

(Abstract) neural representations of spaces and concepts

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Abstract neural representations

- 1) Frames of reference for spatial representation
- 2) Place cells & boundary vector cells
- 3) Neural level model of Spatial Memory and Imagery
- 4) Place and grid cells, environmental and self-motion inputs?
- 5) Grid cells as dynamic imagery?
- 6) Place and grid cells, representing states and transitions for planning?
- A. Hippocampus & striatum: Model-based versus model-free RL?
- B. Dual representations theory, PTSD and intrusive imagery

Multiple parallel representations in spatial memory.

Effects of consistency with 'Visual Snapshots' & Internal 'Spatial Updating'

Wang & Simons 1999



Multiple parallel representations in spatial memory. Visual Snapshots (*egocentric*), Spatial Updating (*egocentric*) and External Cues (*allocentric*).





Burgess, Spiers, Paleologou, 2004



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The hippocampus supports memory (e.g. HM), but how does it work?



Spatial studies in rodents => likely neural representations.







O'Keefe & Dostrovsky, 1971

Place cells show long term memory and pattern completion

Place cell "remapping:" long-term memory for highly distinct environments.

learned distinction remains after 71 days..



Lever, Wills, Cacucci, Burgess, O'Keefe, 2002



Wills, Lever, Cacucci, Burgess, O'Keefe, 2005

and 'pattern completion' depending on CA3 NMDA receptors

Nakazawa et al., 2002



Environmental boundaries particularly influence place cell firing



61cm

O'Keefe & Burgess (1996)

Place Cell firing as a thresholded sum of "Boundary Vector Cell" inputs

Boundary Vector Cells (BVCs) signal distance to boundary along an *allocentric* direction





O'Keefe & Burgess, 1996; Hartley et al 2000

BVCs found in subiculum & entorhinal cortex



JES.

Lever, Burton, Jeewajee, O'Keefe, Burgess, 2009 See also Barry et al, 2006; Solstad et al, 2008

Object Vector Cells





Recently found, in hippocampus



Unit 1





Unit 3



Unit 4

Desmukh & Knierim, 2013

and medial entorhinal cortex







Hoydal..Moser 2019

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Hemispatial neglect in memory of Milan square following right parietal damage.

 ⇒ formation of an egocentric representation in parietal cortex from a stored allocentric representation in medial temporal lobe?



Bisiach & Luzzatti(1978)

Several identified neural representations support spatial cognition

Hippocampal formation (allocentric)

Sensory, **Parietal**, Motor cortices (egocentric)



place cells



O'Keefe & Dostrovsky, 1971



Hafting et al., 2005

boundary cells



Lever et al, 2009 Solstad et al, 2008

retinal receptive fields



trajectory cells,



Nitz 2009

Frames of reference for neural coding

'egocentric'

Body-centred location of objects



Perception Action/Imagery

'allocentric'

World-centred location of agent



Place cells Head-direction cells

Burgess et al 2001

'Gain field' responses in posterior parietal cortex i.e. conjunctive responses to (retinotopic) *visual input x gaze direction*



Andersen et al 1985

Size of retinotopic visual response is modulated by direction of gaze:

or by direction of the head (Snyder et al 1998).

Similar responses seen in parieto-occipital ctx (Galletti et al., 1995)

Gain field neurons can produce 'head-centred' or retinotopic representations.



Pouget & Sejnowski, 1997

Model of memory & imagery for scenes

Egocentric-allocentric translation by 'gain-field' neurons (i.e. conjunctive representations of egocentric sensory input x head direction)



Scene representation by populations of egocentric or allocentric BVCs



Parietal

egocentric representation (e.g. visual)

Scene representation by populations of egocentric or allocentric BVCs



egocentric representation (e.g. visual)

Becker & Burgess 2001; Burgess et al., 2001; Byrne, Becker, Burgess 2007



Byrne, Becker, Burgess 2007 Burgess et al., 2001 see also Pouget & Sejnowski 1997





Bicanski & Burgess, 2018; Byrne, Becker, Burgess 2007; Burgess Becker et al, 2001



Perceptually driven MTL (bottom-up mode)



Encountering an object in a familiar environment

Perceptually driven MTL (bottom-up mode)



Recollection of encountering the object

Imagery (top-down mode) - "Where did I leave my keys?"



