GraphNav

A Behavioral Approach to Visual Navigation with Graph Localization Networks

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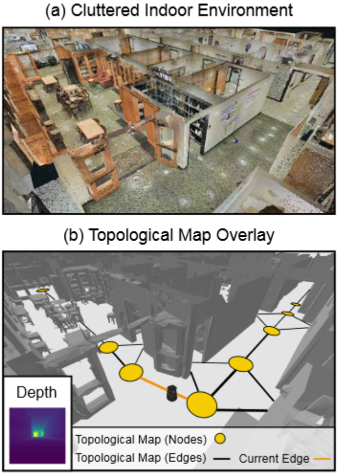
Motivation

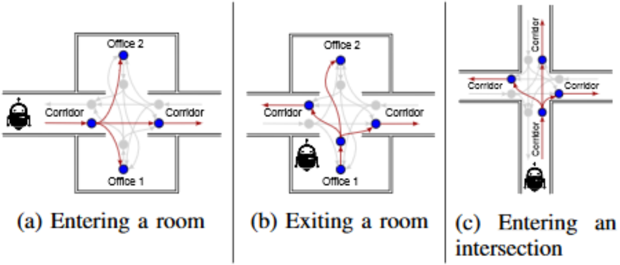
- Navigating cluttered spaces is difficult for robots
- Humans are really good at it
- Behavioral approach founded in psychology
  - proposed by Chen et al. [1]
  - *Cognitive Maps* $\rightarrow$ graph-like structure



Environment and corresponding topological map [1]

Motivation

- Benefits of a graph-like map
  - Coarse/Sparse topological information
  - Navigation planning on a graph
  - High-level abstraction



Navigation examples on topological map [1]

Graph Neural Network (GNN)

- Neural Network performing on graph-like structures
- Captures relational inductive biases
- Graph $G = (\mathbf{u}, V, E)$
  - $\mathbf{u}$ global feature
  - $V = \{\mathbf{v}_i\}_{i=1:n}$ node features
  - $E = \{(\mathbf{e}_k, r_k, s_k)\}_{k=1:m}$ edge features
- Edge features correspond to behaviors
  - *corridor follow*
  - *find door*
  - *turn left*
  - *turn right*
  - *straight (into room)*

Graph Neural Network (GNN)

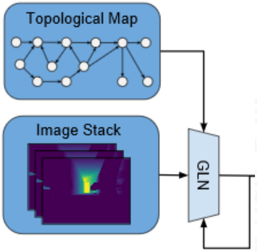
- Graph network blocks
  1. $\phi^e(\cdot)$ update edge features
  2. $\rho^{e \rightarrow v}(\cdot)$ aggregate edge features
  3. $\phi^v(\cdot)$ update node features
  4. $\rho^{e \rightarrow u}(\cdot), \rho^{v \rightarrow u}(\cdot)$ aggregate edge and node features
  5. $\phi^u(\cdot)$ update global feature

Info

The update functions $\phi^e(\cdot), \phi^v(\cdot), \phi^u(\cdot)$ were implemented using multilayer perceptrons (MLPs), the aggregation functions $\rho^{e \rightarrow v}(\cdot), \rho^{e \rightarrow u}(\cdot), \rho^{v \rightarrow u}(\cdot)$ use elementwise summation to ensure symmetry of the function (permutation agnostic)

Graph Localization Network (GLN)

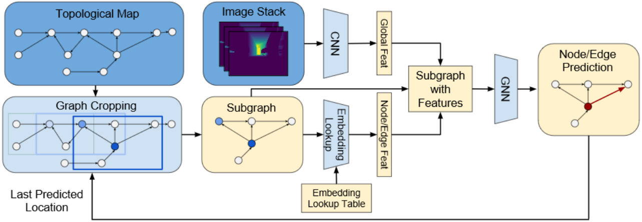
- Predicts location of the agent in the topological map
- Inputs
  - Current visual observation
  - Last predicted location
  - Graph with edge and node features



Graph localization network overview [1]

Graph Localization Network (GLN)

- Topological map is cropped to region around last location
- Edge/Node features from embedding lookup table
- Global feature from CNN processing visual observation
- GNN predicts the current node/edge



GLN architecture in detail [1]

Particle Filtering for GLN

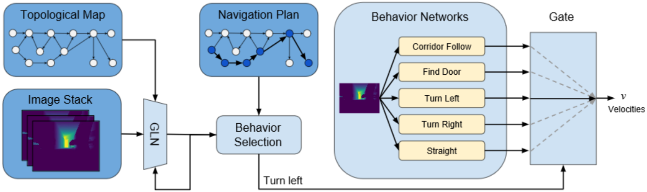
- used to improve GLN predictions
- based on statistical model
- $p(x_t | u_t, x_{t-1})$
  - x_t current state at time step t
  - u_t control input
- $p(z_t | x_t)$
  - z_t observation/measurement at time step t

