Resilient Navigation & Path Planning in Fire

Hari Srikanth, Mira Loma High School, Sacramento, CA

Motivation

Structure fires are responsible for the majority of fire related deaths worldwide. The unpredictable nature of fires reduces the efficacy of predetermined escape strategies, and given that the majority of casualties stem from people trapped by collapsing structures, high heat, and flames, a means of determining safe escape and rescue routes is necessary

Background

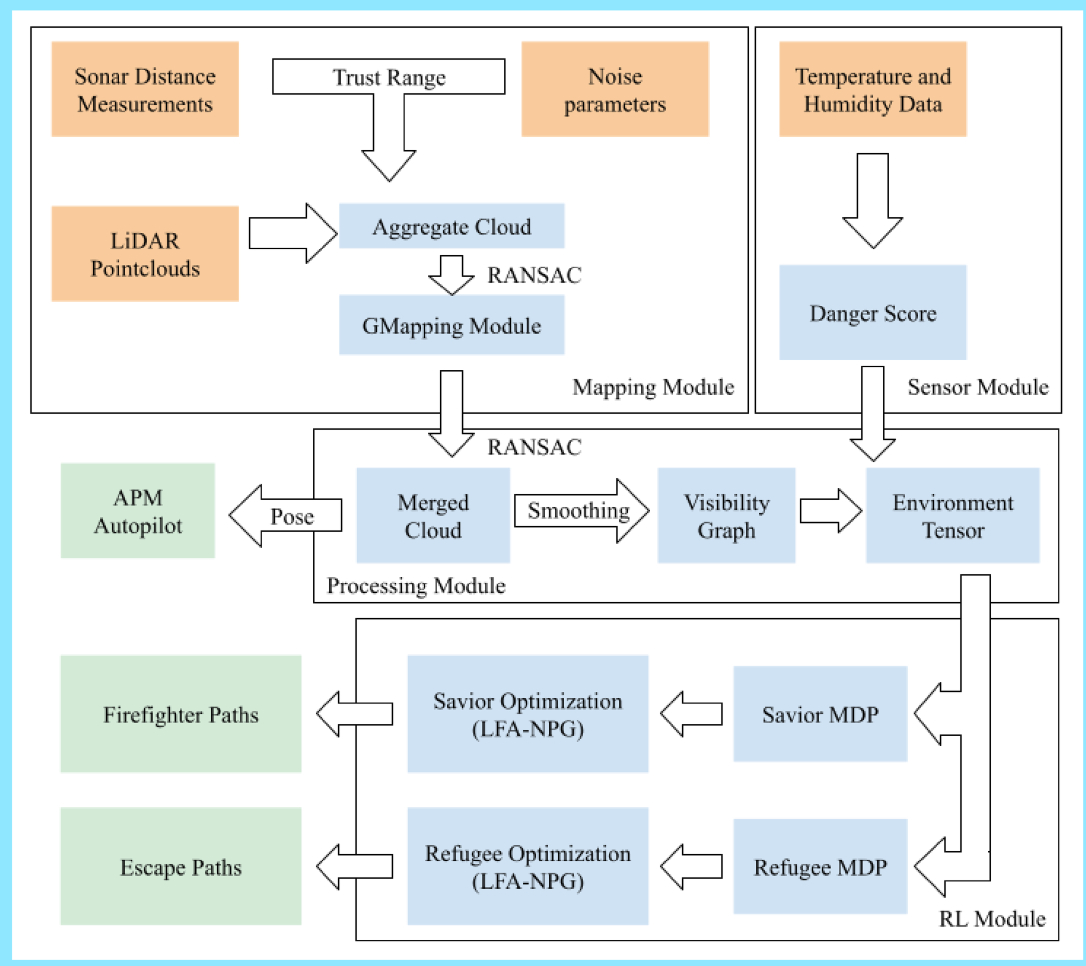
Navigating a fire has traditionally posed a challenge for robotic systems. Traditional LiDAR sensors (often employed for SLAM) lose significant accuracy due to smoke, while comprehensive SONAR and RADAR systems tend to be very bulky, impeding movement throughout space. Even with an accurate representation of the environment, current machine learning algorithms are very computationally expensive, posing challenges for onboard training and processing.

