Graph Neural Networks for Multi-Robot Active Information Acquisition

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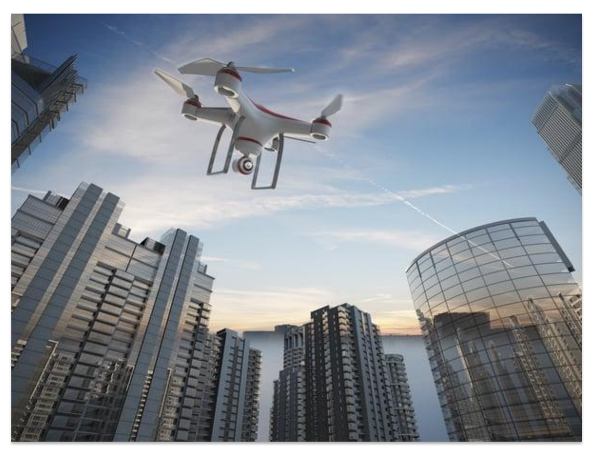
Motivation

Robots need to sequentially make decisions that would allow them to better estimate the extent of the fire, damage on a wind turbine and map of a city.

AIA: Design efficient paths to actively estimate a phenomenon of interest through on-board measurements

Contributions

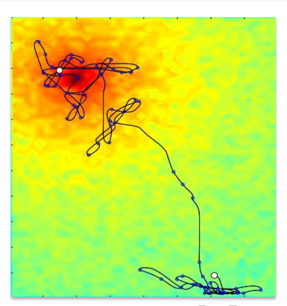
- We introduce the **first** method for Active Information Acquisition using Graph Neural Networks.
- The method is **scalable** with respect to the number of robots and dimensionality of the hidden state to be estimated.
- **Generalizes** to previously unseen multi-robot configurations.
- Our method is **robust** to communication failures.
- It can be applied for **time-varying communication** graphs and **dynamic** hidden state.



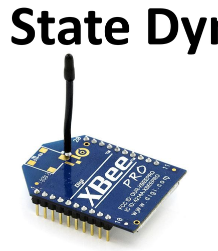
Problem Formulation

Objective

Design efficient paths to actively estimate a hidden state that expresses such a phenomenon of interest (e.g. ocean temperature, source localization).

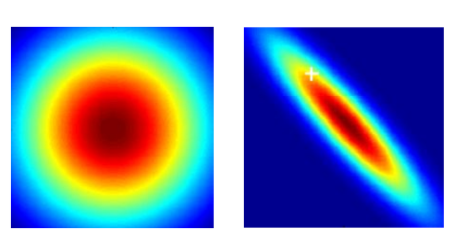


Robot Dynamics **Hidden State Dynamics** **Measurement Model**



$\mathbf{p}_{i,t+1} = f(\mathbf{p}_{i,t}, \mathbf{u}_{i,t})$ $\mathbf{x}_{t+1} = A\mathbf{x}_t + \mathbf{w}_t$ $\mathbf{y}_{i,t} = M(\mathbf{p}_{i,t})\mathbf{x}_t + \mathbf{v}_{i,t}$

Estimator



Prior Posterior

Assumptions

1. Gaussian additive noise, known covariances.
2. Gaussian prior distribution

$$\mathbf{x}_t \sim \mathcal{N}(\mu_t, \Sigma_t)$$

3. Linear Models

Information Metrics

Mutual Information

$$\mathbb{I}(\mathbf{x}_{t+1}; \mathbf{y}_{0:t})$$

Uncertainty

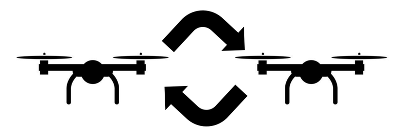
$$\det \Sigma_{t+1}$$

Given N robots and prior distribution, compute a planning horizon F and control inputs $\mathbf{u}_{0:F}$ to minimize the uncertainty over the hidden state

$$\min_{F,\mathbf{u}_{0:F}} \left[J(F, \mathbf{u}_{0:F}) = \sum_{t=0}^{F} \det \Sigma_{t+1} \right]$$

Method

Communication



Robots communicate through an underlying **communication graph** $\mathcal{G}_c$ where vertices are indexed by the robots.

