Investigating the Presence of 'Leaky' Accumulation in a Human Evidence Integration Signal

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Abstract:

A feature common across sequential sampling models is that decisions are formed by accumulating sensory information up to an action-triggering bound. Aside from this central ingredient, numerous model variants exist that invoke distinct algorithmic elements and adaptations. A key area of disagreement has been whether decisions are achieved by integrating evidence 'perfectly', without the loss of already obtained information, or whether evidence accumulation is subject to 'leak' whereby older samples of information are discarded or lost as time passes. The present study used EEG to investigate a previously identified signal of human evidence accumulation (the centro-parietal positivity; CPP) for signatures of leak. Twenty-three participants completed a continuous random dot motion task with the goal of detecting periods of coherent upward motion. Within half of these coherent targets, a brief 200ms 'gap' of incoherent motion was inserted. Preliminary analyses indicate that these evidence gaps produced substantial reaction time delays and a corresponding deceleration in the build-up of the CPP. However, initial analyses do not identify a negative CPP slope during the gap which would be diagnostic of leak. Our data do not support the role of leak in evidence accumulation.

Keywords: decision-making; EEG; evidence accumulation; leak

Introduction

The accumulation of noisy evidence in favour of a certain choice alternative is a key property of the decision process according to many perceptual decision making models, and has received empirical support from neurophysiological investigations in a variety of species including humans. According to the most influential sequential sampling model (the Drift Diffusion Model, Ratcliff, 1978), evidence is integrated perfectly across time, such that infinite viewing time of the stimulus would result in perfect performance accuracy. Mathematical modeling has shown that models making the assumption of perfect integration can provide excellent fits to data when the strength of the sensory evidence does not vary across time. Neurophysiological work has also shown that perfect integration may be instantiated in the human and rat brains (e.g. Brunton, Botvinick, & Brody, 2013).

However, there are several considerations which call this account into question: Firstly, the information received from the external world can change very quickly, and agents need to be able to prioritise this newer information to act accordingly within rapidly changing environments. Secondly, in temporally uncertain tasks, agents may not know precisely when to begin evidence accumulation in order to optimise the decision process and may need an ongoing evaluation of which evidence should be included in the continuous evidence total to prevent target stimuli being missed. How might the brain account for these aspects? One potential solution is the use of a 'leaky' accumulation strategy, whereby older samples of sensory evidence are discounted in favour of more recent ones in the ongoing evidence total. Leaky accumulation is a key parameter in the Leaky Competing Accumulator Model (LCA; Usher & McClelland, 2001) and other similar competing accumulator models, which have been shown to be neurophysiologically plausible. A more recent modeling study by Ossmy and colleagues (2013) showed that, specifically in temporally uncertain environments, leaky accumulation provides optimal model fits. Findings also suggest that decisions are primarily influenced by information from a limited and more recent time window (e.g. Chittka et al., 2009). It is not yet clear how representative these models are of actual brain activity, and to date there has been no neurophysiological demonstration of leak within the evidence accumulation process, making this issue a

key unanswered question in the literature (Gold & Shadlen, 2007).

It may be the case that investigations into the area of leaky integration have been hampered in the past by the standard discrete-trial paradigms often used within the field of perceptual decision making, during which participants can easily predict when the sensory evidence will appear and can alter their decision strategies on the basis of this – for example, altering when they begin their evidence accumulation process. A more realistic everyday experience of perceptual decision making involves sensory evidence that is unpredictable, and which is relayed within a continuous stream of irrelevant sensory noise. For this reason, the present study utilises a continuous version of the random dot motion task in which participants must monitor a path of incoherently moving dots for intermittent periods of coherent upward motion. In addition we leveraged a recently validated EEG signature of decision formation known as the 'Centro-parietal positivity' (CPP; O' Connell, Dockree, & Kelly, 2012; O'Connell, Shadlen, Wong-Lin, & Kelly, 2018) in order to track any potential leak within evidence accumulation. The CPP has been shown to trace the integration of sensory evidence across time, displaying a build-up rate proportional with evidence strength (O' Connell et al., 2012) and consistently preceding effector selective motor preparation signals (e.g. the Lateralised Readiness Potential), indicating that it indexes an intermediate level between sensory evidence representation and motor response preparation (Kelly & O' Connell, 2013). In the present study, the presence of leak in this human evidence accumulation signal is investigated by inserting brief gaps of incoherent motion within coherent motion targets and analysing the effect that these gaps have on the CPP. If leaky accumulation is not present, the CPP should merely exhibit a slowing of evidence accumulation directly following the gap, while if leaky accumulation *is* present, a significant downturn effect should be present in the CPP.

