Affective decision making: effects of arousal on a random dot motion task

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Abstract:

The effects of emotion on decision making have not been fully characterized. In this pilot study we sought to computationally model the effects of arousal on a two alternative forced choice random dot motion coherence task using a Bayesian hierarchical drift diffusion model (HDDM). Subjects were exposed to trials consisting of one of three different levels of arousal condition immediately preceding performance on a random dot motion decision making task. Arousal's effect on decision making was modeled as a constant term modulating evidence accrual rate, decision threshold boundary, both, or neither. These four models were compared using hierarchical Bayesian estimation to determine which hypothesis best fit the data. Additionally, biometric data including galvanic skin response (GSR), heart rate (HR), eye tracking data, and facial emotional expression data was collected for each participant. We found that the threshold only model most accurately characterizes our data. This implies that arousal influences decision making by decreasing participants' conservativeness in their responses, rather than by increasing the accrual of evidence via attentional allocation.

Introduction:

Decision making often involves the categorization of very complex stimuli in our environment in order produce relevant action output. There are many possible ways that emotion may play into decision making. The wide range of emotions is commonly characterized across two overarching dimensions: arousal and valence. Arousal level corresponds to the degree of activity that a particular emotion confers whereas valence corresponds to the positive or negative aspect of that emotion. For this study we narrow our scope to the study of the effect of arousal alone on decision making. Arousal may affect an individual's degree of attentiveness to a stimuli, effectively increasing (or decreasing) his evidence accrual rate. Alternatively, arousal may affect an individual's conservativeness about a particular decision. If evidence is constantly allowed to accumulate a conservative individual may choose to wait a little longer to gather more evidence before making a decision. It is also possible that arousal affects both or neither of these decision making parameters.

Methods:

Five participants were ran in this pilot study. Biometric data was collected, including: eye tracking, galvanic skin response, heart rate, and automatic detection of emotional facial expression. Emotions were tracked via webcam feed to iMotion's Attention tool software. This software reports evidence and intensity values of joy, anger, sadness, surprise, fear, contempt, disgust, frustration, and confusion for every frame of the video feed(Grafsgaard, Wiggins, Boyer, Wiebe, & Lester, 2013). The software is trained on a large corpus of hand coded frame-by-frame videos done by human experts trained in Dr. Ekman's Facial Action Coding System (FACS) (Ekman & Friesen, 1978).

Each participant completed a common random dot motion direction discrimination task (Gold & Shadlen, 2007) with a manipulation to modulate arousal on a trial by trial basis. One hundred white dots were individually displayed on the screen moving in random directions on a black background for a short distance before disappearing to be replaced by another randomly appearing white dot. Some subset of these dots move coherently either towards the left or towards the right. Participant are instructed to respond as soon as they are able with the keyboard arrow key press corresponding to this direction of motion. The level of coherence can be modulated, with 100% coherence meaning all dots appear and move in the same direction, left or right, before disappearing, and 0% coherence meaning all dot motion is in random directions. Task difficulty is controlled by initially exposing participants to a 100 trial thresholding procedure prior to the beginning of the main part of the experiment.

During the main task each trial of dot stimulus presentation was immediately preceded by five seconds of an arousing sound. The dot stimulus was presented for a maximum of two seconds before the stimulus disappeared and the experiment resumed. The three arousing sounds were as follows: calming rain (low arousal – L), a siren (medium arousal – M), or a siren + horn (high arousal – H). Ten seconds of the low arousal sound were played after arousing stimuli in order facilitate return to baseline arousal before beginning the next trial.

Modeling the hypotheses:

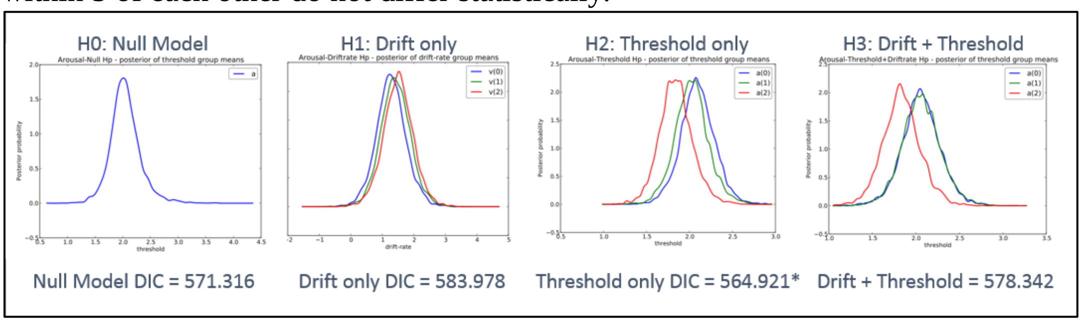
$$\begin{cases} dx = Edt + \varepsilon \\ x < c \\ x > -c \end{cases} \quad \begin{cases} dx = EdtA + \varepsilon \\ x < c \\ x > -c \end{cases} \quad \begin{cases} dx = Edt + \varepsilon \\ x < cA \\ x > -cA \end{cases} \quad \begin{cases} dx = EdtA + \varepsilon \\ x < cA \\ x > -cA \end{cases}$$

Null: No influence | H1: Influences drift | H2: Influences thresh. | H3: Influences both

Bayesian posterior probability estimation was used to estimate the probability that the parameters (E – evidence accumulation rate, c – response threshold) reasonably represent the data (A – arousal level, t – time, x – total evidence accumulated). We place the constant arousal term (A) in different locations in each of the hypothesis to express how arousal may be effecting the decision making process. Our null hypothesis is that arousal has no effect on decision making in this framework. Hypothesis 1 is that arousal influences the evidence accrual rate, perhaps via attentional modulation. Hypothesis 2 is that arousal influences the decision threshold, indicating that participants' level of conservativeness in responding may be modulated by their level of arousal. Hypothesis 3 is that arousal may influence both of these things at the same time. We used Markov Chain MonteCarlo (MCMC) estimation together with a Bayesian hierarchical drift diffusion model (HDDM) toolbox in python (Wiecki, Sofer, & Frank, 2013) allowing us to fit data both across and within subjects.

Results:

Task accuracy remains stable across conditions while the reaction time is faster in the high arousal conditions. However, we can get a much more detailed view of arousals effect on decision making by comparing the models we discussed previously. We used the deviance information criterion (DIC) to compare model fit. The smaller the DIC coefficient the better the model fits the data. The fit of models with DIC values within 5 of each other do not differ statistically.



Hypothesis two, that arousal affects the threshold of decision making only, most accurately fits our data.

Conclusions/ further directions:

Allowing arousal level to modulate the estimated response thresholds improved model fit relative to the null model. This indicates that arousal influences decision making by decreasing participants conservativeness in their responses. The use of this enhanced model allowed us to improve the current representation of the phenomena. To further this study we intend to perform more detailed analysis of the biometric measures we collected. It is important not only to verify the arousing effects of our chosen stimuli, but also to assess what biometric factors may best explain the variations in task accuracy/reaction time. Importantly, this study focused solely on the arousal dimension of emotion. Future work is needed to assess the effects of the positive and negative valence of emotions on decision making.

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