Distributed Estimates

$$\hat{\mathbf{x}}_{i,t} \sim \mathcal{N}(\mu_{i,t}, \Sigma_{i,t})$$

Each robot maintains a local estimate over the hidden state expressed via its a-posteriori Gaussian distribution.

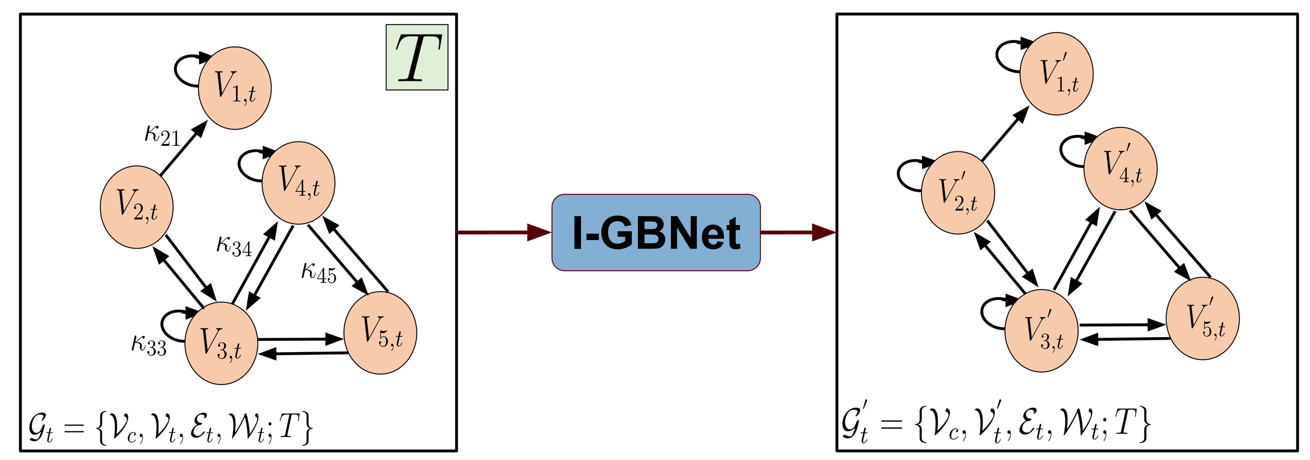
The state of the AIA problem at time t is described by the **network graph** $\mathcal{G}_t$, an adapted version of the communication graph with a set of node attributes $\mathcal{V}_t$