Methods

Data from 23 participants was analysed (12 female). Participants ranged in age from 18 to 30 years (mean age = 23 ± 3.6 years). Participants performed a continuous random dot motion target detection task in which they were required to monitor a noisy, incoherent dot motion stimulus in order to detect intermittent upward-motion targets that stepped to 25% coherence. Gaps of incoherent motion (0% coherence) were inserted during half of the incoherent targets. The targets lasted for a total of 1880ms, while the length of the gap within these coherent targets was 200ms (lasting from 175 to 375ms post evidence onset). This timing was based on the latency of peak

CPP amplitudes in previous studies. The task contained three possible lengths of time between targets (2, 4, or 6 seconds). Participants responded with a right handed mouse click every time they perceived coherent upward motion. Participants carried out 5 blocks of 42 trials. Prior to beginning the task, participants first practiced 20 trials of the task at a coherence level of 50%. Visual stimuli were programmed using the PsychToolbox extension of MATLAB. The stimulus consisted of 75 randomly moving dots, with the diameter of the patch of dots equal to 8 degrees of visual angle. Each dot was sized at 4 pixels, and during coherent motion the dots moved upwards at 90 degrees relative to a positive x-axis, at a speed of 6 degrees per second.
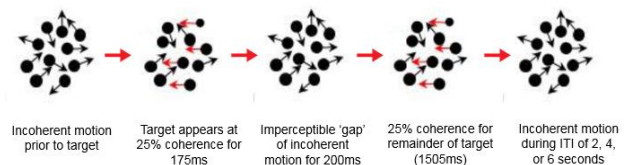

Figure 1: Experimental stimulus featuring a coherent motion target with a gap of incoherent motion inserted within it for 200ms.

Continuous EEG data were recorded from 128 scalp electrodes, digitized at 512 Hz. Data analysis was carried out using custom scripts in MATLAB that drew on EEGLAB routines. Noisy channels were interpolated and the data were re-referenced offline to the average reference. The data were low-pass filtered below 30 Hz. The EEG data were segmented into epochs between -250ms pre- and 2 seconds post-stimulus onset, and were baseline corrected relative to the average signal in the interval from -200 to 0ms relative to stimulus onset. These data were further segmented into a window of -650ms to 300ms relative to response execution for response-aligned analyses. The data were also converted to Current Source Density. The CPP was examined as an index of evidence accumulation. In the present study, for each participant, ERPs were created by averaging across single trials at a single electrode located between standard sites Cz and Pz using the 10-20 co-ordinate system, identified by visual inspection of the grand average topography. CPP build-up was defined as the slope of a straight line fitted to the stimulus-locked waveform at 450ms to 600ms.

Results

Behavioural results indicated that reaction times were significantly longer in the Gap Condition (M = 594.21, ± 112.95) compared to the No-Gap Condition (M =

495.63 ± 143.21), *t* (21) = 7.76, *p* < 0.001). Histograms are shown in figure 2.

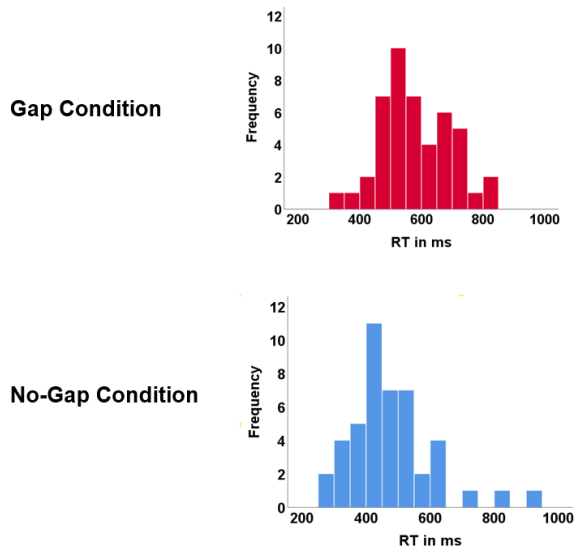**Gap Condition**

No-Gap Condition

Figure 2: Distributions of RT across Gap (red, above) versus No-Gap (blue, below) conditions.

The grand average stimulus-locked topography is shown in figure 3, with the CPP clearly visible around centro-parietal regions. The corresponding stimulus-locked CPP waveforms are also shown in figure 3 for the Gap and No-Gap conditions. The mean slope value in the Gap condition was -0.02 (± 0.20), while the mean in the No-Gap condition was 0.11 (± 0.16). This difference across Gap and No-Gap conditions was significant, *t* (21) = 3.77, *p* = 0.001. However, analysis across multiple time bins revealed that there was no time window within which the mean CPP slope was significantly negative-going.
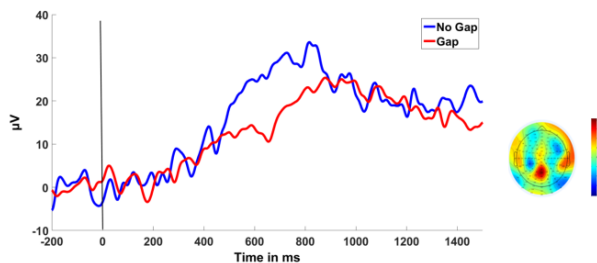

Figure 3: Grand average stimulus locked waveform across Gap and No-Gap conditions (left); Grand average stimulus locked topography in the time window 450 to 600ms (right).

Discussion

The present study aimed to use EEG data to directly track evidence accumulation in order to investigate whether human participants implement leaky evidence accumulation. It was found that, on trials containing a gap of noise within the coherent target, reaction times were significantly longer, however, previously accumulated evidence was not lost at a significant rate from the cumulative total, as would be demonstrated by a significantly negative-going CPP slope within the time period following the gap. This pattern of results provides preliminary neurophysiological evidence against the presence leak in a human evidence accumulation signal. Future directions include fitting a leaky accumulation model to the data and comparing this against a standard Drift Diffusion Model containing no leak parameter.

Acknowledgements

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