NRI: FND: Life-long Learning for Motion Planning in Human Populated Environments

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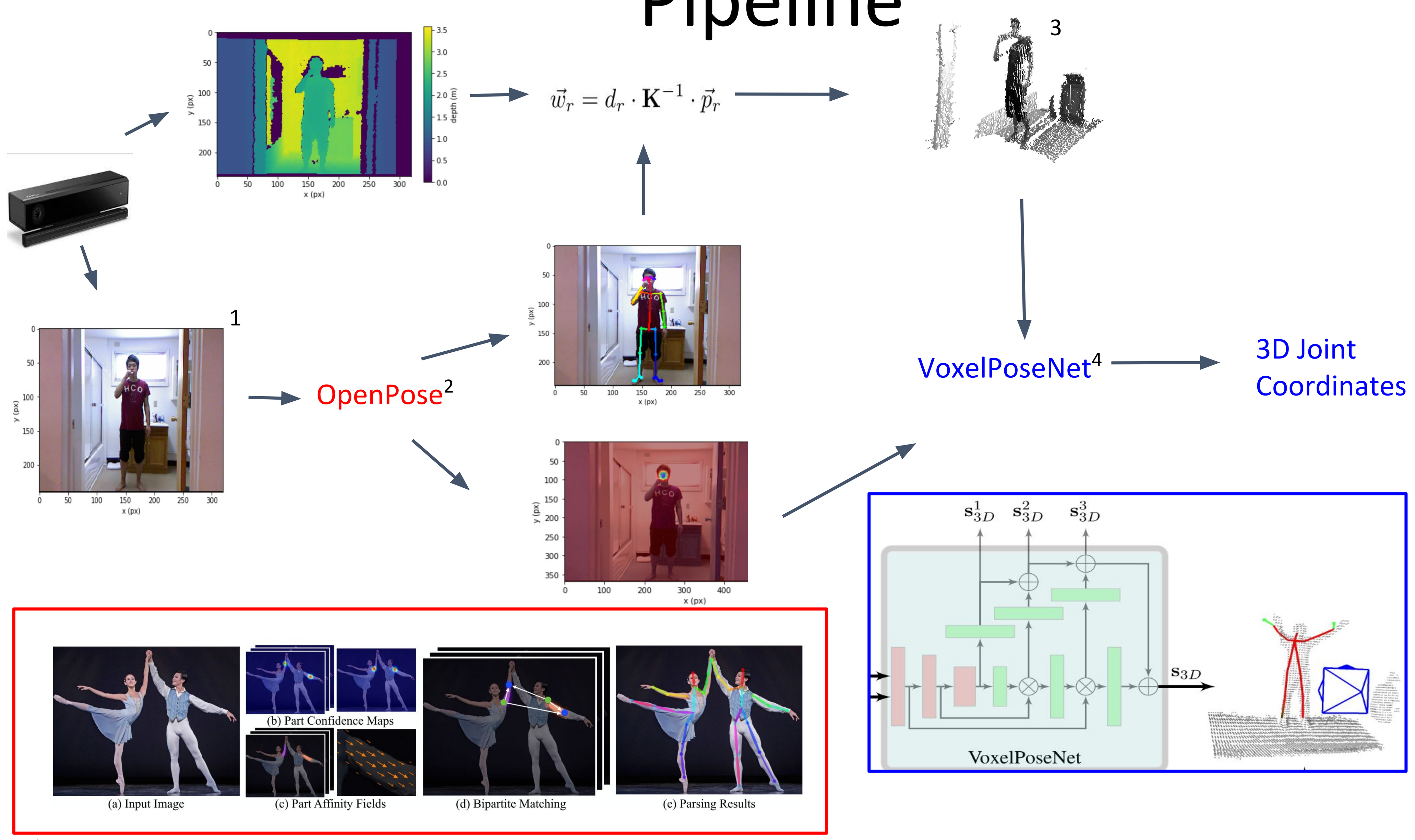
Human Detection and Pose Estimation Pipeline



