

Behavioral Indoor Navigation With Natural Language Directions

X. Zang¹, M. Vázquez¹, J.C. Niebles¹, A. Soto², S. Savarese¹

¹Stanford University

²P. Universidad Católica de Chile

Introduction

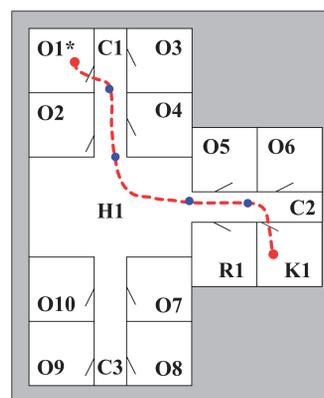
Man-made environments are composed of *navigational structures*, such as corridors or stairs, that in turn are intended to connect meaningful neighboring places, such as rooms or halls.

We hypothesize is that by providing robots with suitable abilities to understand the world at this semantic level, it is possible build robust navigational systems.

Behavioral Navigation Approach

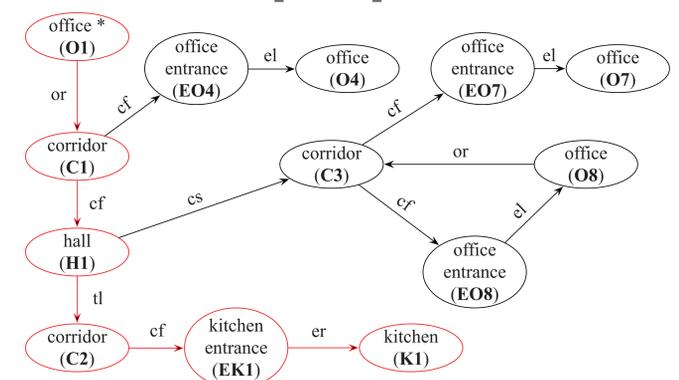
The proposed robot navigation approach [1] revisits the ideas of behavioral robot control [2] and early topological map representations [3].

In our approach, complex navigation routes are composed of simple, parameterized visuo-motor behaviors that leverage the semantic structure of indoor environments. These routes are generated by planning over a behavioral graph that encodes relations among navigational structures.



O1* Start location
--- Route

Behavioral Graph Representation



Following Navigation Instructions

Inspired by prior work [4, 5], we cast the problem of following navigation instructions in natural language as a machine translation task. We perform end-to-end learning to translate commands into navigational routes.

Translating Natural Language

We estimate a function f that maps navigation commands to a sequence:

$$S = \langle p_1, b_1, R_1, p_2, b_2, R_2, \dots, p_n \rangle$$

of places p , behaviors b , and reference sequences R . These reference sequences:

$$R = \langle ("", l_1, r_1, l_2, r_2, \dots, "") \rangle$$

are ordered collections of reference actions r grounded on landmarks l . These references guide the execution of the prior behavior b in S .

As an initial proof of concept, we implemented the function f as a differentiable sequence-to-sequence deep learning model with attention [6]. We trained the model using an adaptation of the learning environment DeepMind Lab.

Experiments

We evaluated our approach on a dataset of 16,370 unique examples using 5-fold cross-validation. The target sequences in the dataset were composed of 40.18 elements on average (STD = 9.75).

# GRU Units	Avg. Accuracy	Std. Dev.
64	99.53%	0.01
128	99.99%	0.0002
256	99.99%	0.0002

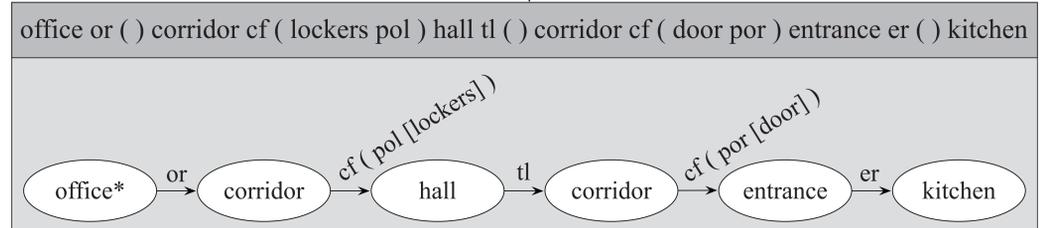
With less than 32 GRU units, the performance dropped significantly and learning was unstable.

Input: Navigation Commands in Natural Language

"Go out of the office and turn right, pass the lockers on your left, cross the hall and turn left, pass a door on your right, and enter the kitchen on your right"

SEQ-TO-SEQ MODEL

Output: Graph



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Contact

marynelv@stanford.edu

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