Memory enhanced 'perception' of a familiar environment

Model allows interpretation of fMRI patterns during recollection/ imagery



In a familiar environment, MTL connections ensure generation of a coherent scene, consistent with a single viewpoint (place cells) and direction (HDCs)

RSC supports egocentric-allocentric translation, required to associate (allocentric) internal representations with (egocentric) sensory representations (Egocentric BVCs and OVCs have now been found, Hasselmo & Derdikman labs)

Model allows interpretation of fMRI patterns during recollection/ imagery



Burgess et al, 2001

Hartley et al, 2004

The network performs coherent spatial imagery, i.e. related to planning, 'episodic future thinking' and 'scene construction' Addis and Schacter, 2007;

Hassabis and Maguire, 2007

POS/RSC activity and change of viewpoint in memory

Viewpoint or table will rotate to avatar before test

table

table >



RSC associates internal (allocentric) representations to (egocentric) sensory inputs - strong associations form to stable sensory features (e.g. Auger et al., 2012)

Relation to pattern completion and models of Episodic Memory

- Pattern completion is seen in reconstruction of location-object-identity in scene.
- Consistent with Marr's model of hippocampus & Tulving's idea of holistic episodic recollection/ re-experience.
- Consistent with measures of pattern completion in Episodic memory *see Horner et al (2015).*



Marr, 1971; Gardner-Medwin, McNaughton, Alvarez, Squire, McClelland, O'Reilly, Treves, Rolls, Teyler & DiScenna; Damasio;

Functional roles for Papez's circuit?

Hippocampus (place cells): imposing a common viewpoint on retrieval/ imagery.

Fornix:

Head-direction cells: imposing a viewing direction Theta cells/VCOs: grid cells, path integration, moving viewpoint in imagery. ACh/novelty/learning

Diencephalic amnesia

(Aggleton & Brown, 1999; Gaffan; Delay & Brion 1969). E.g., patient NA (Squire & Slater, 1978),Korsakoff's syndrome.



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Grid cells – thought to represent location by integrating self-motion.

The grids of nearby cells share orientation & scale





Hafting et al., 2005









Two ways to know where you are:

1. Environmental information

(Environmental boundaries particularly influence place cells)

2. Path integration



Grid cells



Hafting et al., 2005



Two ways to know where you are:

1. Environmental information

(Environmental boundaries particularly influence place cells)



Grid cells



Hafting et al., 2005



Interactions between place cells and grid cells

Estimating self-location combines environmental & self-motion information



2D VR for mice (invisible reward task)





Guifen Chen, John King, Yi Lu, Francesca Cacucci, Neil Burgess, eLife 2018

2d VR allows expression of normal place, grid & head-direction firing patterns, controlled by virtual cues (e.g. 180° rotation of VR and entry point)



Correlation with baseline



Chen et al, eLife 2018

Grid cell firing patterns reflect self-motion more than vision



Guifen Chen, Yi Lu, John King, Francesca Cacucci, Neil Burgess, Nat Comms, 2019

Place cell firing patterns reflect vision more than self-motion



Guifen Chen, Yi Lu, John King, Francesca Cacucci, Neil Burgess, Nat Comms, 2019

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Burgess et al, 2007

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Grid cells and memory/imagery



Allocentric updating of (imagined) location

Bicanski & Burgess, eLife, 2018

Grid cells in the human autobiographical memory system?

Doeller, Barry, Burgess, 2010

misaligned runs

aligned runs

Ø+60

0.5

0

populations of *aligned* grids (modules) => changes in fMRI signal with virtual running direction



Task designed by John King



Autobiographical memory system

=> Grid cells allow path integration, and movement of viewpoint in imagery?



Grid-like processing of movement of viewpoint in imagery





60° symmetry in fMRI signal with *imagined* running direction in Entorhinal cortex (aligned with that in virtual movement)



Horner et al., 2016



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Hippocampal cells can represent abstract concepts, such as 'place' but also, e.g., personal identity or sound frequency?



Quiroga et al., (2005)





Grid cell firing patterns reflect the transition structure of learned conceptual spaces?



Interactions between place cells and grid cells

Representing bodies of conceptual knowledge (states) and transitions between them?



'Intuitive Planning..'



