## Towards Uncertainty-Aware Path Planning On Road Networks Using Augmented-MDPs

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#### **Navigation under uncertainty**



#### **`B` is the most likely position**



#### If the robot is at `A` instead



## Safer to go up and turn at `C`



## Safer to go up and turn at `C`



#### Objective

#### Select actions that reduce the risk to make mistakes during navigation with large position uncertainty



#### Planning on road networks



#### Planning on road networks



#### Markov Decision Process (MDP)





#### **Optimal actions at intersections**



#### MDP state is fully observable



#### **Uncertainty is ignored**



#### **Uncertainty-aware planning**

- Reduce the risk to make wrong navigation decisions
- Consider position uncertainty during planning
- General formulation as Partially Observable MDPs or **POMDPs**
- POMDPs are hard to solve for real-world applications

#### Augmented-MDPs (A-MDP)

- Efficient POMDPs approximation
- Augment MDP state space with position uncertainty
- Approximate state estimate during planning with isotropic Gaussian



#### **Transitions between beliefs**



# Localizability information Estimate the localization accuracy



OpenStreetMap



Vysotska et al. 2017

# Localizability information Estimate the localization accuracy



 Image: marked system
 high

 Image: marked system
 low

 Image: marked system
 Image: marked system

OpenStreetMap

# **EKF prediction + Localizability** Estimate the **belief propagation** $p(x_t \mid x_{t-1}, u_t, \mathcal{Z}) = \mathcal{N}(\hat{\mu}_t, \, (\hat{\Sigma}_t^{-1} + \Sigma_{\hat{\mu}_t, \mathcal{Z}}^{-1})^{-1})$ $\boldsymbol{S}$ $\boldsymbol{U}$ high low Z

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## **Transition probability**

#### According to **Bhattacharyya distance** between **posterior** and **output state**



#### **Augmented-MDP**

- Transitions between beliefs
- Rewards minimize the travel time

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Optimal policy **minimizes travel time** while **reducing the mistakes** during navigation















#### **Shortest path policy**



























#### Safest path policy







#### Safest path, large uncertainty Η Ρ J F $\mathbf{S}$ goal Ε Κ $\mathbf{Q} ullet$ $\mathbf{T}$ • M 1 0 Т U • N V В W A • () <u>10 m</u> start 47

#### Safest path, large uncertainty Η Ρ J F $\mathbf{S}$ goal $\mathbf{E}$ Κ $\mathbf{Q} ullet$ $\mathbf{1}$ $\mathbf{T}$ • M 1 D 0 Т U • N V В W A • () <u>10 m</u> start 48

#### Safest path, large uncertainty Η Ρ J F $\mathbf{S}$ goal Ε Κ $\mathbf{Q} ullet$ $\mathbf{T}$ • M 1 D 0 Т U • N V В W A • () <u>10 m</u> start 49





#### Safest path, small uncertainty Η Ρ **\_** J F S goal Ε Κ $\mathbf{Q} ullet$ • M 1 D 0 Τ U • N V В W 🖕 Α • 0 <u>10 m</u> start 52

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# Shorter avg. travel time than the shortest and safest path policy



## Summary

- Planning on road networks explicitly considering position uncertainty
- Augmented-MDP approximates efficiently POMDP
- Localization prior estimates belief propagation through the network
- Policy trades-off safety and travel time given the current belief

#### Thank you for your attention