System Implementation

General Priorities:
- Speed: Data must be sampled at a sufficiently high rate for the system to react appropriately
- Robustness: Processing algorithms must be resistant to adversarial noise, an inherent factor when live systems are considered

Case Specific:
- System self evaluates accuracy

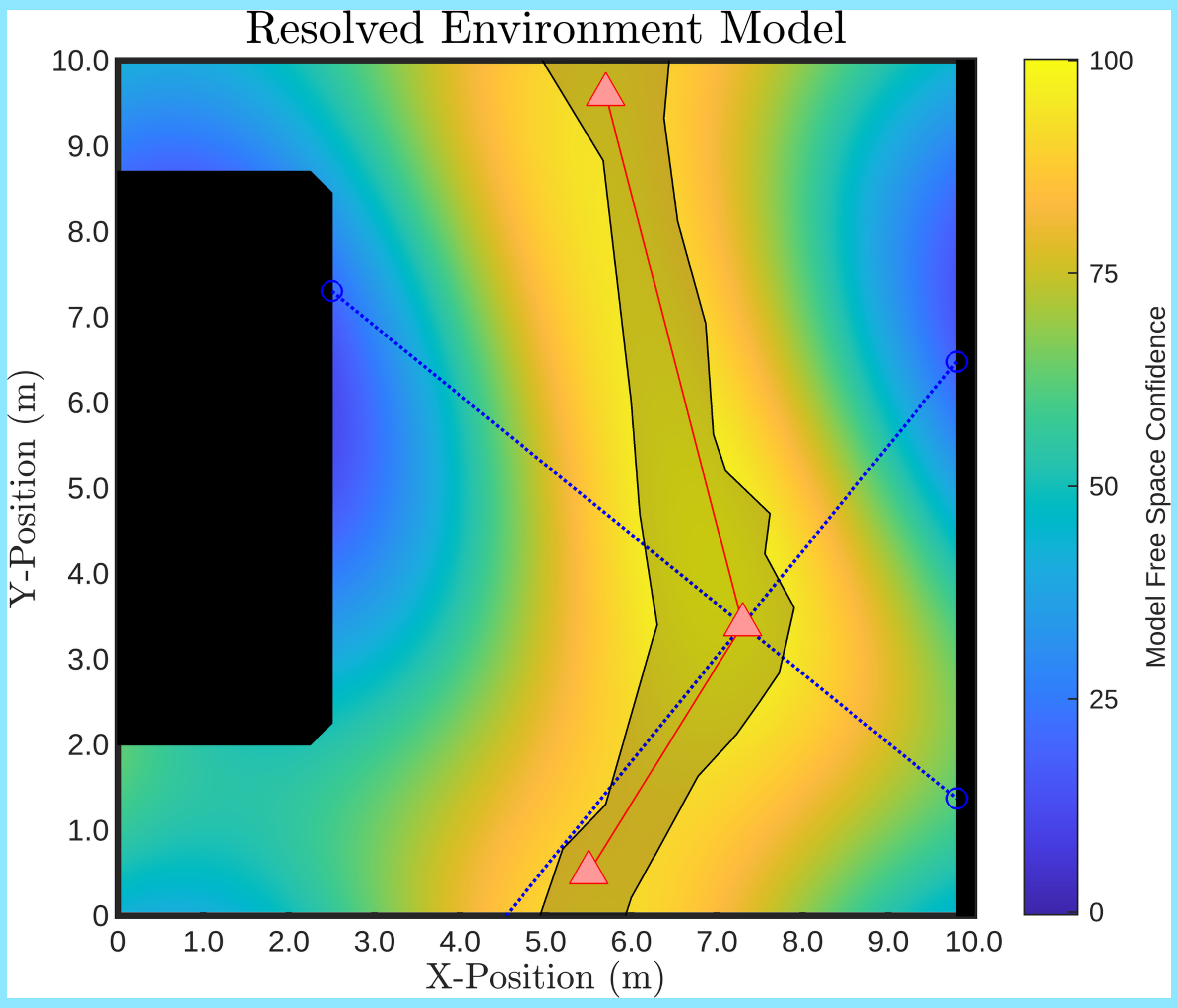
Organization:
- Multi Robot Network
- LiDAR+SONAR modules
- Merging
- Escape route gen via RL



