial and discrete

processing. (However, for higher-level cognitive processes, the debate continues; cf. Dale, 2008; Dietrich & Markman, 2003; Rogers & McClelland, 2004.) A majority of perception researchers seem to agree that real-time perception is a highly parallel, distributed, and interactive process (e.g., Balota & Abrams, 1995; Bar, 2003; McClelland, Mirman, & Holt, 2006; Tipper, Howard, & Jackson, 1997). This assumption is also broadly accepted in neuroscience research (e.g., Mumford, 1992; Rolls & Tovee, 1995; Zeki, 1998). Thus, although perception has been conceived of as a discrete process in the past, recent research strongly favors the assumption of continuous parallel processing.

In the field of psycholinguistics in particular, spoken word recognition is almost unanimously accepted as involving a continuous uptake of acoustic-phonetic input contributing to the activation of multiple lexical representations simultaneously (e.g., Allopenna, Magnuson, & Tanenhaus, 1998; Gaskell & Marslen-Wilson, 2002; Marslen-Wilson, 1987; McClelland et al., 2006; Samuel, 1997). Therefore, making such a claim was not the primary message of Spivey et al. (2005). The primary message was that by tracking continuous reaching movements, we can access richer evidence for this temporal continuity in mental representation than has been observed in the past with reaction times and with saccadic eye movements; because the graded character of processing is present even in response dynamics, suggesting that this continuity in perception may blend all the way through cognition into action.

However, Van der Wel et al.'s (2009) simulation elegantly demonstrates that the overall pattern of curvature from such data could be produced by a model that asynchronously smoothes together two discrete commands of the motor system in time (i.e., one movement straight upward and then one movement toward the target object). The van der Wel et al. simulation assumes that the correct lexical representation is the only one that is transmitted from the word recognition system to the motor output systems. That is, the model does not incorporate errors into its performance. As traditional spoken word recognition experiments (using lexical decision and naming tasks) tend to exhibit rather few errors, one can imagine that this omission is of little concern. However, eye-tracking experiments with spoken language tasks (e.g., Allopenna, Magnuson, & Tanenhaus, 1998; Eberhard, Spivey-Knowlton, Sedivy, & Tanenhaus, 1995) have shown a substantial proportion of what might be called "proto-errors," brief eye movements to the foil object with a name (e.g., "candle") that is similar to the spoken target word (e.g., "candy"). These proto-errors indicate that competing lexical representations routinely make their way out of the word recognition system to drive motor movement, at least briefly.

In addition to those errant eye movements, recent analyses of computer-mouse data provide further evidence that multiple competing cognitive alternatives tend to find a way to influence motor output. For example, the greater curvature for competition conditions than for control conditions in mouse-tracking tasks arises not only from late deflections in the trajectory (which the van der Wel et al. simulation nicely accommodates) but also from early ones. When Dale, Kehoe, and Spivey (2007) had participants categorize animals into their taxonomic classes by mouse-clicking options on the computer screen, atypical category members (such as whale being a mammal) not only elicited greater overall trajectory curvature, but also showed subtly different angles of movement

initiation (when compared to typical category members, such as a horse being a mammal). Thus, even the very first pair of mouse-position samples revealed that control conditions immediately elicit computer-mouse trajectories that are reliably aimed more directly at the correct target than do competitive conditions. Because the current version of the van der Wel et al. model employs an initial straight-upward movement that is unaffected by perceptual and cognitive processes related to the response alternatives, it cannot accommodate those data.

