Isolating Behavioural and Neural Metrics of Within-Trial Noise in Perceptual Decision-Making

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Abstract:

According to mathematical models, neural noise operating on a within-trial timescale has a major impact on the timing and accuracy of our perceptual choices. However, the models themselves do not provide a means of estimating the noise levels of individual observers. Through a combination of psychophysics and neurophysiological recordings, the present study aims to identify reliable signatures of within-trial noise in EEG. This work can contribute to the development of novel 'neurally-informed' decision models that would be particularly beneficial in studies of individual differences or group comparisons.

Keywords: decision-making; EEG: computational modelling; neural noise

Introduction

To date, research on perceptual decision-making has relied heavily on computational 'sequential sampling' models to give insight into the latent psychological processes underpinning choice behaviour. These models hold that decisions are formed by encoding a decision variable that accumulates noisy senosry evidence to a bound (Schubert, Frischkorn, Hagemann, & Voss, 2016). A key component of many of these models is 'within-trial noise': the standard deviation of the momentary fluctuations in the decision variable's path arising from variability in the physical stimulus and/or internal sources of neural noise. However, within-trial noise is typically set as a scaling parameter in modelling studies such that it is fixed to a single arbitrary value for all individuals or experimental conditions (O'Connell, Shadlen, Wong-Lin, & Kelly, 2018). Importantly, there is mounting evidence from a variety of sources that neural noise varies considerably across individuals and clinical groups (Dinstein, Heeger, & Behrmann, 2015; Krystal et al., 2017; Saville et al., 2015). Thus there is a significant need to develop methods and models through which within-trial noise can be reliably estimated alongside the other parameters of the decision making process.

Parallel research on visual psychophysics has developed methods for estimating levels of internal noise, including the equivalent noise procedure (Dakin, Mareschal, & Bex, 2005; Tibber, Kelly, Jansari, Dakin, & Shepherd, 2014) which furnishes a behavioural estimate of an individual's internal noise and sampling efficiency in the context of one of the canonical paradigm for perceptual decision making research: random dot motion direction discriminations. This method has been used to highlight significant differences in internal noise levels between a range of clinical and non-clinical groups (Dakin et al., 2005; Manning, Dakin, Tibber, & Pellicano, 2014; Tibber et al., 2015, 2014) but has not yet been incorporated into decision modelling investigations. Here we seek to leverage the equivalent noise method in order to individually estimate within-trial noise parameter values when fitting sequential sampling models to behavioural data.

A limitation of the equivalent noise method is that it cannot allow internal noise to be estimated on a trial-by-trial basis. Therefore, another aim of the present study is to validate a novel electrophysiological marker of within-trial, internal decision noise. Recent work on human EEG isolated discrete signals that trace the neural evidence accumulation process that gives rise to perceptual decisions (O'Connell, Dockree, & Kelly, 2012; Twomey, Murphy, Kelly, & O'Connell, 2015). The present study will examine rapid fluctuations in these signals, operating within the time-course of a typical decision, in order to isolate a neural marker of within-trial decision noise.

Methods

Procedure

30 healthy adults will complete the study. Participants will first complete the equivalent noise task (Tibber et al., 2014). in which they are required to complete 150 interleaved trials detecting either minimal changes in offset-from vertical (zero-noise) or global motion direction clockwise or anti-clockwise (high-noise). In the high-noise condition the direction of each globally moving dot is chosen from a Gaussian distribution with a mean of 45°. Noise levels will be titrated using a Bayesian Quest procedure to estimate levels of tolerable noise for each trial. Estimated levels of internal noise, sampling efficiency and maximum tolerable noise will be calculated and recorded using the equivalent noise function (Tibber et al., 2014). Participants will then complete a further 8 blocks of an EEG-adapted version of the EQN task. Dots move randomly for 500ms followed by global motion ±45° from vertical for 1500ms. External noise levels will be set at each individual's maximum tolerable noise ±33%. To isolate effects that cannot be attributed to external stimulus variability (Ratcliff, Voskuilen, & McKoon, 2018), each block is comprised of 60 unique stimulus configurations which are repeated three times in random order to give a total of 180 trials per block (See Figure 1)

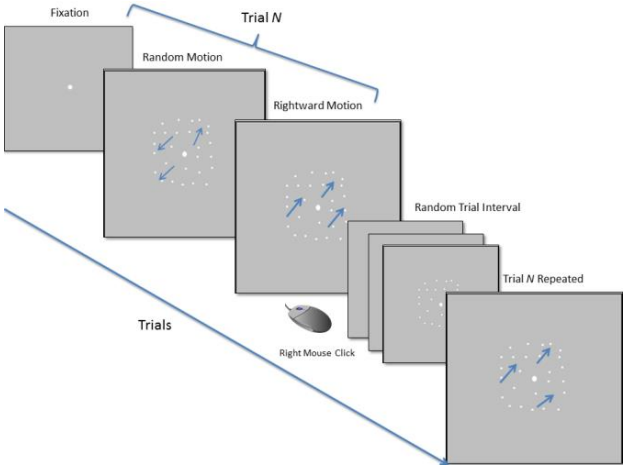

Figure 1: Task schematic for EEG-adapted experimental procedure. Dots move randomly followed by coherent global motion direction; in this case right. Each stimulus is repeated randomly three times through each block