Particle Filtering for GLN

- Assumption 1: Two time steps $t-1$ and t don't differ a lot in topological location
  - $p(x_t|u_t, x_{t-1}) = p(x_t|x_{t-1})$
  - Chen et al. use $p(x_t = x_{t-1}|x_{t-1}) = 0.8$
- Assumption 2: $p(z_t)$ and $p(x_t)$ are uniform distributions for all time steps
  - $\gamma = \frac{p(z_t)}{p(x_t)} = \text{const.}$
  - Bayes rule: $p(z_t|x_t) = \gamma \cdot p(x_t|z_t) \propto p(x_t|z_t)$
  - Approximate $p(x_t|z_t)$ by aggregating edge probabilities from the GLN

Behavior Networks

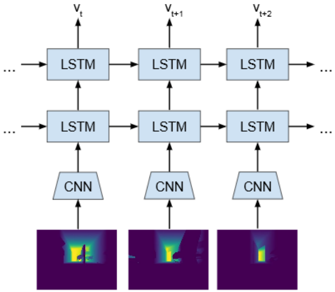
- Separate networks for each behavior
- Correspond to edge features
- CNNs and LSTMs used to implement



Overall architecture of *GraphNav* including behavior networks [1]

Behavior Networks

- CNN-based behavior networks
  - *corridor follow*
  - *find door*
- LSTM-based behavior networks
  - *turn left*
  - *turn right*
  - *straight (into room)*



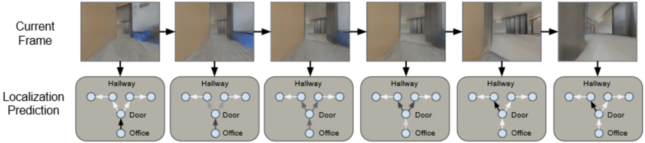
Architecture of LSTM-based behavior networks [1]

Baselines

- Evaluation of the results by comparing to baselines
  - *PhaseNet*[2]: LSTM-based, predicts temporal progress of behavior and when to switch to a new one
  - *BehavRNN*[3]: Sequence-to-sequence deep learning model, behavior classification from visual input
  - *GTL*: Ground Truth Localization, used to evaluate behavior networks independently

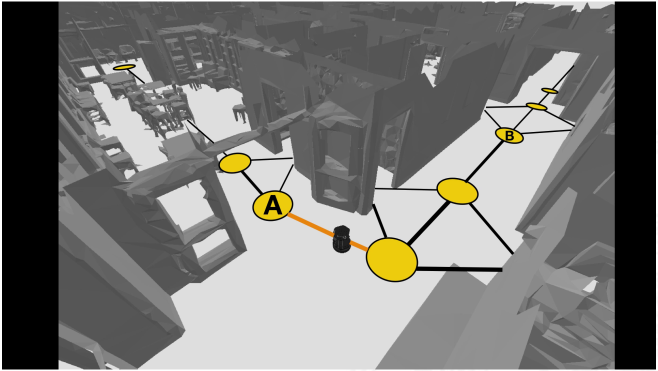
Evaluation

- *GraphNavPF* (with Particle Filtering) has highest performance compared to baselines
- Per-behavior success (90%) and path completion rate (70%) are resonable
- *PhaseNet* and *BehavRNN* perform significantly worse on seen and unseen environments
- *GTL* baseline shows that behavior networks work well, struggles in open spaces



Output of the localization network [1]

Video



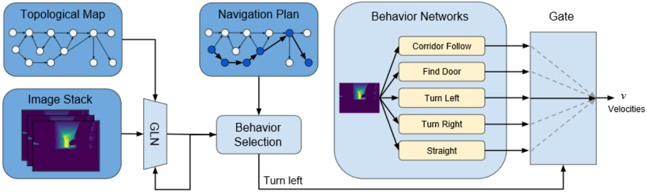
Video example of the GraphNav approach working [4]

Future Research

- Topological map has to be created and annotated by hand
- Set of behaviors has to be pre-defined
- Chen et al. propose data-driven approach to automate this
- Simulation-to-reality has to be tested

Conclusion

- Navigation approach that uses topological map and visual information as input
- Graph neural networks for localization
- Separate behavior networks with behavior selection
- Outperforms several baselines



Overall architecture of *GraphNav* including behavior networks [1]

References

[1] Chen, Kevin, et al. "A behavioral approach to visual navigation with graph localization networks." arXiv preprint arXiv:1903.00445 (2019).

[2] Yu, Tianhe, et al. "One-shot hierarchical imitation learning of compound visuomotor tasks." arXiv preprint arXiv:1810.11043 (2018).

[3] Sutskever, Ilya, et al. "Sequence to sequence learning with neural networks." In Advances in neural information processing systems, pages 3104–3112 (2014).

[4] Chen, Kevin, et al. "GraphNav: A behavioral approach to visual navigation with graph localization networks." March 2019, URL: www.youtube.com/watch?v=nN3B1F90CFM, Acessed 17.01.2020.