This kind of early deflection is also present in the original data from Spivey et al.'s (2005) spoken word recognition task. Although it is not significant in the leftward movements, the rightward movements reveal a reliable angular difference between the mean direction formed by the first two samples in the cohort condition and in the control condition ($p < .05$). This pattern can be seen in van der Wel et al.'s Figure 1 (reproduced from Spivey et al., 2005). Panel A of that figure shows close overlap between control and cohort departures, but panel B shows some detectable separation between the two trajectories even early on.
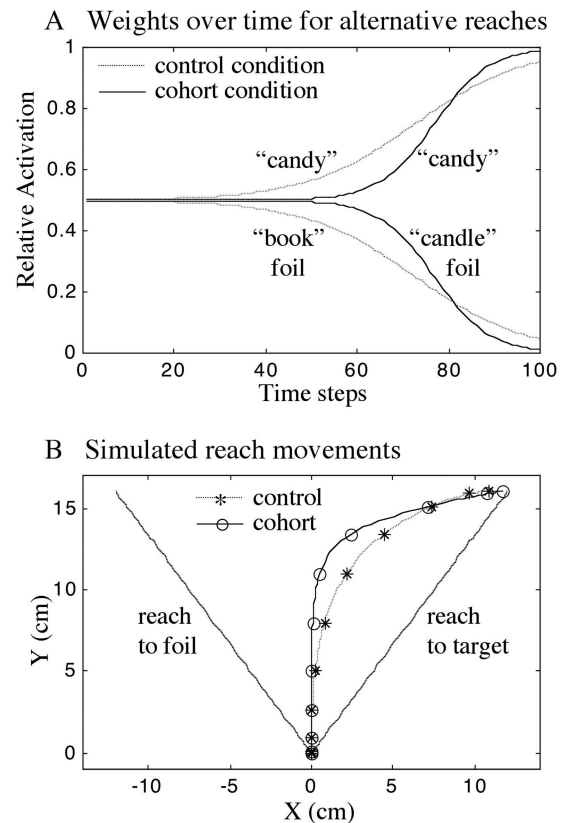

A Weights over time for alternative reaches

B Simulated reach movements

Figure 1. Panel A shows relative activation curves that are representative of those produced by continuous-processing spoken word recognition models. These curves are used as weights-over-time for the "reach to target" and for the "reach to foil" (dashed lines in panel B, constructed via Henis & Flash's, 1995, polynomial equation), and then added together. The result is a smoothly curved movement, where the cohort condition (solid line) shows greater curvature than the control condition (dotted line), because of the prolonged activation of the competing foil lexical representation (panel A). Circles and asterisks indicate the 0th, 10th, 20th, and so forth, normalized time-steps.

A further challenge for the van der Wel et al. model comes from a recent experiment by Kukona, Rueckl, Aicher, Magnuson, and Theophanis (2008), where they replicated Spivey et al.'s (2005) design but with three pictures of objects instead of two. The target object (e.g., a goat) was presented in the upper center of the screen and was flanked either by a pair of neutral distractors (control condition) or by a cohort competitor (e.g., a ghost) on one side and a neutral distractor (e.g., a pickle) on the other side. With a display arrangement like this, the current version of the van der Wel et al. model can predict interesting velocity changes as a result of presence or absence of the cohort competitor, but is unable to predict any curvature in the trajectory because the initial routinized movement and the subsequent target-directed movement are both straight upward. However, Kukona et al. (2008) found that computer-mouse trajectories reliably curved toward the competitor object on their way up to the target object.

Thus, van der Wel et al.'s (2009) assumption that discrete signals from cognition are serially entered into the motor system does not seem to be well supported by recent data from eye-tracking and reaching tasks. A framework that allows multiple perceptual representations, with graded activation levels, to act as bias weights for multiple simultaneously available movement commands can naturally accommodate those data, as well as reaction time data from more traditional cognitive tasks (Spivey, 2007; Spivey et al., 2005; for related models, see Bullock & Grossberg, 1988; Cisek, 2007; Erlhagen & Schöner, 2000; Schutte & Spencer, 2007; Tipper, Howard, & Houghton, 2000).

