Navigation

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Problem

we talked about how to plan motion toward targets avoiding obstacles

in many cases, information about targets may be available through a map that represents where relevant locations are in the world

to use a map, a robot/organism needs to known “where it is” on the map: ego-location estimation

that estimate must be updated as a robot/organism moves…
Dead-reckoning/path integration

if the agent knows its current velocity=heading direction + speed (and keeps track of time), it can estimate its change of position by integration

[McNaughton et al., Nature reviews neuroscience 2006]
Dead-reckoning/path integration

- a long history in technology… dating back to literal “navigation”: sailing ships…
  - estimating heading direction based on a compass
  - estimating speed by counting “knots”… which entails an estimate of time
  - updating position in a map
Dead-reckoning/path integration

- Modern technology increases the precision
  - E.g. inertial guidance by measuring acceleration
  - Precise measurement of time
  - With good control, the control signals can also be used to predict the new state …
  - Optimal estimation integrates prediction and measurement…
Dead-reckoning/path integration

- fundamental problem
  - the integration leads to an accumulation of uncertainty…
  - the principle of Brownian motion…

![Graph showing time, t, and u(t) with a resting level and probability distribution of perturbations.](image)
Dead-reckoning/path integration

- a need for “recalibration” or re-setting of the estimate based on “recognizing” the true location on the map...

- historical solution:
  - landmark recognition…
  - triangulation

- modern variants based on special beacons, GPS etc
Dead-reckoning/path integration

- animals including humans use path integration

[Loomis, Klatzky, 1993]
Dead-reckoning/path integration

- animals including humans use path integration

blind from birth     blind from accident     seeing
Landmark recognition

- Landmarks are not necessarily objects...
- Empirical evidence that views serve to estimate ego-position and pose
- Evidence for views used from animal behavior and neural data

[Peer, Epstein, 2021]
Maps

- when can we say does an animal use a map?
- rather than use stimulus-response chaining
- => when it can take short-cuts

[Peer et al, 2020] [Poucet, 1993]
Simultaneous Localization and Mapping

SLAM

[Durrant-Whyte, Baily, 2006]
SLAM

- problem of learning/optimizing path integration... and using this to associated landmark information with locations

- problem of loop closure
(Neural) dynamics of navigation

- dynamics for ego-position estimation
- dynamical approach to learning the map: network of locations (home bases) at which the agent knows where it is relative to others
- dynamics of path planning

Self-calibration based on invariant view recognition:
Dynamic approach to navigation

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Neural and behavioral architecture
Visual place navigation

- A visual surround (unsegmented) acquired in clusters around particular locations (home bases)
- Views are stored together with current position estimate (translation/rotation)
Evidence for home bases

- Animals in given terrain build home bases by rearing in locations where they spend most of their time.

[Table of data]

[Eilam, Golani, 1989]
Visual place navigation

- Each view in home base is matched to current view.... with all possible rotations actively generated from memorized view.

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Current view

Home-base associative matrix memory

<table>
<thead>
<tr>
<th>rot=0</th>
<th>r</th>
<th>2r</th>
</tr>
</thead>
<tbody>
<tr>
<td>base 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>base 2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>base 3</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