EEG

128-channel continuous EEG data will be recorded on each block to measure electrical brain activity using an Active Two Biosemi system. Analyses will center primarily on the Centro-Parietal Positivity (CPP) which has been previously validated as a neural signature of evidence accumulation (O'Connell et al., 2012; Twomey et al., 2015). Consistent with the predictions of sequential sampling models and analogous single-unit signals observed in monkeys, the CPP builds at an RT-predictive, evidence-dependent rate and reaches its peak at the time of the decision report. We will examine the time-frequency spectrum of the CPP and identify frequencies that are within the time-scale of a typical decision (>1Hz) and that discriminate between the three external noise levels. We will then examine if inter-trial variations in these frequency components impact on choice behaviour and if inter-individual variations correspond to differences in the behavioural estimates of internal noise. In parallel we will also examine signatures of motor-preparation (lateralized 11-30Hz beta-band activity). Muscle activity at the effector level will be measured using electromyography to record bursts of electrical muscle activity at the thumbs. Pupillometry eye-tracking data will also be recorded. Channels with substantial noise will be interpolated with reference to surrounding channels. Low and hi-pass filters will be applied, minimising frequencies above 40Hz and below 0.1Hz. This data is segmented into epochs from -300ms to 2000ms from stimulus presentation and from -400 to 300ms from response execution. Trials containing excessive muscle activity around the eyes measured through external VEOG channels above and below the eye are also removed.

Results

Thus far, one participant has completed two blocks of the final version of the experiment. Mean reaction times were 514ms for Low Coherence, 651ms for Medium Noise and 729ms for High Noise. Mean accuracies were 90.83% for Low Noise, 78.33% for Medium and 55% for High Noise.

Preliminary analysis of electrophysiological data indicates an effect of coherence level on peak amplitude of the response and stimulus locked CPP's (See Figures 1 & 2). Further analysis will investigate components of this build up and bound in relation to external noise level and pass number.

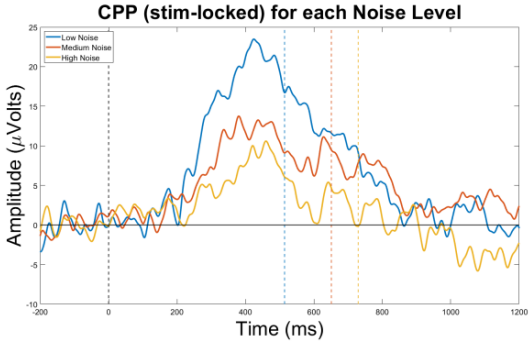

Figure 2: Stimulus-locked (-200ms to 1200ms from stimulus presentation) CPP collapsed across trials and split by noise level (blue = low, orange= medium, yellow = high). Dashed lines represent average reaction time for that condition.

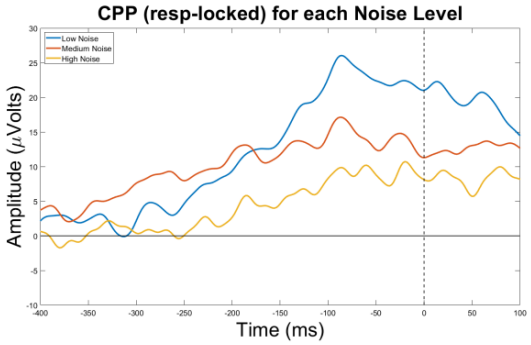

Figure 3: Response-locked (-400ms to 100ms from time of response) CPP by external noise level (blue = low, orange= medium, yellow = high).

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Discussion

The preliminary data confirm that the external noise manipulation has noticeable effects on behavioural and neural indices of decision formation. Future analysis on a fully collected sample will investigate the relationship between variability in neural signals and variability in behaviour on different passes of the same stimulus and in different noise conditions. Fast-Fourier Transforms of response and stimulus aligned CPP data will investigate high-frequency noise in the signals relatable to behavioural variability and stimulus noise. Furthermore, analysis of beta-band activity over the motor cortex and electromyographic activity over the decision-making hand will investigate the effects of within-trial noise on non-decisional components of the decision-making process. Analysis of alpha-band activity/pupil dilation will identify trial-by-trial fluctuations in attentional engagement as sources of noise in order to ultimately identify and isolate the influence of random, non-decision related within-trial noise

Ultimately it is hoped that this work will make it possible to study within- and between-individual differences in internal decision noise, providing new insights into its effects on decision making and furnishing more refined models of decision making.

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