Node Attributes $V_{i,t}$

Robot's position $\mathbf{p}_{i,t}$

Prior Estimate $\{\mu_{i,t}, \Sigma_{i,t}\}$

Measurements $\{M(\mathbf{p}_{i,t}), R_{i,t}\}$



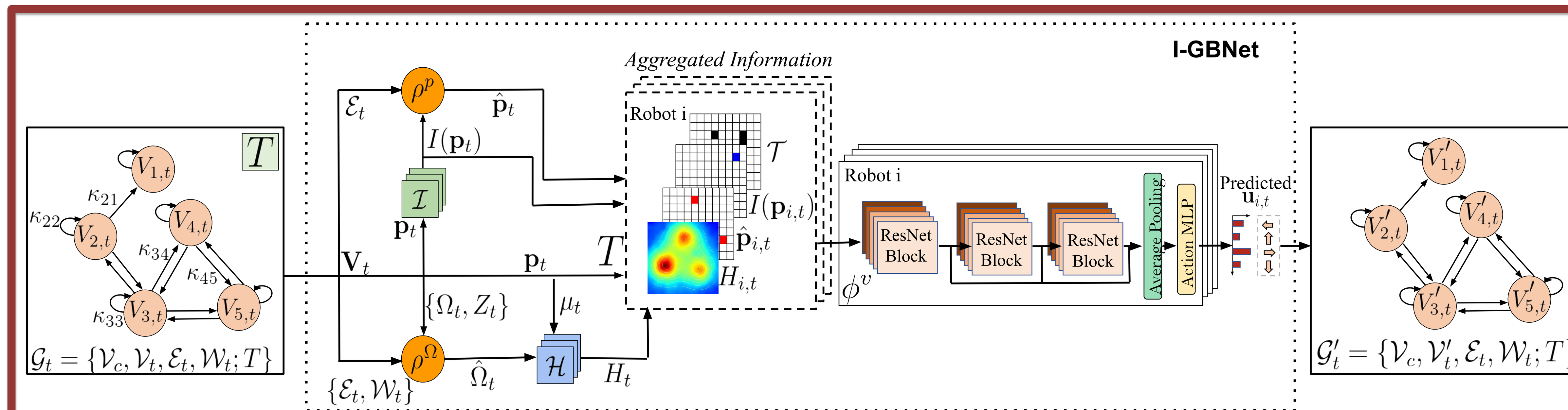
Updated Node Attributes $V'_{i,t}$

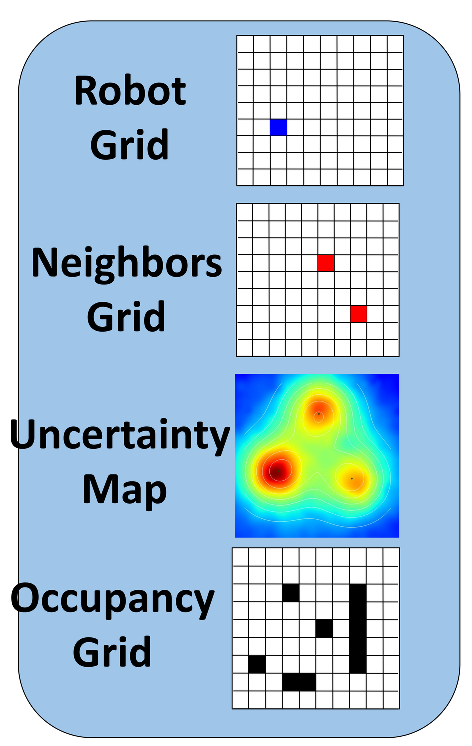
Robot's Action $\mathbf{u}_{i,t}$

Multi-Robot Active Information Acquisition with GNNs

A sequential decision-making problem, where an Information-aware Graph Block Network (I-GBNet) each timestep takes as input the network graph, updates the node attributes into a categorical distribution over the admissible control inputs and outputs the final action for each robot.

Architecture & Training





$$V_{j,t} \xrightarrow[\kappa_{ji}]{\{\mathbf{p}_{j,t}, \Omega_{j,t}\}} V_{i,t} \xleftarrow[\kappa_{gi}]{\{\mathbf{p}_{g,t}, \Omega_{g,t}\}} V_{g,t}$$

Robots receive from neighbors their positions and estimates to compute i) neighbor's grid and ii) final uncertainty via DKF

Distributed Kalman Filter

$$\Omega_{i,t+1} = \sum_{j \in \mathcal{N}_{i,t} \cup \{i\}} \kappa_{ij}\Omega_{j,t} + M_{i,t}R_{i,t}^{-1}M_{i,t}^T$$

$$\Omega_{i,t} = \Sigma_{i,t}^{-1}$$

Training

- Created 1500 randomly generated 20mx20m environments with:

  10 robots, 10 static targets
  All-to-all communication

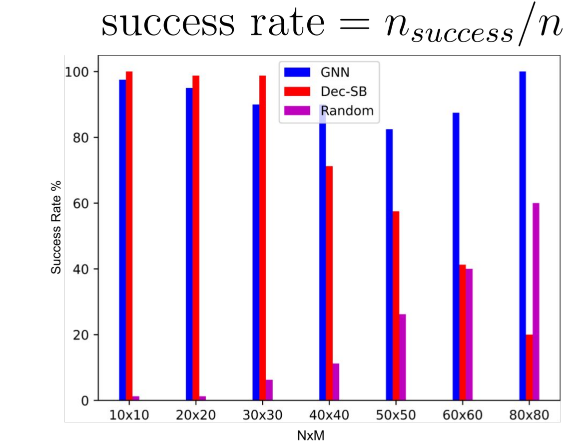
  to collect in total 15000 data.
- Used Imitation Learning to train I-GBNet.
- The expert is a Centralized sampling-based non-myopic Active Information Acquisition method.