Data Aquisition & Processing

Raw Sensor Data:
- LiDAR (outlined grey) makes up the core of the mapping system due to its high resolution for its power consumption and price
- Four SONAR sensors (blue dashes) take high fidelity measurements of the environment
- Particulate Matter Sensors determine the level of smoke, which is the main source of disturbance to the LiDAR & SONAR

Blending:
- Fuzzy logic system
- Trust range determined by discrepancy between SONAR & LiDAR as well as Adversarial Noise
- Each point is assigned model free space confidence, based on the likelihood that it is empty.



Merging & Simplification

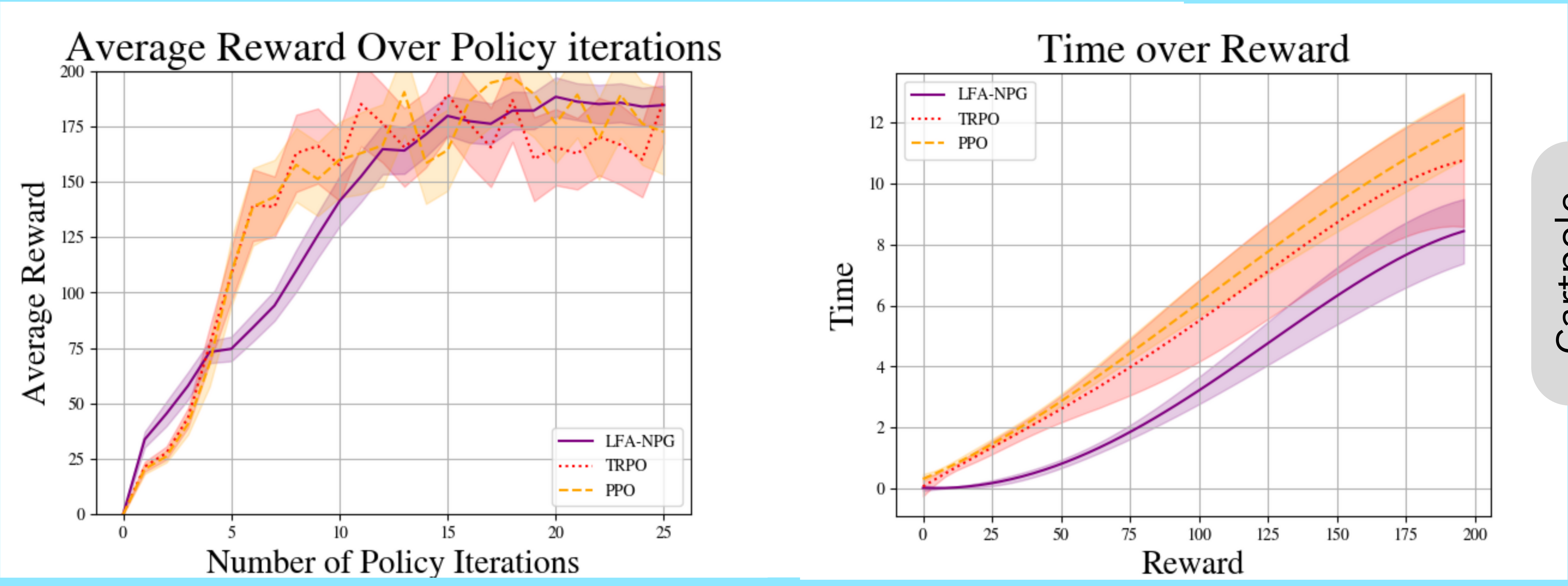
Global Map Merging Algorithm (RANSAC):
1. A correlative scan matcher identifies matching edges of scans from each robot
2. Each edge solution is added to a pool of candidates
3. For any two maps, a translation is determined such that one candidate edge has zero error
4. The errors of all other candidate edges is determined, enabling inliers and outliers to be identified
5. Once the correct translation has been determined, the two maps are merged into a global map. This global map is then merged with the each successive map, until a comprehensive picture of the environment has been formed.

