Human aware navigation using Bayesian data fusion

Zeynab Talebpour[1] Deepak Viswanathan[2] Alcherio Martinoli[3]

Abstract— **In this work, we present a novel approach to human aware navigation, by probabilistically modelling the uncertainity in the perception components of a networked social robotic system and using this probabilstic model to dynamically create appropriate cost maps for human aware navigation.**

I. Introduction

a) Story: - Quantify uncertainity in perception. Use this for generating cost maps adaptively. FMM creates plans using this uncertainity model.

b) Motivation and approach: - Perception will never be perfect. Unlike other works which choose to ignore this very important aspect of the uncertainity in perception, we propose a model which computes the uncertainity of the location and orientation of multiple people in an environment. We use this model to make informed choices about the cost function for navigation which is then used by a state of the art navigation model using FMM. We dynamically replan based on the perception information available. The key idea is that in cases where the perception is unreliable, we need to make sure that the robot navigates prioritizing safety over social norms.

c) Note: Active perception is also important. The robot movement causes uncertainity which can be actively reduced by taking paths which improve the perception information.

II. Benchmark Task

task

III. Background

background

IV. Learning Algorithms

[1].

$$\bar{X}_n = \frac{(n-1)\bar{X}_{n-1} + X_n}{n} \tag{1}$$

$$\sigma_n^2 = \frac{(n-2)}{(n-1)}\sigma_{n-1}^2 + \frac{(x_n - \bar{x}_{n-1})^2}{n} \tag{2}$$

[1,3]Distributed Intelligent Systems and Algorithms Laboratory, School of Architecture, Civil and Environmental Engineering, École Polytechnique Fédérale de Lausanne {zeynab.talebpour, alcherio.martinoli}@epfl.ch

[2]Deepak Viswanathan, Department of Informatics, University of Amsterdam D.geethaviswanathan@uva.nl

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TABLE I

PARAMETERS COMMON TO ALL PSO ALGORITHMS

Parameter	Value
Number of robots N_{rob}	4
Population size N_p	24
Evaluation span t_e	30 s
Personal weight w_p	2.0
Neighborhood weight w_n	2.0
Neighborhood size N_n	3
Dimension D	24
Inertia w	0.8
V_{max}	20

TABLE II

PARAMETERS FOR *PSO std*, *PSO rep*, AND *PSO pbest*

Parameter	*PSO std*	*PSO rep*	*PSO pbest*
Evaluations of new candidates	1	10	1
Re-evaluations of pbests	0	0	1
Iterations N_i	500	50	250

Initialize particle
for N_i iterations **do**
  Evaluate new particle position n_0 times
  Share evaluation results in neighborhood
  Receive and store evaluation results from neighborhood
  remaining budget := iteration budget - $n_0 \cdot N_p$
  while remaining budget>0 **do**
    Allocate Δ samples among current positions and personal bests in neighborhood using OCBA
    Evaluate allocated samples
    Recalculate mean and variance for new evaluations
    Share evaluation results in neighborhood
    Receive and store evaluation results from neighborhood
    remaining budget := remaining budget - Δ
  end while
  Update personal best
  Update neighborhood best
  Update particle position
end for

Fig. 1. Pseudocode for the *PSO ocbaD* algorithm.

V. FMM BASED HUMAN AWARE NAVIGATION MODEL

VI. PROBABILISTIC DATA FUSION MODEL

Multiple sensing sources (over head cameras, onboard kinect and lasers). MCMC based tracking model for integrating multiple sources. Joint state representation which reasons about multiple people in the environment.State of the art models of observation functions which reasons about the uncertainity of the different detectors (overhead camera detectors, kinect skeleton tracker, leg detector) which aids in accurate computation of uncertainity.

VII. EXPERIMENTS WITH REAL ROBOTS

real

VIII. CONCLUSION

IX. ACKNOWLEDGMENT

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REFERENCES

[1] K. O. Arras, O. M. Mozos, and W. Burgard, “Using boosted features for the detection of people in 2d range data,” in *2007 IEEE International Conference on Robotics and Automation,*, 2007, pp. 3402–3407.