A cognitive map of a subjective value space

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Abstract

Individuals are thought to make choices based on subjective valuations of options that combine multiple attributes into a unified subjective value (SV) signal in the brain. However, it is not yet known how the multiple attributes of choice options are transformed into SV. One possible mechanism is the cognitive mapping system in the entorhinal cortex (EC) and medial prefrontal cortex (mPFC), which efficiently represents relational, multi-dimensional information. Here, we develop a novel risky decision-making task and use fMRI to show that a two dimensional (2D) SV space of reward probability and amount is represented in the cognitive mapping system as both a grid-like representation of decision vectors and a 2D 'positional' code of options. Further preliminary work using the same task in intracranial EEG (iEEG) shows theta coupling between medial temporal lobe (MTL) and PFC and a grid-like representation of decision vectors in mPFC theta power. These findings connect the brain's cognitive mapping and valuation systems and provide a possible mechanism by which individuals convert an options' multiple attributes into an SV signal, suggesting a new framework for understanding how the brain constructs and compares values.

Keywords: decision-making; fMRI; iEEG

Introduction

A dominant theory is that SV is represented in the brain as a unified, 1D signal (Bartra et al., 2013; Clithero & Rangel, 2014). However, the mechanisms by which a stimulus is converted from its objective characteristics into its SV remain poorly understood.

One mechanism by which individuals may represent and relate reward values subjectively is via the cognitive mapping system. Cognitive maps are thought to arise, in part, from place and grid cells in the hippocampus, and EC and mPFC, respectively (Hafting et al., 2005; Jacobs et al., 2013; O'Keefe & Dostrovsky, 1971). In both memory-guided spatial navigation and value-guided decision-making tasks MTL and PFC have been shown to communicate via theta coupling (Adams et al., 2020; Knudsen & Wallis, 2020).

Here, we develop a risky decision-making task with two decision option attributes (reward probability and amount) to test the hypothesis that individuals represent relationships between these dimensions in a cognitive map and that this coding reflects subjective preferences. In a group of fMRI subjects we test for two characteristics of a cognitive map: 1) hexagonal modulation of decision vectors between options and 2) a two-dimensional (2D) positional code in EC and mPFC. In preliminary analyses of iEEG data from the same task collected in epilepsy patients, we further examine grid-like representations and information transfer between MTL and PFC.

Methods

We developed a risky decision-making task for two groups of individuals—one group of 35 healthy controls undergoing fMRI and patients undergoing presurgical iEEG monitoring for treatement-refractory epilepsy. In this task, we trained individuals to associate reward amounts and probabilities with two (one for iEEG) sets of shapes which varied continuously along two dimensions. These shapes were shown sequentially to participants who were asked to choose their preferred shape based on the reward characteristics.

First, we used cumulative prospect theory–informed computational modeling to estimate individuals' parameters capturing risk preference and probability weighting (Prelec, 1998; Tversky & Kahneman, 1992). These values were used to calculate SV and distort cognitive maps based on subjective weighting of each dimension (amount and probability).

FMRI: Next, we utilized univariate GLM analysis to test for neural representations of SV (SV of chosen – unchosen options) and a grid-like representation of decision vectors ($\cos(6\theta)$, where θ is the angle of the decision trajectory through a 2D SV space; Figure 1A) at the time of the second shape (when all the information was available to make a choice). We utilized representational similarity analysis (RSA) to test if the Euclidean distances between shapes' 'positions' are neurally represented in a 100-voxel searchlight procedure. All fMRI results reported are significant at $P < 0.05$ based on small volume threshold-free cluster-enhancement (Smith & Nichols, 2009).

iEEG: To look for a grid-like representation, we performed regression between theta band signal and $\cos(6\theta)$. To analyze intertrial coherence at the time period of the second shape, we calculated phase locking value (PLV) across time and frequency. To further analyze inter-region coherence, we calculated PLV in the theta band across 7 MTL and 2 PFC electrodes.

Results

We first replicated prior work by showing this new task elicits a 1D SV representation in ventromedial PFC (vmPFC; P = 0.016) and posterior cingulate cortex (PCC; P = 0.051).

Next, we tested for a key component of cognitive maps—a grid-like code. We tested for this using individually estimated SV spaces based on cumulative prospect theory. We show that individuals utilize a grid-like code in EC (P = 0.021) and mPFC (P = 0.033) in these SV spaces (Figure 1B)—these effects were significantly stronger than a grid-like code defined over an objectively defined value space in EC (P = 0.046).

If individuals are using a cognitive map in this task, we also might expect to find a neural representation of a general 2D positional code in the SV space. To test this, we implemented an RSA which compared neural data to an RDM specifying Euclidean distance between shape locations across shape sets in each individuals' SV space. We found such a 2D positional code in EC (P = 0.0070) and mPFC (P = 0.021; Figure 1C).

We tested for correlations between the EC beta estimates from the grid-like analysis and the vmPFC and PCC beta estimates from the 1D SV analysis and observe a positive correlation between these regions' effects ($\rho s > 0.30$, $Ps < 0.042$).

We next turn to iEEG to ask: how are EC and mPFC communicating with each other? After replicating grid-like representation of decision vectors in (m)PFC (Figure 2A), we observe strong inter-trial theta phase alignment in PFC and MTL (Figure 2B, C). Further, testing for theta phase coherence between these regions at the time of choice, we observe high PLV (Figure 2D).

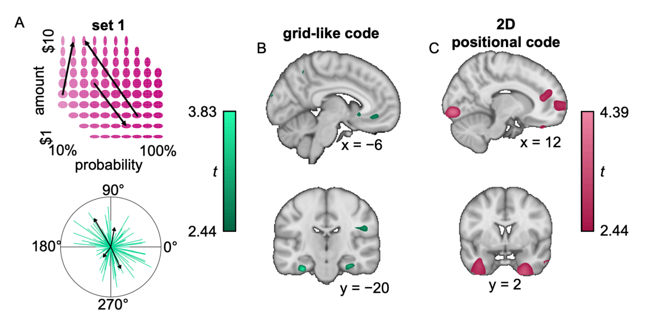

Figure 1: Decision vectors in a 2D value space and two signatures of a cognitive map.

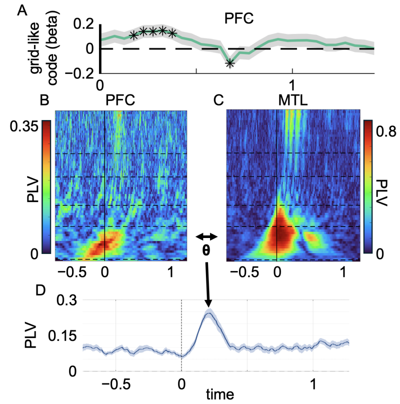

Figure 2: iEEG regression and coherence.

Discussion

In this study we observe a 1D SV difference signal in vmPFC and PCC and two signatures of 2D subjective cognitive maps in EC and mPFC in a value-based decision-making task. These two representations were correlated, suggesting they work in tandem. We showed this information transfer occurs in theta band between MTL and PFC.

These findings suggest one potential mechanism by which objective information can be transformed into SV. Further work is needed to understand the particular circumstances in which the cognitive mapping system is utilized in value-based decision-making and the directionality and content of MTL–PFC information transfer.

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