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Identification of canonical neural events during continuous gameplay of an 8-bit style video game

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ABSTRACT

Cognitive neuroscience suffers from a unique and pervasive problem of generalizability. Since neural findings are often interpreted in the context of a specific manipulation during a carefully controlled task, it is hard to transfer knowledge from one task to another. In this report we address problems of generalizability with two methodological advancements. First, we aimed to transcend status quo experimental procedures with a continuous, engaging task environment. To this end, we created a novel 8-bit style continuous space shooter video game that elicits a multitude of goal-oriented events, such as crashing into a wall or blowing up an enemy with a missile. Second, we aimed to objectively define the psychological significance of these events. To achieve this aim, we used pattern classification of EEG data to derive predictive weights from carefully controlled pre-game exemplar events (oddball target detection and gambling wins and losses) and transferred those weights to EEG activities during video game events. All major goal-oriented events (crashes into the wall, crashes into an enemy, missile hit on an enemy) had a significant between-task transfer bias towards oddball target weights in the time range of the canonical P3, indicating the presence of similar salience detection processes. Missile hits on an enemy were specifically identified as gambling wins, confirming the hypothesis that this goal-oriented event was appetitive. These findings suggest that it is possible to identify the contribution of canonical neural activities during otherwise ambiguous and uncontrolled task performance.

Introduction

The field of cognitive electrophysiology has used punctate presentations of sights and sounds to elicit reliable neural responses for over 50 years (Sutton et al., 1965), yet the generalizability of these findings remains a major unaddressed issue. Successful translation of laboratory findings will be a critical milestone towards the development of brain-computer interfaces (Bogue, 2010), augmented cognition programs (St. John et al., 2004), disease biomarkers (Meyer-Lindenberg and Weinberger, 2006), decoding of real-world cognition (Debener et al., 2012; Derix et al., 2012), as well as for mechanistic interpretation of cognitive training effects (Anguera et al., 2013). Here we address problems of generalizability and limits of isolated stimulus presentation with a novel methodological advancement. This advancement additionally satisfies a rarely achieved desideratum in cognitive neuroscience tasks: it is fun for the participant. We created a novel 8-bit style continuous space shooter video game that elicits a multitude of goal-oriented events. By leveraging pattern classification of pre-game exemplar events in the EEG (target detection, wins, and losses) and applying those weights towards video game events, we were able to identify the contribution of canonical neural activities during this ambiguous gaming context. In this report, we describe how these combined techniques reveal the generalizability of some well-known EEG phenomena (salience, reward) but not others (punishment).

It is a paradox that the exquisite temporal fidelity, multidimensionality, and sensitivity of EEG to canonical neural operations are some of the barriers that have actually hindered generalizability. Previous experiments have recorded EEG while participants played established gaming suites (Havranek et al., 2012; Salminen and Ravaja, 2008; Spapé et al., 2013; Subhani et al., 2012), or novel virtual reality environments (Callan et al., 2013; Clemente et al., 2014), yet they have only provided enough fidelity for stationary analyses. While multiple groups have developed methods for tightly integrating video game performance with external recording devices (Anguera et al., 2013; Mathewson et al., 2012; Sivanathan et al., 2014; Spüler and Niethammer, 2015), very few groups have sought to answer a priori

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questions of psychological interest, likely due to limitations of reverse inference (Poldrack, 2006).[1] A notable standout is the use of EEG activities to predict cognitive training effects and learning rate in the Space Fortress game (Maclin et al., 2011; Mathewson et al., 2012), yet these findings were limited by the slow refresh rate (~20 to 25 Hz).

Here we introduce a novel video game and analytic suite that leverages the fidelity, dimensionality and sensitivity of EEG to overcome the paradoxical limitations of this complexity. Our game operates with the same fidelity as standard EEG tasks. By classifying multidimensional EEG activities to target detection, wins, and losses during performance of standard psychological tasks and applying these classifier weights to the video game, we provide strong quantitative constraints on reverse inference. This procedure has the potential to reveal the manner of canonical neural operations during otherwise ambiguous video game events.

Materials and methods

Participants

The experiment was approved by the University of New Mexico (UNM) Institutional Review Board and all participants provided written informed consent. Participants were N = 17 undergraduates (11 male) from the UNM who received course credit for participation. The average age was 20.94 years old (SD = 5.02). All participants had normal or corrected-to-normal vision and no history of neurological, psychiatric, or any other relevant medical problem. All participants were right handed as defined by Chapman and Chapman (1987). Participants also completed the Behavioral Inhibition/Activation System scales (BIS/BAS: Carver and White, 1994). EEG was recorded continuously across .01 to 100 Hz with a sampling rate 500 Hz and an online CPz reference on a 64 channel Brain Vision system. The vertical and horizontal electrooculogram (VEOG and HEOG) were recorded from bipolar auxiliary inputs. All experiments were run on a Dell Optiplex 9010 PC (Intel i7-3770 processor) running Windows 7, with an AMD Radeon HD 7570 video card and a Dell P2213 LCD display (1680 × 1050 @ 60 Hz refresh rate). Photodiode tests indicated a reliable 40 ms delay from trigger onset to visual change; this time was accounted for in all analyses.

