EEG measures of neural processing speed reflect human visual encoding time

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Abstract

A method of estimating and verifying individuals' visual encoding time is proposed using traditional EEG measures before decision processing of visual information. Hierarchical Bayesian inference was used to jointly obtain posterior distributions of drift-diffusion model parameters as well as the effect of traditional and singletrial ERP measures on these parameters in a single-step. The possibility of using single-trial N200 and traditional N1 ERP latencies as estimates of human visual encoding time is explored in the framework of a neurocognitive theory of visual encoding, rapid decision-making, and motor preparation. Using data from two experiments, posterior distributions of linear-effect parameters suggest that EEG responses to the onset of visual stimuli reflect stimulus encoding times in low visual noise conditions. However the ability of these neural signals to track visual encoding time is dependent upon the quality of the external signal itself.

Keywords: Visual encoding; EEG; Perceptual decision making; Drift-Diffusion Models; Hierarchical Bayesian inference

Introduction

While research exists on the time course of primates' visual system in response to external visual inputs (Schmolesky et al., 1998), the time course of humans' visual response remains largely unexplored due to the invasiveness of prevailing techniques (e.g. single-cellular recordings). The electroencephalogram (EEG) is a noninvasive technique that records cortical synaptic activity that is synchronized across the cortex and is thought to represent higher-level function in electrophysiology (P. L. Nunez & Srinivasan, 2006). In an exploratory analysis, we propose a method of estimating and verifying individuals' visual encoding time using traditional EEG measures before decision processing of visual information. These techniques are based on joint estimation of traditional eventrelated potentials (ERPs) and cognitive models of perceptual decision making that describe human reaction time and choice distributions.

A quantitative neurocognitive theory of visual encoding, rapid decision-making, and motor preparation is proposed that explains EEG measures of encoding, EEG measures of moAishwarya Gosai (agosai@mgh.harvard.edu) Department of Psychiatry Massachusetts General Hospital and Harvard Medical School Boston, MA USA

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tor preparation, behavioral accuracy in two alternative forced choice (2AFC) tasks, and reaction time distributions. The theory is an extension of a class of Decision-Diffusion Models (e.g. "drift-diffusion" models, see Ratcliff & McKoon, 2008, for a review) which predicts that reaction time and accuracy are explained by a continuous accumulation of evidence towards certain pre-decided evidence thresholds (see Figure 1).

It is thought that particular latencies of peaks in event related potentials (ERPs; EEG in response to stimuli at certain time points) on single trials predict decision making processes (M. D. Nunez et al., 2017) and, in particular, reflect encoding time of visual stimuli (Loughnane et al., 2016). Here *encoding time* is defined as the amount of time for visual processing to occur in the human brain before decision processes can begin. Behaviorally, trial-to-trial differences and subjectto-subject differences in encoding time are predicted to affect only trial-to-trial and subject-to-subject differences in the onset of reaction time distributions, not the reaction time distribution shapes or accuracy, reflecting the fact that encoding does not affect the decision making process itself.

Methods

Decision-diffusion modeling was applied to reaction time and accuracy data from Experiment 1 that accounted for singletrial changes in non-decision time $\tau = \tau_e + \tau_m$, within-trial evidence accumulation rate δ and within-trial evidence accumulation standard deviation ς that were linearly related to singletrial changes in single-trial N200 amplitudes, single-trial N200 latencies, single-trial P300 amplitudes, single-trial P300 latencies, and two steady-state visual evoked potential (30 Hz and 40 Hz stimulus frequency tagged EEG responses). These linear relationships were estimated in a single-step in a hierarchical Bayesian framework (e.g. see M. D. Nunez et al., 2017). Decision-diffusion modeling was also applied to reaction time and accuracy data from Experiments 1 & 2 jointly (data consisted of 12 unique subjects with 2 sessions of EEG each and 4 unique subjects with 7 sessions of EEG each respectively), containing between session-differences in non-decision time τ , within-trial evidence accumulation rate δ , and speed accuracy trade-off parameter α that were explained by session differences in traditional N1 latencies (first negative peak latencies of ERPs; see Luck et al., 2000) of subject-level ERPs



Figure 1: A graphical illustration of a Neural Decision Diffusion model in which the encoding time τ_e on single-trials describes the latency of the negative peaks of the EEG on 146 single-trials in occipital and parietal locations. Single-trial observations of the N200 latency are found by using a decomposition of the average ERP response at each electrode and then biasing the raw EEG by the resulting channel weights (this algorithm is detailed by M. D. Nunez et al., 2017). Total non-decision time τ reflects both stimulus encoding time τ_e as well as residual motor response τ_m (i.e. motor preparation time distributions.

Discussion of results

Posterior distributions of model parameters for 7 subjects' single-trial N200 linear effects on single-trial non-decision time (the sum of encoding and motor response time as estimated by a hierarchical Bayesian account of a decision-diffusion model) support the hypothesis of a 1-to-1 correspondence (see Figure 2) during a two alternative forced choice (2AFC) task in which participants had to differentiate between high and low spatial frequency Gabors. However, this relationship between N200 latency and non-decision time was weaker and non-existent in medium and high noise conditions. In medium and high noise conditions. In medium and high noise conditions, further processing may be required to estimate encoding time from single-trial N200 latency measures by introducing other sources of variance. In low noise condition, the evidence suggests that the EEG response to the onset of the stimulus reflects visual encoding time.

When exploring the relationship between cortical processing time (as measured by early ERP latencies) and subjectto-subject differences in non-decision time, the ability of ERP latencies to reflect visual encoding time is more clearly dependent upon the quality of visual stimuli. In two experiments with different noise types (checkerboard visual distractor overlayed on Gabor stimuli in Experiment 1 and bandpass filtered broadband noise overlayed on Gabor stimuli in Experiment 2), the effects of session-level N1 latency differences on sessionlevel non-decision time differences (assumed by the model to be the sum of visual encoding and residual motor response time) are mediated by the contrast condition of the visual distractors. This suggest that how well the peak neural signal latency tracks visual encoding time is dependent upon the guality of the external signal itself. It is also possible that the simple decision-diffusion model does not provide a satisfactory



Figure 2: The posterior distributions of the effect of a trial's N200 latency (a visual processing component of the signal stimulus) on trial-specific non-decision times for each subject in a low noise condition. Thick lines forming the distribution functions represent 95% credible intervals while thin lines represent 99% credible intervals. Crosses and vertical lines represent posterior means and modes respectively. Also shown are the topographic representations of the channel weights of the first SVD component of each subject's ERP, indicating the location of single-trial N200s over occipital and parietal electrodes.

account of visual encoding. Or that the beginning of the negative deflection of the single-trial and subject-level EEG is a better indicator of encoding time. Initial evidence for this latter hypothesis is that early negative deflections better match visual encoding time as estimated by other modalities (e.g. see Schmolesky et al., 1998)

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