Socially-Aware Path Planning for a Flying Robot in Close Proximity of Humans

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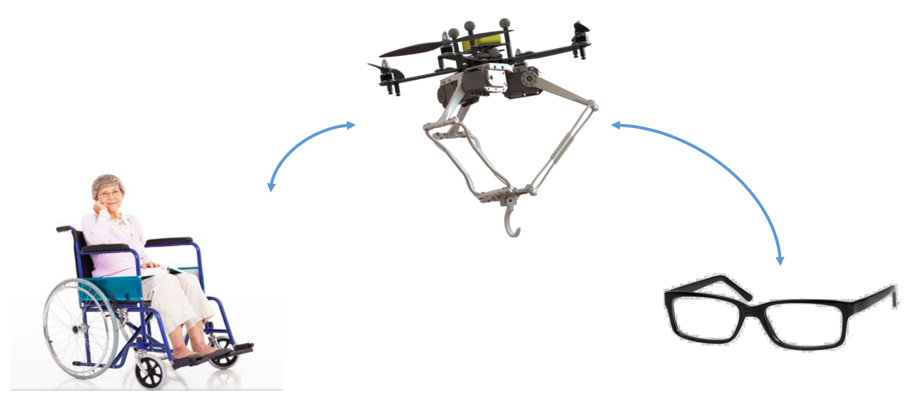
MOTIVATION

The growth of the elderly population creates a critical need to develop technologies to assist humans in daily activities.



This research provides a solution to the problems:
1. How do humans perceive autonomous mobile robots?
2. How to control mobile robots to improve comfort and perceived safety?

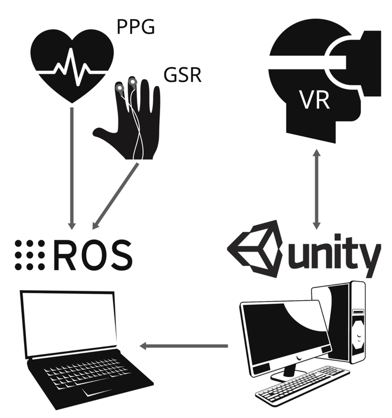
VR EXPERIMENT AND DATASET GENERATION

Virtual Reality Human-Robot Environment

We collected human test data utilizing a virtual reality (VR) environment. The subject observes a flying robot in the proximity.

VR runtime analytics, EDA, and PPG are synchronized with ROS and logged for subsequent analysis.

Data Acquisition System

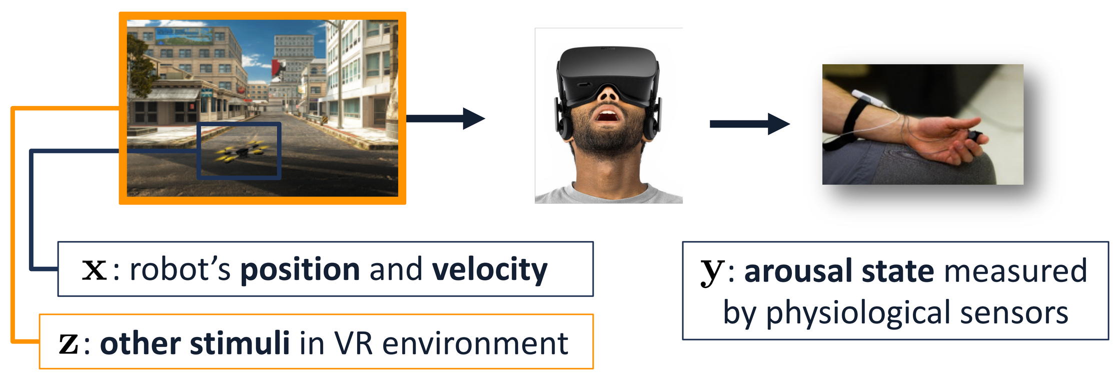


- Electrodermal activity (EDA)
- Photoplethysmography (PPG)
- Drone position
- Drone velocity
- User head position
- Drone visibility