Simplification:
- Global Map smoothed to visibility graph
- Heuristics at each node:
  - Model Free Space Confidence
  - Danger Score (Temperature & PM Concentration)
- Unpopulated nodes receive interpolated scores

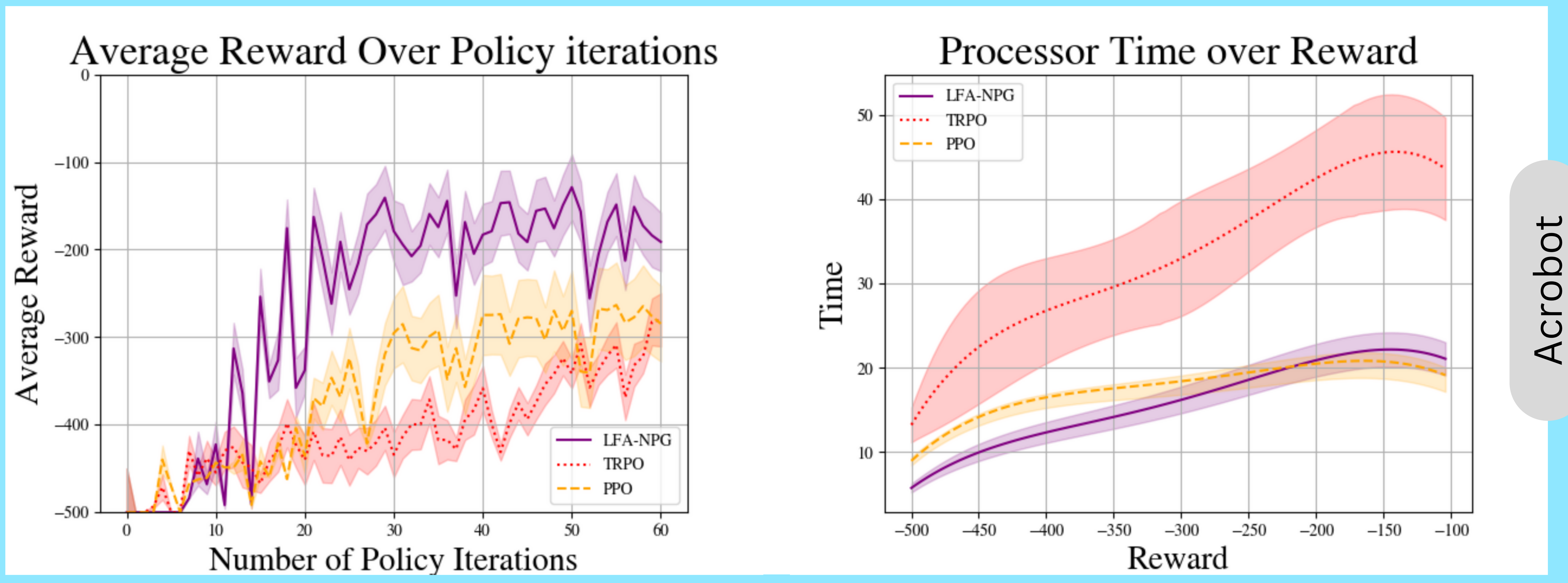
RL-Path Generation

RL Solvers:
- First Responders: Environment tensor used to determine optimal route to rescue
- Inhabitants: Environment tensor used to determine safest escape route