[1]Human Activity Detection from RGBD Images, Jaeyong Sung, Colin Ponce, Bart Selman, Ashutosh Saxena. In AAAI workshop on Pattern, Activity and Intent Recognition (PAIR), 2011.
[2]Z. Cao, G. Hidalgo, T. Simon, S.-E. Wei, andY. Sheikh. OpenPose: realtime multi-person 2D poseestimation using Part Affinity Fields. InarXiv preprintarXiv:1812.08008, 2018.
[3]Q.-Y. Zhou, J. Park, and V. Koltun. Open3D: A modern li-brary for 3D data processing. arXiv:1801.09847, 2018.
[4]C. Zimmermann, T. Welschehold, C. Dornhege, W. Burgard, T. Brox, "3-D human pose estimation in RGBD images for robotic task learning", *Proc. IEEE Int. Conf. Robot. Autom.*, pp. 1986-1992, 2018.

Research Thrusts

T1: Continual adaptive learning of context-aware predictive models for human activity

- T1.1: Establish baseline context-aware human models for responding to the presence and movement of a mobile robot.
- T1.2: Developing a lifelong-learning approach to human motion modeling.
- T1.3: Simulation for dynamic human-populated environments

T2: Risk-Aware Path Planning Using Learned Models for Cost-of-Failure Minimization

- T2.1 Optimal control in stochastic environments
- T2.2 Reinforcement learning for policy optimization
- T2.3 Importance sampling for optimal policy search

T3: Extensions to Other Platforms

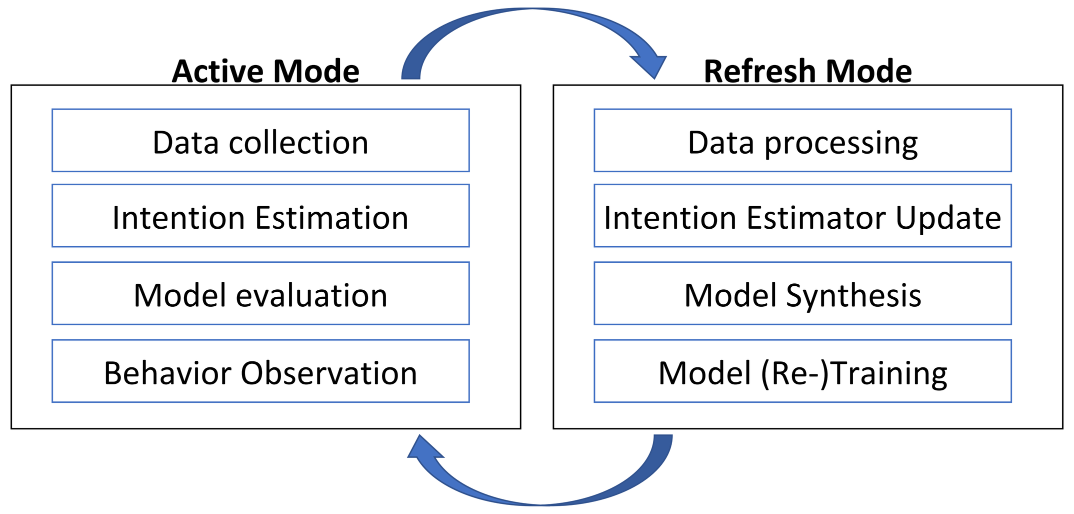
- T3.1 Application to mobile platforms without manipulators
- T3.2 Applications to socially expressive platforms