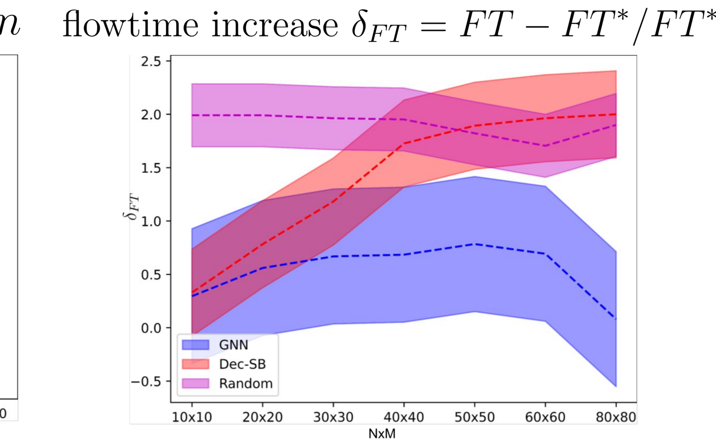
Experiments

Scalability & Comparisons

Run the expert on n = 100 random configurations of N(robots)xM(targets) and compare the trained network on i) a Random Walker method and ii) a Decentralized Sampling-based Non-myopic method.

success rate $= n_{success}/n$ flowtime increase $\delta_{FT} = FT - FT^*/FT^*$

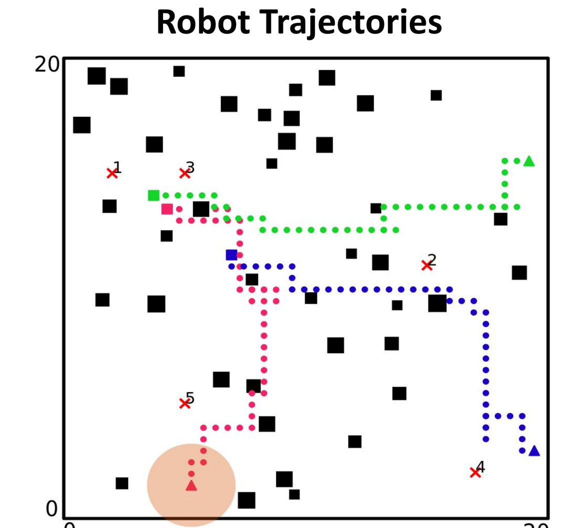




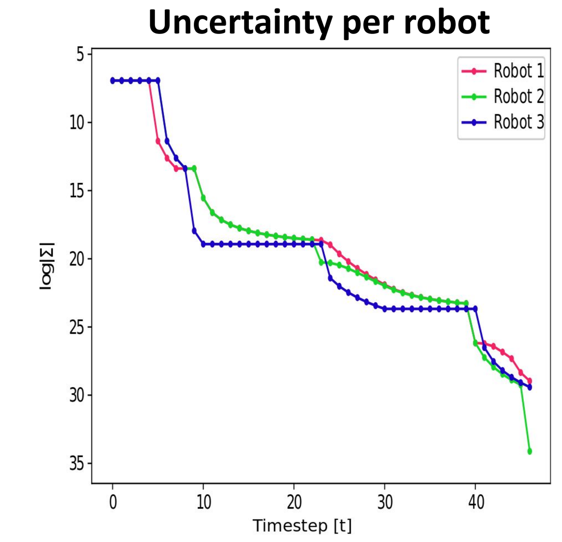
Static & Dynamic Targets

Task: localize 5 static landmarks, while avoiding the obstacles.