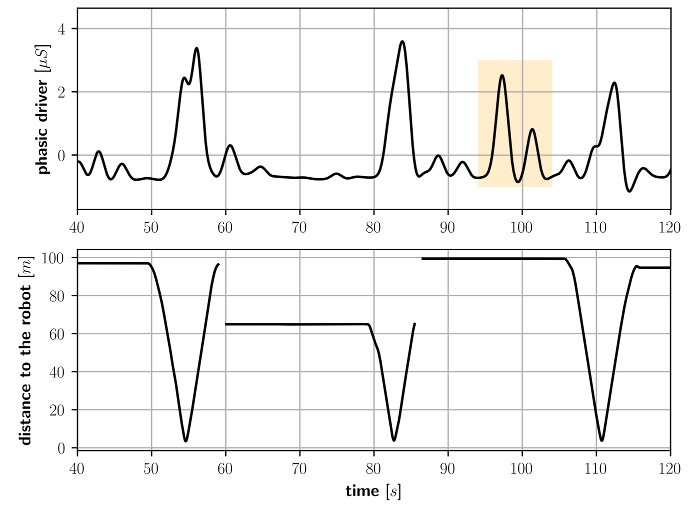
PROPOSED MODEL

Unknown factors

There are **unknown factors** not contained in the data that may influence the outcome (human arousal).



The plot shows that the phasic driver (arousal) increases although the flying robot is virtually invisible to the subject.



A **latent variable model** is proposed to consider the **effect** of **unknown factors**.

A Hidden Markov Model

1. Human attention state (a latent variable) **models change of the focus of the attention.**

$$z_n := \begin{cases} 1, & \text{if the human is attentive to the robot.} \\ 2, & \text{otherwise.} \end{cases}$$

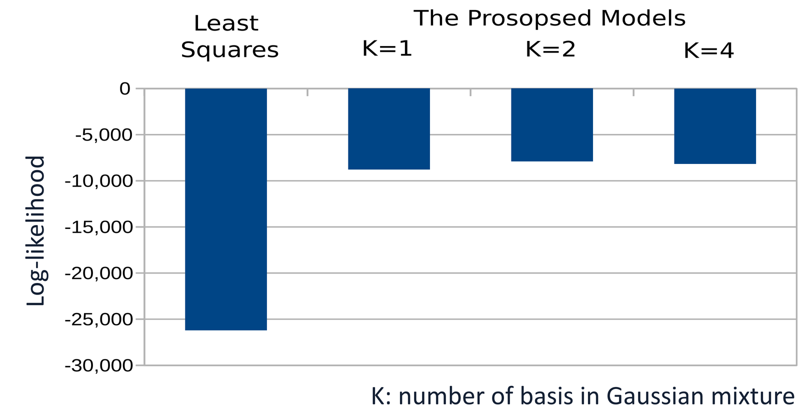
2. Regression Model:

$$y_n = \mathbf{1}_{\{z_n=1\}}(f_\beta(x_n)+\epsilon) + \mathbf{1}_{\{z_n=2\}}\delta\ ,$$

where $f_\beta : \mathbb{R}^9 \to \mathbb{R}$ is a mapping with parameter β and δ denotes the random source (e.g. Gaussian Mixture).

Maximum likelihood estimate of the model parameter is determined using an **EM** algorithm.

1. Significant improvement of the likelihood

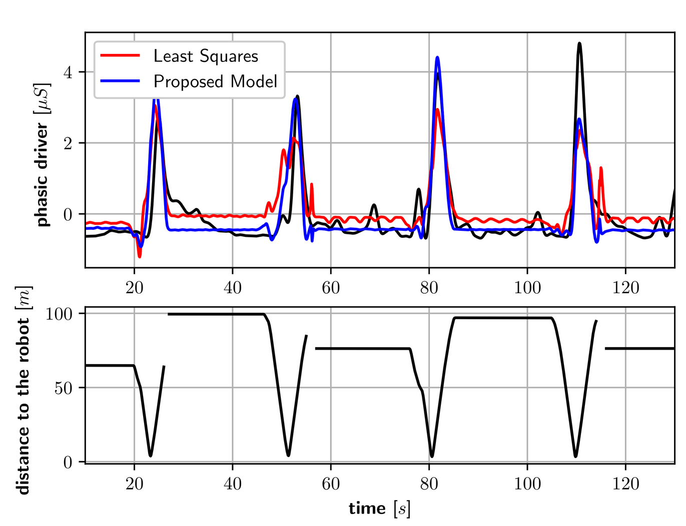


2. Prediction of Arousal

The proposed method puts greater **weight based on the posterior of the attention** state.