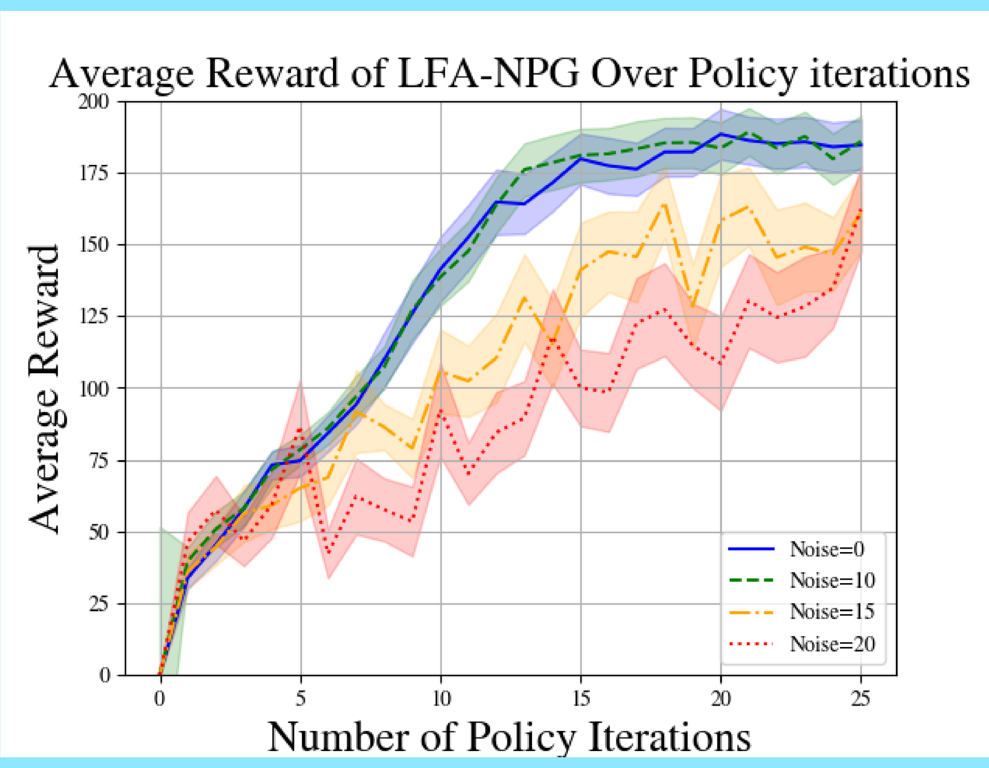
As the use cases only differ by initial conditions, the same architecture can be applied. The environment tensor is inputted into an MDP, which is then passed to the RL Algorithm LFA-NPG.



Cartpole



Acrobot



LFA-NPG:
- Policy Space RL Methodology
- Natural Actor Critic Architecture
- Linear Function Approximation based value evaluation

Why LFA-NPG:
- Use case has simplified inputs, low DOF
- Evaluated performance on standard low dimensionality benchmarks Cartpole & Acrobot vs TRPO & PPO
- LFA-NPG Matched performance/iteration on Cartpole, exceeded performance on Acrobot
- LFA-NPG reaches reward in lower compute time
- Exhibits strong resistance to adversarial noise

Next Steps

- Large Scale Swarm Testing
- FMCW Radar Integration
- Human Identification
- Thermal Imaging
- Perception at high speeds testing
- LFA vs OR Methodologies

Phone: +1 (916) 693 0389 **Email: harinsrikanth@gmail.com** **Linkedin: harisrikanth**