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On-line confidence monitoring during decision making

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ABSTRACT

Humans can readily assess their degree of confidence in their decisions. Two models of confidence computation have been proposed: post hoc computation using post-decision variables and heuristics, versus online computation using continuous assessment of evidence throughout the decision-making process. Here, we arbitrate between these theories by continuously monitoring finger movements during a manual sequential decision-making task. Analysis of finger kinematics indicated that subjects kept separate online records of evidence and confidence: finger deviation continuously reflected the ongoing accumulation of evidence, whereas finger speed continuously reflected the momentary degree of confidence. Furthermore, end-of-trial finger speed predicted the post-decisional subjective confidence rating. These data indicate that confidence is computed on-line, throughout the decision process. Speed-confidence correlations were previously interpreted as a post-decision heuristics, whereby slow decisions decrease subjective confidence, but our results suggest an adaptive mechanism that involves the opposite causality: by slowing down when unconfident, participants gain time to improve their decisions.

1. Introduction

Confidence is defined as our degree of belief that a certain thought or action is correct (Grimaldi, Lau, & Basso, 2015; Meyniel, Sigman, & Mainen, 2015). There is growing evidence that humans and other animals possess a sense of confidence in their decisions (Baranski & Petrusic, 1994; Grimaldi et al., 2015; Kepecs & Mainen, 2012; Kiani & Shadlen, 2009; Meyniel, Schlunegger, & Dehaene, 2015). Although confidence can be subject to various biases, the very fact that animals and humans are able to approximate the likelihood of a decision being correct is an impressive feat that fits with the increasingly influential view that the brain is able to compute with probabilities and their distributions (Beck et al., 2008; Kording & Wolpert, 2004; Pouget, Drugowitsch, & Kepecs, 2016). However, precise knowledge of how confidence is computed is still lacking. Two classes of models of confidence computation can be contrasted. One class emphasizes that confidence is computed in a post hoc manner, in order to retrospectively evaluate a recent decision (Balakrishnan & Ratcliff, 1996; Ferrell, 1995), using heuristics and post-decision variables (Kahneman & Tversky, 1982; Pleskac & Busemeyer, 2010; Resulaj, Kiani, Wolpert, & Shadlen, 2009). For instance, one model proposes that subjects use a summary of the decision process, namely, reaction time, as an index to confidence: trials that are responded fast are judged as more likely to be correct, which is indeed a valid heuristic in many situations (Kiani, Corthell, & Shadlen, 2014). Another computational model proposes that confidence is based not only on the evidence accumulated to make the decision, but also on additional evidence accumulated after the decision (Pleskac & Busemeyer, 2010). In general, this approach tends to view confidence judgment as a slow and imperfect mechanism, that follows decision making and uses memory and heuristics to re-evaluate our decisions (Dunlosky & Metcalfe, 2008).

Another class of models, however, emphasizes that a sense of confidence can emerge from the decision-making process itself. According to this account, confidence is computed online throughout the decision-making process, in parallel to or even as part of the accumulation of evidence that supports the decision (Fetsch, Kiani, & Shadlen, 2014; Kiani & Shadlen, 2009; Meyniel et al., 2015). For example, one computational model proposes that the brain can process probability distributions and therefore, throughout the decision-making process, carries a full representation of the probability that a given inference is correct (Pouget et al., 2016). Such online monitoring of confidence could be helpful in regulating our decisions while they are being made, for instance in order to withhold decision and look for more information (Meyniel et al., 2015).

The online and post-decisional accounts of confidence are not mutually exclusive but complementary: even if confidence is computed

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online, it can still be submitted to various post-decisional transformations and biases before one reaches a conscious, reportable level of subjective confidence in a decision. However, while evidence for post-decisional confidence processing is well-established (Pleskac & Busemeyer, 2010; Resulaj et al., 2009), the existence of online, pre-decisional confidence monitoring processes is still debated (Pouget et al., 2016).

Measuring pre-decision confidence poses methodological challenges. Most metacognitive paradigms are retrospective, asking participants to rate their subjective confidence in a past decision (Dunlosky & Metcalfe, 2008). Other paradigms, allowing the participant to opt out of the decision (Fetsch, Kiani, Newsome, & Shadlen, 2014; Kiani & Shadlen, 2009), provide behavioral information about the decision (when the participants do not opt out) or about confidence (by comparing opt-out and no-opt-out trials), but not about both on a given trial. Implicit measures of confidence derived from neural recordings (Charles, King, & Dehaene, 2014; Fetsch et al., 2014; Kepecs, Uchida, Zariwala, & Mainen, 2008; Kiani & Shadlen, 2009; Kiani et al., 2014) avoid these problems, but they rely on invasive electrophysiological or costly brain-imaging measures from which it remains difficult to disentangle decision and confidence signals. Here, we show how an elementary behavioral measurement – tracking the participants' finger movement during decision making – can be used to analyze the decision-making process and obtain separate implicit measures of a prospective decision and the associated confidence.