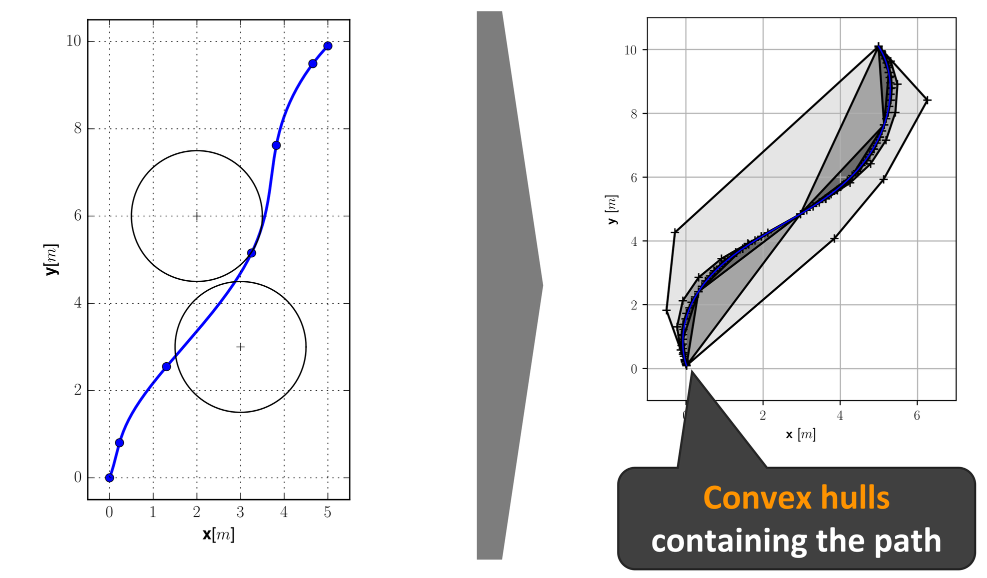
$$\beta^* := \underset{\beta}{\operatorname{argmin}} \sum_{n=1}^{N} P(z_{n,1}|\mathbf{x},\mathbf{y},\theta)(y_n - f_\beta(x_n))^2$$

The plot below shows that the least squares method's prediction is **oscillatory** and has a greater **offset** in the base.



OPTIMAL PATH PLANNING

Bernstein Polynomial based Trajectory Generation



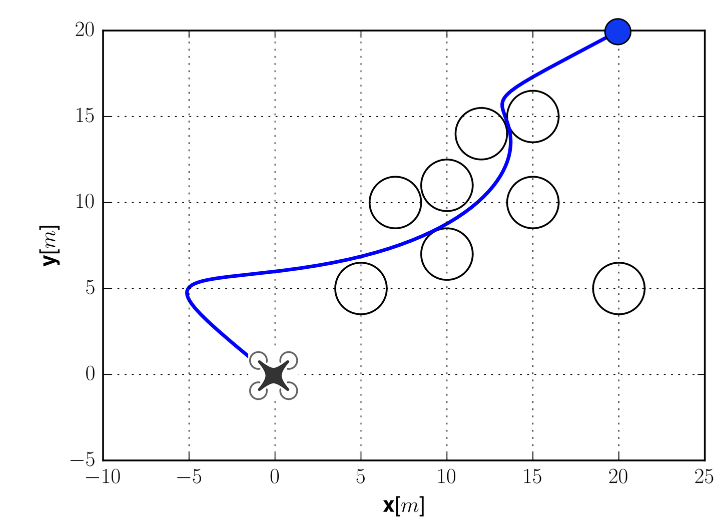
Collision can happen **between time nodes.**

Using **Bernstein polynomial** collision avoidance is ensured.