match

best match here: home-base 2, dPhi=r
```
Visual place navigation

- Correlation function across rotation angle peaks sharply at true angular orientation of agent, even if translation is not precise...

- So that estimation of orientation is possible while agent is in receptive field of place cell
Correlation with actively shifted memory views decays spatially in way that reflects how distal the view is…. place field.
Visual place navigation

The level of correlation across multiple views within a home base generates a place view representation of translation $\Rightarrow$ position estimate
Neural and behavioral architecture
Integration by an attractor dynamics

- every sensory estimate contributes a “force-let” to a dynamical system whose attractor is the estimate of ego-position …

- for vision: space to rate code… removes the problem of normalization
Recalibration from instability

- with visual match, a strong attractor force-let induces instability in which the estimate gets reset to the visually specified estimate
- which resets the dead-reckoned estimate as well
Recalibration from instability

- with visual match, a strong attractor force-let induces instability in which the estimate gets reset to the visually specified estimate
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Neural and behavioral architecture
Integrating it all: dynamics all the
a reset event

X-Position (solid: X_real  dotted: X_int)

Visual match for home base recognition

Relaxation times (solid: tau_int,vis  dashed: tau_int,dr  dotted: tau_dr)
Further development:

- complex behavioral organization
- robotic implementation
Autonomous behavioral organization

neural dynamics organizes sequence of behaviors...
Autonomous behavioral organization

- neural dynamics organizes sequence of behaviors...
How neurally realistic is this?
Neural mechanisms of navigation

neural representation of path integration

[McNaughton et al., Nature reviews neuroscience 2006]
Heading direction

- Neural evidence for head-orientation cells… that function as heading direction representation

- Neural attractor dynamics (neural field) for heading direction

[McNaughton et al., Nature reviews neuroscience 2006]
Place and grid cells

- neural representation of location in Hippocampus and Entorhinal Cortex

[McNaughton et al., Nature reviews neuroscience 2006]
Place and grid cells

- support building a place representation by a neural field

[McNaughton et al., Nature reviews neuroscience 2006]
Neural dynamics of path integration

[McNaughton et al., *Nature reviews neuroscience* 2006]
Neural dynamics of path integration

[McNaughton et al., Nature reviews neuroscience 2006]
Neurally inspired technical solution

RAT-Slam

[Ball, Wyeth, Cork, Milford, 2013]
RAT-Slam

[Ball, Wyeth, Cork, Milford, 2013]
Autonomously explore this environment. For this dataset, a human who gave directives on which way to turn at each intersection. The dataset was obtained while the iRat explored a road movie set based on Australian geography, containing prominent Australian landmarks such as the Sydney Opera House and Uluru. A camera mounted overhead provided images that allowed us to extract ground truth information. The iRat ROS bag data set is approximately 16 minutes long and includes the camera images (shown in Fig. 13 (b-c)), range and odometry messages, the overhead FDP HUD (shown in Fig. 13 (a)) and tracked pose information.

Fig. 12. (a-b) The labeled iRat robot internals. (c) The iRat along side a standard computer mouse to show scale.

Fig. 13. The iRat 2012 dataset (a) overhead view and (b-c) sample frames from the onboard camera.

[Ball, Wyeth, Cork, Milford, 2013]
The New College dataset is a well known dataset from the Oxford University taken in England in 2008. The full dataset includes, laser, odometry, stereo camera images, panoramic images, and GPS recordings in a custom format. Data collection was performed outdoors on the 2.2km path shown in Fig. 11 using a Segway RMP200 robot. In order to run the dataset with OpenRatSLAM the panoramic images and odometric information have been re-encoded into a ROS bag file. Timestamps were extracted from the original dataset to ensure proper timing. The odometric information has been integrated to match the panoramic image rate of 3Hz.

![Experience map, showing the topological map after epoch A then at the end of the experiment. The final map is similar to the ground truth map, except for a twist at the single entry point between the large loop on the right and the rest of the map.](image)

Fig. 18 shows a graph of the active experience and visual template over the duration of the experiment. As in the St Lucia dataset, experiences are learnt at approximately double the rate of visual templates, consistent with the tuning process indicated in Section 4.2. The forward backward matching of the panoramic images can be seen by the segments of increasing and decreasing visual templates and experiences. An example of panoramic image matching is shown in Fig. 19.

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**RAT-Slam**

[Ball, Wyeth, Cork, Milford, 2013]
Event-based place recognition

spiking neural vision system...

Fig. 8: Example matches of the ensemble and ground-truth (GT) matches on the DDD-17 dataset. Top two rows: success cases where the majority of individual methods failed. Bottom two rows: failure cases.

[Fischer Mildord, 2020]
Neuromorphic head-direction estimate

using DFT

Figure 2. Overview of the path integration and map learning network: Two identical SNNs with five functional layers each estimate the yaw and pitch of the iCub's head pose, integrating the respective motor velocities. When the robot's gaze is directed at a visual landmark, the yaw and pitch angles are stored in plastic synapses connecting the Vision and Goal neurons to the Reset Head Direction and Goal Head Direction layers, respectively. Excitatory synapses (red lines) between layers connect neurons in a one-to-one manner. The velocity input neurons are connected to shift layers in a one-to-all manner. Plastic connections (purple lines) are one-to-all, and inhibitory connections (blue lines) are all-to-all-but-one. Only exemplary connections are shown in order to avoid clutter. See Section 4.3 for details.

4 THE HEAD-DIRECTION SNN

4.1 Network overview

The path integration network consists of two identical SNNs for yaw and pitch estimation, Fig. 2. Each of these SNNs, similar to networks used in Kreiser et al. (2018c,a), consists of six layers of $N = 200$ neurons:

- the current head direction layer (CHD),
- the shift left layer (SL),
- the shift right layer (SR),
- the integrated head direction layer (IHD),
- the reset head direction layer (RHD),
- the goal head direction layer (GHD).

[Kreiser et al. Sandamirskaya, Frontiers 2019]
Neuromorphic head-direction estimate

- using DFT

Figure 3. (a) Parameters of iCub movements in the experiments. (b) Histogram of the algorithmic time step duration as recorded by Y ARP in our experiments. The average timestep is 1.6 ms, but in rare cases, time steps can be as long as 40 ms. Note, these values hold for the specific version of the Loihi API used.

Figure 4. (a) The iCub robot and visual fiducial (dot pattern). (b) The visual trajectory of the fiducial over dataset 1. (c) An example of the ATIS camera output.

• Head-shaking: The robot shakes its head side-to-side between the joint limits ($j_2\text{min}$ and $j_2\text{max}$). No vertical motion.

• Random: The robot chooses random velocities at which to move both vertically and horizontally. The velocity is chosen as a uniform distribution between 0 to $v_0$ and 0 to $v_2$ for the vertical and horizontal motion, respectively. If a joint limit is reached, the velocity of the respective joint is reversed. New velocities are chosen after $r \text{timeout}$ seconds.

In addition to direction, we changed the speed of the robot’s movements: $v_0$ and $v_2$ are the base velocities used, during experiments the speed was increased such that $v_2$ is doubled and $v_4$ is quadrupled the base speed, applied to both joints simultaneously (see Table 3a).

Five datasets were recorded with the robot beginning in the home position and then proceeding with the following strategy: nodding, home, head-shaking, home, random with speed $v_1$ for approximately 30 seconds, random with speed $v_2$ for approximately 30 seconds, random with speed $v_4$ for approximately 30 seconds, and, finally, home. The data was recorded from one of the ATIS cameras on the robot after a pre-processing stage to eliminate saving uninformative events (a noise filter). The motor-control module output the velocity of the head when the commanded velocity changed; the data was saved along with the

[Kreiser et al. Sandamirskaya, Frontiers 2019]
Conclusions

- the navigation problem entails both knowing where you are and how to go places
- navigation can be performed by behavioral and neural dynamics
- recalibration of location based on recognition … can be view-based
- integration by (neural) dynamics … in which space-time continuous processes… lead to discrete transitions at instabilities