30 human adults performed a simple two-alternative forced-choice task on a touchscreen. On each trial, 1, 3, or 5 arrows, each pointing leftward or rightward, were presented sequentially, and participants were asked to decide whether most arrows pointed to the left or to the right. This paradigm is inspired by the classical Shadlen-Newsome motion direction detection task in which sensory evidence must be accumulated across time (Shadlen & Newsome, 2001). However, our stimuli were not continuous but employed few discrete bouts of evidence, thereby allowing for a precise analysis of changes in decision making (de Lange, Jensen, & Dehaene, 2010; de Lange, van Gaal, Lamme, & Dehaene, 2011; Yang & Shadlen, 2007). In the Discussion, we elaborate further on the similarities and differences between our paradigm and classical paradigms of perceptual decision making. Crucially, our participants responded by continuously moving their finger on the touchscreen from a fixed starting point to one of two response buttons, without ever stopping (Fig. 1). Previous studies showed that changes in finger direction reflect intermediate stages of decision making (Berthier, 1996; Erb, Moher, Sobel, & Song, 2016; Friedman, Brown, & Finkbeiner, 2013; Pinheiro-Chagas, Dotan, Piazza, & Dehaene, 2017; Resulaj et al., 2009). Here, given previous results on confidence and decision times (Baranski & Petrusic, 1994; Kiani et al., 2014), we propose that, additionally, the instantaneous finger *speed* reflects online fluctuations in the participant's prospective confidence that the final decision will be correct.

2. Method

2.1. Participants and task

The participants were 30 university students (mean age = 25;11, SD = 4;0) and gave informed consent prior to participating. One participant rated almost all trials (97%) as "100% confident" and was excluded. On each trial, participants saw on a tablet computer a sequence of arrows that included one arrow (2 possible sequences, each presented 64 times), 3 arrows ($2^3 = 8$ sequences, 16 times each) or 5 arrows (32 sequences, 12 times each). The numbers of arrows were not disclosed to the participants. They were instructed to indicate where the majority of arrows pointed to by dragging their finger from a starting point at the bottom of the screen to a response button on the top-right or top-left corner of the screen (Fig. 1a). Touching the starting point triggered a central fixation dot on the top of the screen, where arrows appear, and finger movement (crossing y = 50 pixels from the bottom of screen) triggered the arrow sequence. We used an Apple iPad air with 1024 × 768 resolution (5.2 px/mm), black background, white arrows (150 × 50 px), and grey response buttons (200 × 100 px) and starting point (60 × 40 px). Lifting the finger in mid-trial, moving the finger backwards, or starting a trial with sideways (rather than upward) movement, aborted the trial. Trials were also aborted when the finger movement was too slow (excluding a grace period of the trial's first 300 ms): less than 3 s per trial or less than 1.5 s to reach the first third of the screen. Aborted trials were excluded from analysis and presented again later in the experiment. Immediately after each trial, participants rated retrospectively their subjective confidence about their decision (i.e. the probability of the decision being correct) on a continuous vertical scale (top = "I'm sure"; middle = "I have no idea"; bottom = "I'm sure I was wrong"). The scale was presented in the middle of the screen, i.e., to rate their confidence, the participants first had to move their finger from the top of the screen, where it was at the end of the trial, back to the middle of the screen. Statistical analyses were done with Matlab and R (R Core Team, 2015). In http://trajtracker.com, we provide our trajectory-tracking analysis tools as well as a Python-based experimentation software equivalent to the one that we used here. The trajectory raw data is enclosed as Supplementary online material.

2.2. Data processing and terminology

Evidence is the sum of all stimulus arrows (→ is +1, ← is −1). |*Evidence*| is its absolute value. *Accuracy* is the fraction of correct responses. *Confidence rating* refers to the participant's post-decision subjective rating (0–100 scale). *Movement time* is the time from the first arrow onset (which is immediately after the finger started moving) until the finger reached a response button, and *average speed* is the inverse of movement time. *Time point* refers to a particular time within a trial,

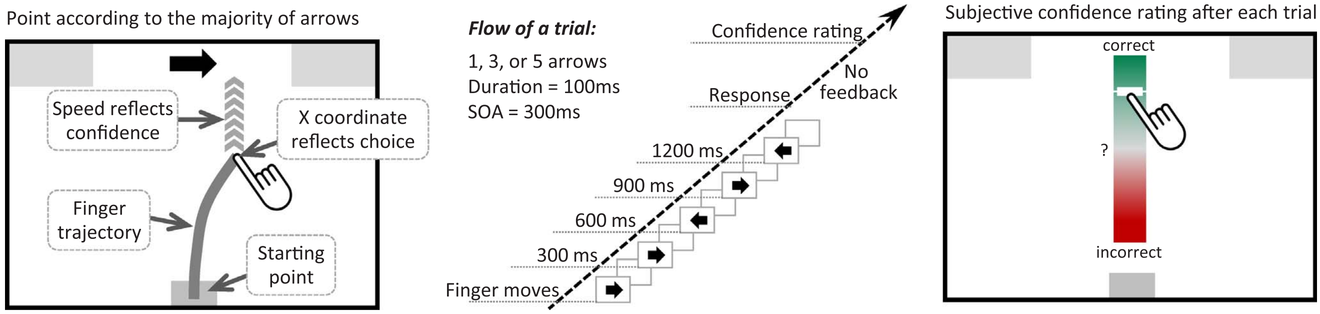

Fig. 1. Task and screen layout. On each trial, 1, 3, or 5 arrows, each pointing left or right, were presented sequentially. Participants dragged their finger on a touchscreen towards the response button corresponding to the majority of arrows. Their finger movement was continuously recorded. The onset of the first arrow was triggered by finger movement. After touching a response button, a slider appeared and participants rated their confidence about their decision, from "certainly correct" to "certainly incorrect". A color version of this figure is available in the online version of the article.