# A Survey on Trajectory Encoding Methods for Social Robots

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#### **ACM Reference Format:**

# 1 ABSTRACT

# 2 INTRODUCTION

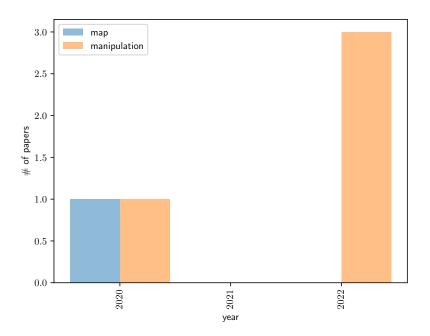


Fig. 1. Number of publications according to Scope.

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#### 3 RELATED WORKS

#### 4 ENCODINGS

### 4.1 Recurrent Neural Networks

[just for testing] [5] The paper uses relatively normal combination of rnn and attention to encode the past, its most important contribution comes in the recursive reasoning of the decoder.

### 4.2 Long-Short Term Memory

[just for testing] [4] focus on learning human-compliant behaviors for robots navigating in human crowded environments, by optimizing trajectories both for comfort (the absence of annoyance and stress for humans) and naturalness (the similarity between robots and humans).

They state "reinforcement learning approaches tend to optimize on the comfort aspect of the socially compliant navigation, whereas the inverse reinforcement learning approaches are designed to achieve natural behavior."

A Long Short-Term Memory (LSTM) encoder-decoder is defined for each of three social-interaction force (intention, social interaction and fluctuation) from [2] to improves interpretability, which are used with a adversarial training to reduce the data-bias tendency of LSTMs.

The trajectories of the robot and other agents (humans) are encoded with LSTMs, for intention just the robot trajectory is encoded, for social interaction and fluctuation all trajectories are encoded and passed through a maxpooling layer before the LSTM. Both encoding are passed to an adversarial training using demonstrations.

## 4.3 Graph Neural Networks

[just for testing] [1] In this paper, they suggest PAGA, which is an improvement on LaneCGNB [3]. Namely, the update the method for calculating the attention weights in the GNN used to encode the map. Instead of simply using an the four different adjacency matrices, the replaces that with a more complex matrix able to include connection via intermediate steps.

- 5 MULTI-LAYERS
- 6 MULTI-AGENTS
- 6.1 1x1
- 6.2 1xN
- 6.3 nxN

[just for testing] [6] In this paper, the encoding will be done in multiple steps.

- Extract for each agent its surrounding region (other agents and lanes) and encoded the corresponding past
  observations, using a coordinate system that is normalized to this agent last observed position and velocity,
  where we embed the agents own trajectory as well as the surrounding agents trajectory.
- We apply multi head cross attention with the agent as the query and its neighbors as key and values, and a recursive layer afterwards.
- The spatial encodings are then encoded temporally using a time axis transformer block
- Similar to the encoding of the neighbors, the encoded agent position is enhanced by cross attention with the neighboring lane segments (here, each vector in a polyline is treated individually)

- An transformer is used to encode the interactions with each agent, where their states are expanded by the translations and rotations between the coordinate systems.
- The decoder used is simple, however, the joint prediction are not really joint, just parallel

Here, using for the local encoding two different transformers, first along the agent axis and then along the time axis, significantly reduces the computational cost of the model.

- 6.4 NxN
- 7 APPLICATIONS
- 8 HUMAN ASPECTS
- 9 DATASETS, BENCHMARKS AND SIMULATORS
- 10 CONCLUSIONS

### **ACKNOWLEDGMENTS**

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