The polynomial trajectory generation is cast as a **nonlinear optimization**:

$$\min_{\mathbf{y}} F(\mathbf{y}),$$
$$\mathbf{g}_l \le \mathbf{G}(\mathbf{y}) \le \mathbf{g}_u.$$

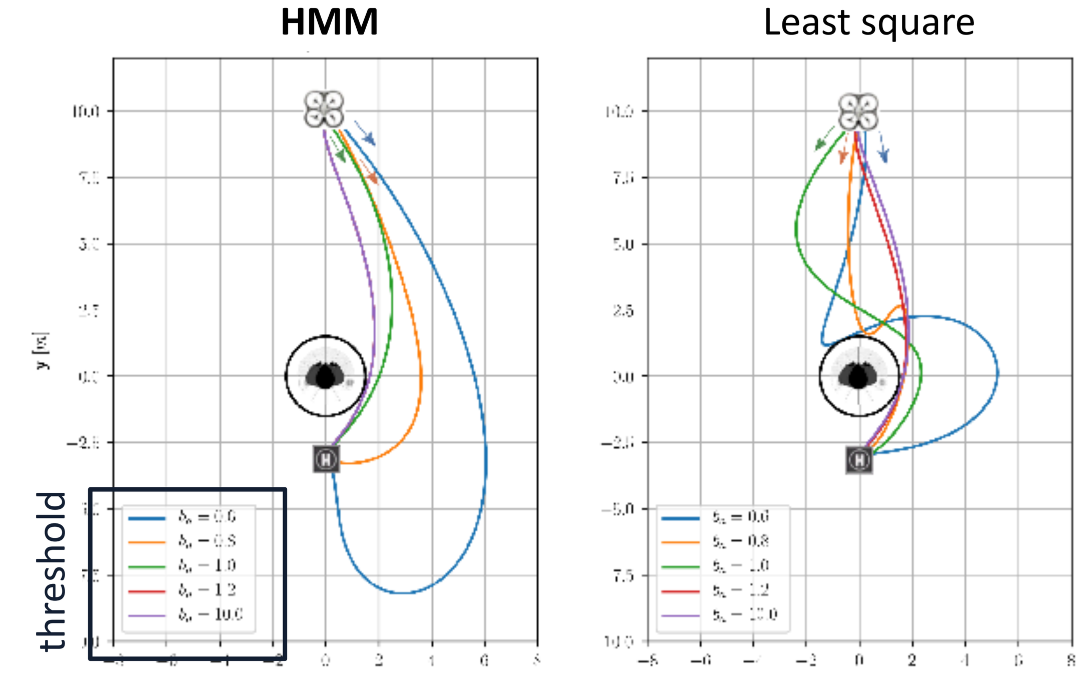
1. Quadrature techniques approximately calculate the cost (e.g. flight time, energy spent, etc.).
2. Distance from the obstacle to the **convex hulls** is incorporated into the inequality constraints to ensure collision avoidance.



Minimal flight time path generation.

Path Planning considering Safety Perception Models:

The cost considers the safety perception model so that the phasic driver signal is below certain thresholds.



Hidden Markov model (**HMM**) is **robust** compared to least square (**LS**) minimization.

CONCLUSIONS

We present a path planning framework that takes into account the human's safety perception in the presence of a flying robot.