T4: Policy Exploration for Development of Novel Social Navigation Strategies

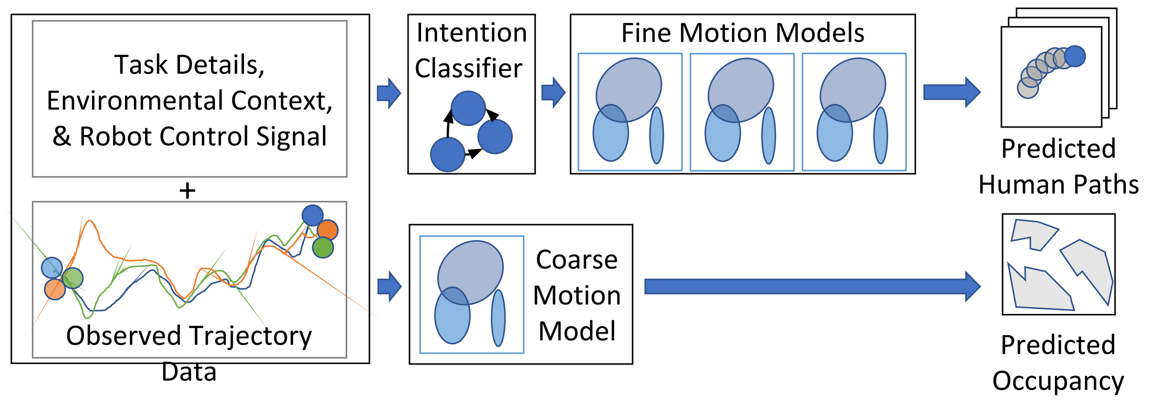
- T4.1 Seed expressive motions based on human behaviors
- T4.2 Apply exploration-exploitation strategies

Self-Supervised Life-Long Learning for Social Navigation Strategies

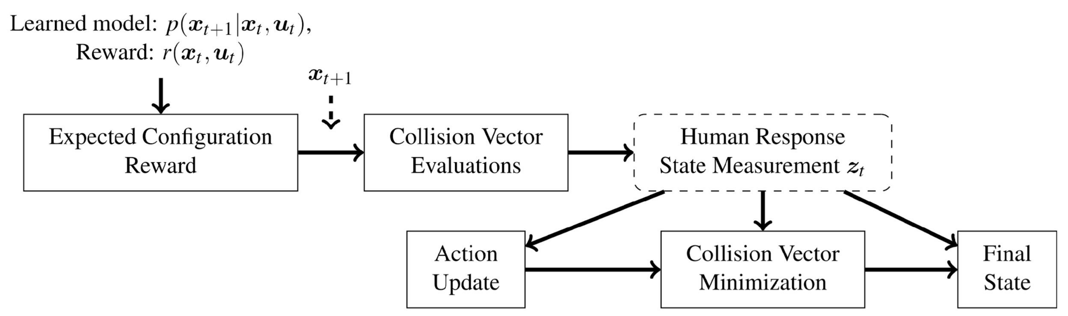
- Conduct long term deployments of mobile robots in populated public spaces, including academic building hallways, coffee shops, and building lobbies. Robots will collect data and re-train their models based on their experiences throughout the day.
- Develop and merge novel techniques of goal and intention inference with motion modeling and prediction, conditioning predictions on contextual cues including location, time-of-day, crowdedness, objects held, and pose.
- Create and release a simulation environment for populating virtual spaces with various goal-directed humans, pairing agent objectives with learned behavioral models for realistic navigation.



Risk-Aware Dynamic Motion Planning



- Informed by learned context-aware models of human motion, agents will plan through time optimizing for collision-free paths in short time-horizons, while minimizing co-occurring occupancy probability mass (i.e., anticipated collision).
- Utilizing inferred collision points as inputs, the risk-aware planning agent will then solve for an optimal upper-kinematics configuration to minimize the cost of collision (e.g., if carrying a cup of coffee with the left hand, using the right arm to create a bumper around it)
- Iterate between applying optimization updates to ground path and kinematic configurations through time to determine low risk behaviors.



Intention-Aware Behavior Prediction

- Using an observation-driven process, a robot is able to map observations of human behavior in a room to an occupancy heatmap indicating areas of interest.
- Once sufficient data has been collected, the robot waits until human traffic dissipates and explores these areas of interest to identify features and objects in their vicinity.
- These features are then associated with being possible areas of interest in novel settings.
- The robot is able to associate the presence of these features with desirable destinations for humans, allowing for generalization of past observations into new environments.
- These priors, coupled with contextual observations of objects humans are carrying (e.g., associating humans carrying mugs with having a coffee machine as a goal destination), facilitate more accurate human path prediction.