..with neural populations

 $\underline{P}(x(t))$ is a vector over states x_i :

PC_i firing profile is \underline{F}_i firing rate is $f_i(x(t))$

 $\underline{P}(x(t)) \sim \sum_j f_j(x(t)) \ \underline{F}_j$

 $\underline{P}(x(t+1)) \sim \sum_{j} f_{j}(x(t)) \mathbf{T} \underline{F}_{i}$

 GC_i firing profile = \underline{G}_i firing rate = $g_i(x(t))$

$$\begin{split} \underline{P}(x(t)) &\sim \sum_{j} g_{j}(x(t)) \underline{G}_{j} \\ \underline{P}(x(t+1)) &\sim \sum_{j} g_{j}(x(t)) T \underline{G}_{j} \\ \text{If } T \underline{G}_{j}(x) &= \lambda_{j} \underline{G}_{j}(x) \\ \underline{P}(x(t+1)) &\sim \sum_{j} \lambda_{j} g_{j}(x(t)) \underline{G}_{j} \end{split}$$

 $\underline{P}(x(\tau \ge t) = x_i)$ $\sim \sum_j (\gamma \lambda_i + \gamma^2 \lambda_i^2 + ...) g_j(x(t)) \underline{G}_j$ $\sim \sum_j g_j(x(t)) / (1 - \gamma \lambda_i) \underline{G}_j$

Stachenfeld, Botvinick, Gershman, Gerstner, Baram.. Behrens





Place cell read-out of GCs

PC_i firing profile is \underline{F}_i , firing rate is $f_i(x(t))$ driven by GCs?

If $f_i(x(t)) \sim \sum_j w_{ij} g_j(x(t))$

[e.g. Hebbian $w_{ij} \sim \underline{F}_i . \underline{G}_j$]

then $f_i(x(t)) \sim P(x(t) = x_i)$

If $f_i(x(t)) \sim \sum_j \lambda_j w_{ij} g_j(x(t))$

then $f_i(x(t)) \sim P(x(t+1) = x_i)$

If $f_i(x(t)) \sim \sum_j w_{ij} g_j(x(t)) / (1 - \gamma \lambda_i)$ Then $f_i(x(t)) \sim P(x(\tau \ge t) = x_i)$



 $\underline{P}(x(t)) \text{ is a vector over states } x_i:$ $PC_i \text{ firing profile is } \underline{F}_i \qquad \underline{F}_i$ $firing \text{ rate is } f_i(x(t)) \qquad \underline{F}_j \qquad \underline{F}_i$ $\underline{P}(x(t)) \sim \sum_j f_j(x(t)) \underline{F}_j \qquad \underline{F}_i$ $\underline{P}(x(t+1)) \sim \sum_j f_j(x(t)) T\underline{F}_i$

 GC_i firing profile = \underline{G}_i firing rate = $g_i(x(t))$

 $\underline{P}(x(t)) \sim \sum_{j} g_{j}(x(t)) \underline{G}_{j}$ $\underline{P}(x(t+1)) \sim \sum_{j} g_{j}(x(t)) T \underline{G}_{j}$ If $T \underline{G}_{j}(x) = \lambda_{j} \underline{G}_{j}(x)$ $\underline{P}(x(t+1)) \sim \sum_{j} \lambda_{j} g_{j}(x(t)) \underline{G}_{j}$

 $\underline{P}(x(\tau \ge t) = x_i)$ $\sim \sum_j (\gamma \lambda_i + \gamma^2 \lambda_i^2 + ...) g_j(x(t)) \underline{G}_j$ $\sim \sum_j g_j(x(t)) / (1 - \gamma \lambda_i) \underline{G}_j$









Baram.. Behrens (bioRxiv)

So.. If you want a set of basis vectors to represent where you are in state space, choosing Eigenvectors of the task Transition Matrix makes planning easy.

And.. Grid firing profiles might be Eigenvectors of a diffusive transition matrix **T** (i.e. $T \underline{G}_i(x) = \lambda_i \underline{G}_i(x)$), or of the covariance matrix of PC firing (e.g. learned via Oja's rule)



Implications

- Place cell read-out shifts from current location to future locations by re-weighting GC inputs, can give Successor Representation (SR)
- Gradient ascent on SR allows navigation to any other state
- Local changes to Transitions require re-learning of eigenvectors (GCs): via replay?
- Common transition structure across tasks captured by GCs, while PCs 'remap' to specific stimuli, allows generalisation to new tasks (aka 'schemas' & 'consolidation' of statistical structure), see 'T.E.M.' (Whittington et al BioRxiv, 2019)

Conclusions

- Considerable progress has been made in understanding how environmental and self-motion information combine in neural representations of location and orientation in rodents.
- We can use this to create a neural-level understanding of spatial memory, learning and imagination in humans, and begin to apply it to conceptual knowledge?

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