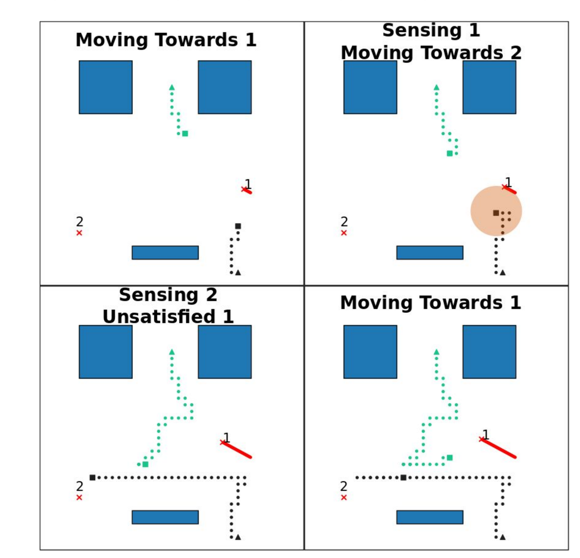
Robot Trajectories



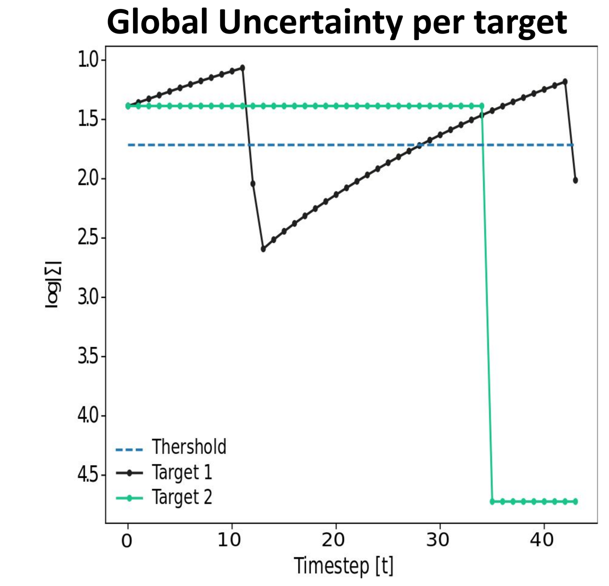
Uncertainty per robot



Task: localize a static landmark and a dynamic target of known dynamics in a 20m x 20m environment



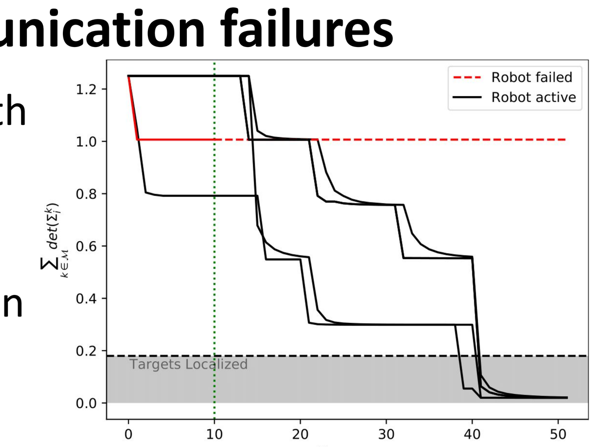
Global Uncertainty per target



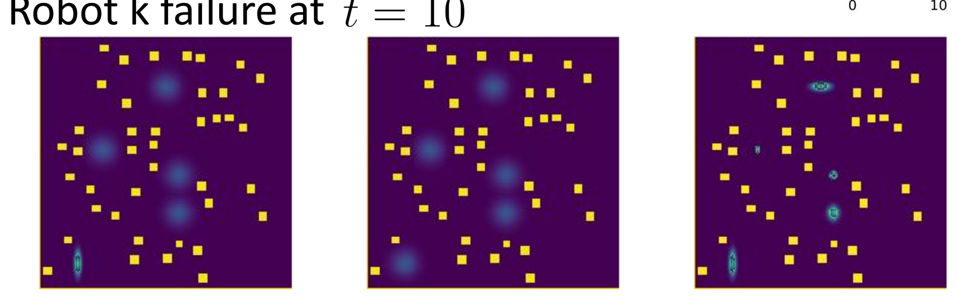
Robustness to robot & communication failures

Time varying communication graph with communication range of 4m

Loss of packets by introducing edge deletion based on a Poisson distribution (λ = 1)



Robot k failure at $t = 10$



Robot k uncertainty @ t=9 Robot 2 uncertainty @ t=9 Robot 2 uncertainty @ t=49