In fact, the Henis and Flash (1995) model that van der Wel et al. borrow is amenable to this framework. To explore this, we created a modified version of this model that incorporates simultaneous and competing motor commands. In our simultaneous-commands Henis and Flash simulation, we do not assume a routinized straight-upward first movement that is unaffected by perceptual input, followed by a second movement that is toward the correct target. Rather, we instead simultaneously compute two alternative movement commands (much like what is seen in premotor cortex; Cisek & Kalaska, 2005), which combine in a weighted average to produce the actual movement. All that is needed is to have one of those weights gradually ramp up from 0.5 to 1.0, whereas the other weight gradually ramps down from 0.5 to 0. The resulting weighted average of these two simultaneous movement commands is a single continuous trajectory that starts out toward the midpoint of the two alternative destinations and then smoothly curves toward one of them. Importantly, those gradually ramping weights for the two alternative movement commands can come directly out of a parallel competitive spoken word recognition system (such as McClelland and Elman's [1986] TRACE model), in the form of relative activations of the corresponding lexical representations.

Figure 1A shows an example of the kinds of relative activation curves that are produced by parallel competitive spoken word recognition models, where multiple lexical alternatives are simultaneously partially active, and over time one of them wins while the others lose. We have simplified the curves here with a variant of the logistic function. The winning representation (corresponding to the target object) rises in activation over the course of 0 to 100 idealized time-steps via the following equation: $.5 + 1/(2 + e^{-(x-80)/k})$, where the parameter k determines how quickly the curve rises (set at 12 for the control condition and half that for the cohort condition). The losing representation (corresponding to the foil object) drops

over time with an activation of 1-target. By multiplying the direct reach to the target (dashed line on right side of Figure 1B) by the target's activation curve (Figure 1A), then multiplying the direct reach to the foil (dashed line on left side of Figure 1B) by the foil's activation curve (Figure 1A), and simply adding the two resulting x-vectors and the two resulting y-vectors, our simultaneous-commands Henis and Flash model produces the curved mouse movements shown in Figure 1B. It is worth noting that, as seen with Dale et al.'s (2007) angle differences in movement initiation discussed above, the control-condition trajectory (asterisks) begins to detectably deviate from the vertical midline, leaning rightward by a fraction of a cm, by time-step 5. In contrast, the cohort-condition trajectory (circles) does not detectably deviate from the vertical midline until time-step 20.

Overall, the converging data from eye-tracking and mouse-tracking tasks, as well as results from a simulation that uses the Henis and Flash equations, convince us that simultaneous competing action plans do generate systematically graded trajectories in such processes as spoken-word recognition, categorization, and sentence processing. Nonetheless, we agree with van der Wel et al. (2009) that the discrete approach to planning may be important in certain contexts. Under certain circumstances, reaching movements are consistent with a model that emits one discrete motor command followed by another. For example, Farmer, Anderson, and Spivey (2007, Experiment 3) gave participants a "click the green square" task where a small portion of the trials changed which square was green once the mouse began its movement. About 90% of these trick trials produced very angular curved trajectories, indicative of a sequence of two discrete motor commands. Some cognitive-motor tasks may involve "sudden changes of mind" that would be described better as a sequence of discrete commands to the motor system than as a dynamically weighted average of two simultaneous commands.

The work presented by van der Wel et al. (2009) is therefore a valuable contribution to understanding the relationship between cognition and action in higher-level cognitive processes where such discrete changes may occur frequently, such as decision-making (e.g., McKinstry, Dale, & Spivey, 2008). This work speaks directly to the pressing need to have computational models that capture the unfolding of high-level processes from cognition all the way into action planning and execution. For example, movement properties such as force, velocity, acceleration, jerk, movement duration, and trajectory disorder may all relate in systematic and interesting ways to processing that spans quite a range of cognitive complexity (e.g., Balota & Abrams, 1995; Bullock & Grossberg, 1988; Dale, Roche, Snyder, & McCall, 2008; McKinstry et al., 2008). Thus, we hope the current work inspires further exploration of both discrete and continuous simulations as contenders for describing cognitive and motor processes.

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