Exemplar tasks

Participants first completed two small tasks developed in Java with custom C code that sent triggers to the Brain Vision amplifier: an oddball task and a gambling task. The oddball task used images of the video game's Delton-class Starfighter as a standard and the enemy Glion Patroller as an oddball. Oddballs occurred with 20% probability, after at least 3 but before 10 standards (there were 40 oddballs and 160 standards). Participants were instructed to count the number of oddball images to "*determine if their neuro-perceptual processing is adequate for piloting a starfighter*". Images were centrally displayed for 500 ms with a 1000–2000 ms random inter-trial-interval marked by a fixation cross. There were no other instructions and no response requirements. Participants then completed a simple two alternative forced choice gambling task where they chose one of two doors using left or right index finger triggers on a gamepad to receive a gambling outcome (random selections without replacement from a set of 40 wins of 75 credits and 40 losses of 60 credits). Participants were instructed to "*Outsmart the artificial intelligence … to win money to purchase their starfighter*". Doors were presented for 4000 ms or until a response was made. Immediately following response, reward or punishment outcomes (see Fig. 2A) were presented for 500 ms and were immediately followed by a 1000 ms inter-trial-interval with a fixation cross. Unique triggers were sent for standards, oddballs, wins, and losses. For three participants, triggers failed to occur in the gambling task; all analyses of gambling exemplar data were thus based on the remaining N = 14 participants. EEG data from these exemplar tasks were subjected to the same event-related pre-processing as the *Escape from Asteroid Axon* video game, described below.

Escape from Asteroid Axon

Escape from Asteroid Axon, also referred to here as the video game, was written also in Java with custom C trigger code. Fig. 1 displays the exemplar tasks and *Escape from Asteroid Axon* screenshots. The video game was played for 30 consecutive minutes based on an external timer (one participant played for 45 min). Participants used a Logitech F310 gamepad, with a left thumb omni-directional controller and a right index finger button for missile launches. Participants were given brief instructions about the nature of controls, the location of the health bar and ammo magazine, how stars increased health and ammo boxes refilled the magazine, and how enemy crashes and wall crashes diminished the health bar. If the participant's health bar reached zero, the round ended, and they had to press the missile launch button to begin a new round. Event triggers were sent for a variety of relevant game events: 1) missile launch button press, 2) collect star, 3) collect ammo box, 4) crash into wall, 5) crash into enemy, and 6) missile hit enemy. There was also a unique EEG trigger sent at the beginning of each new round. A wealth of continuous data was also recorded in comma separated values log files at about 100 Hz during video game play; however we do not further discuss the use of this log in this report.

EEG processing

EEG data were re-referenced to an average reference and CPz was re-created via the EEGLab pop_reref function (Delorme and Makeig, 2004). Very ventral temporal sites were removed, as they tend to be unreliable, leaving 60 electrodes. Epochs were created around the exemplar task events and six relevant video game events enumerated above (−2000 to 2000 ms). Since the crash into wall and collect star events tended to occur in continuous streaks separated by only a few milliseconds, many of these events were not likely experienced as isolated occurrences. To hone in on the punctate nature of these events, only the first crash into wall or collect star events within a 500 ms window were included. Bad channels and bad epochs were identified using the FASTER algorithm (Nolan et al., 2010) and were subsequently interpolated and rejected respectively. Eye blinks and horizontal eye movements were removed following ICA (Delorme and Makeig, 2004). A median of 2 electrodes (range 1 to 3) were interpolated and an average of 3.27% epochs (range 1.91% to 4.6%) were removed. Blinks and horizontal eye movements were identified by correlation with VEOG and HEOG, respectively. The lead author verified all artefactual components. All participants had a single IC that accounted for blinks. Thirteen participants had two components for eye movements and four had one component. In all cases except one, the blink or movement-related components were the first ones (the exception had the 1st and 3rd components). All single trial EEG epochs used for ERPs or for classification were high-pass filtered at .1 Hz and low-pass filtered at 20 Hz and corrected to a −200 to 0 ms baseline.

Time–frequency measures were computed by multiplying the fast Fourier transformed (FFT) power spectrum of single trial EEG data with the FFT power spectrum of a set of complex Morlet wavelets (defined as a Gaussian-windowed complex sine wave: $e^{i2\pi tf} e^{-t^2/(2 \times \sigma 2)}$, where t is time, f is frequency (which increased from 1 to 50 Hz in 50 logarithmically spaced steps), and σ defines the width (or "cycles") of each frequency band, set according to 4/(2πf)), and taking the inverse FFT. The end result of this process is identical to time-domain signal

[1] Here, reverse inference is referred to as the process of inferring cognition from patterns of brain activation (e.g.: the amygdala is active, so the participant must be fearful!). While this comically egregious example demonstrates the potential for problems, reverse inference remains a valid method for abductive inference (Poldrack, 2006), particularly with experimental (Hutzler, 2014) and quantitative (Yarkoni et al., 2011) constraints.