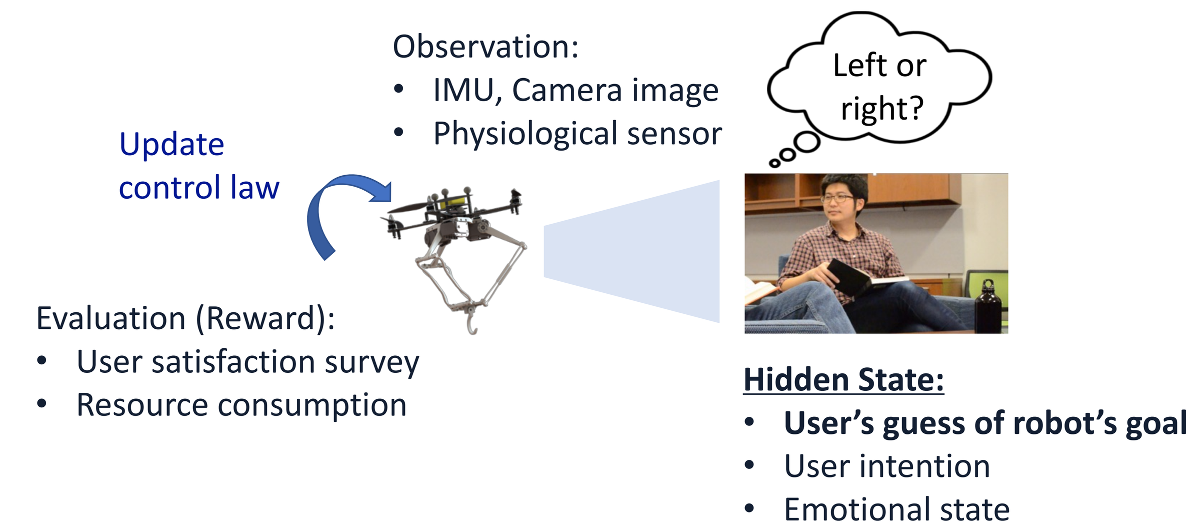
We devise a machine learning method to estimate the uncertain parameters of the proposed safety perception model based on test data collected using Virtual Reality (VR) testbed.

Also, an offline optimal control computation using the estimated safety perception model is presented.

FUTURE WORK

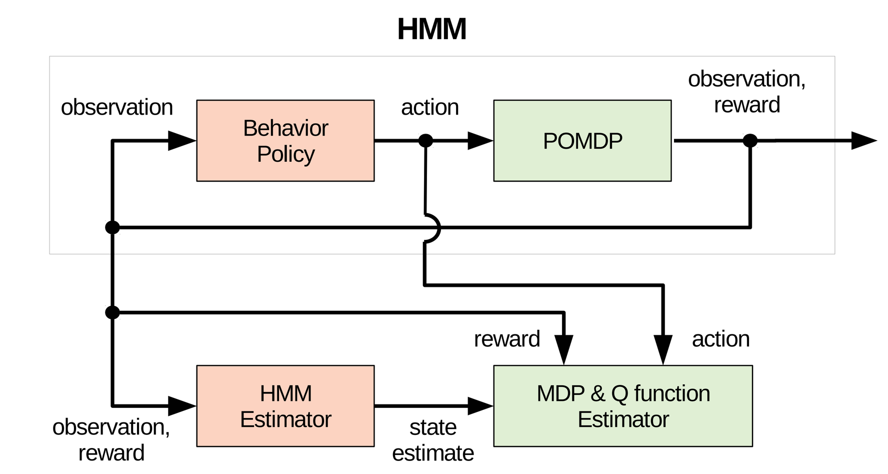
A drawback of the proposed path planning framework is the lack of adaptability because the algorithms for estimation and path planning are **off-line** algorithms.

Reinforcement Learning (RL) under Incomplete State Observation



Hidden Markov Model Online Estimation for RL

Reinforcement learning with partially observable Markov decision process (POMDP) is cast as online HMM estimation problem.



PUBLICATION

1. Christopher Widdowson, Hyung-Jin Yoon, Venanzio Cichella, Ranxiao Frances Wang, and Naira Hovakimyan. "VR Environment for the Study of Collocated Interaction Between Small UAVs and Humans." *International Conference on Applied Human Factors and Ergonomics*. Springer, 2017.
2. Hyung-Jin Yoon, Christopher Widdowson, Thiago Marinho, Ranxiao Frances Wang, and Naira Hovakimyan. "A Path Planning Framework for a Flying Robot in Close Proximity of Humans." *Annual American Control Conference (ACC)*. IEEE, 2019. (Submitted)
3. Hyung-Jin Yoon, Donghwan Lee, and Naira Hovakimyan. "Hidden Markov Model Estimation-Based Q-learning for Partially Observable Markov Decision Process." *arXiv preprint arXiv:1809.06401* (2018).

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