Uncertainity Based Human Aware Navigation

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***Abstract*— In this work, we present a novel approach to human-aware navigation based on the fast marching method, by probabilistically modeling the uncertainty of perception for a social robotic system and investigating its effect on the overall social navigation performance. We have extended the model of the social costmap around a person to consider this new uncertainty factor which plays an important role in situations with noisy perception. Additionally, a variation of the Dynamic Window Approach, which takes social costs into account, has been considered for navigation to discard or penalize velocity candidates that lead to unnatural or uncomfortable movements in the vicinity of humans. Real robot experiments have been carried out to show the effectiveness of our approach given noisy perception, in the presence of single/multiple, static/dynamic humans. Results show how our approach has been able to achieve trajectories which are more socially-aware compared to the basic navigation approach, and the human-aware navigation approach which relies solely on perfect perception.**

I. Introduction

**[DV] Need to have 6 paragraph. First para stays.
Second should motivate human aware navigation using FMM. This means motivating FMM and then human aware navigation using FMM. Also in this para, mention about global and local path planning strategies.
Next para should be about the social cost map using proxemics.(I prefer this order since social cost map can only be mentioned after you explain the framework (FMM or DWA which is the path planner).
4th para seems ok now. We motivated social path planning using social cost maps and planners like FMM or DWA. In this para we talk about how and why uncertainty should be used.
5th para is the place where we talk about our two models.
6th Para should be our results. "We also show from our experiments that...global path planning has these positives and negatives when used for real human aware planning using uncertainty, whereas local strategies have these these issues. **

[DV] Motivating our work in one para. Looks good for now Human aware navigation is a key problem in social robotics. If robots need to be actively used in natural social environments, one of the main functionalities required is navigation. Robots have to navigate in environments shared with humans and the quality of their movement strongly influences how their intelligence is perceived [1]. Conventionally, comfort, naturalness and scalability, are the main focus of such human aware navigation techniques [2]. In this work, we attempt to model one essential aspect of human aware navigation which has been overlooked in this area, uncertainty in the perception.

[DV] How do we do human aware navigation. We do it by using social costmaps fed into a navigation planner. So first talk about the path planning, I think we should say that people have tried to do this using global planners. And also talk about local planners. Add a para here about social path planners.

One important concept which is used in numerous studies [3]–[6] in this area is virtual space around a person that is mutually respected by other humans, called *proxemics* [7]. Based on this concept, depending on the relationship and the interaction that exists between humans, people choose different social distances relating to intimate, personal, social or public contexts. Changes in the expected distance may indicate dislike if it is too large or cause discomfort if it is too small.**[DV] avoid ideas like these. This has no relevance to our story**

Social costmaps are a common way to model this principle and have been used in various studies in the field. There are many factors that have a role in shaping this costmap, but the proxemics distance is mainly addressed. Other factors such as speed of a person's movement, gender, age, etc. have also been considered in the literature, but are much less common.**[DV] This way of phrasing the available works, makes it feel like uncertainty is just another factor that people ignored to consider. we need to rephrase this idea of social cost maps**

[DV] By the time we are here, we should get the idea about social cost map clear, socially aware path planner clear. then the next para makes sense. A socially-aware path planner should take into consideration individual people and possible social interactions taking place between the people in the environment. However, perception will never be perfect and is affected by various elements such as the movement of the robot, movement of the people, complexity of the environment in terms of occlusions, etc. Due to the approximate nature of the models and the less than perfect detectors available, we often can only provide estimate of location of the people with an associated uncertainty. Any planning algorithm which needs to rely on real perception sources must be able to use this less than perfect estimates.

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The assumption of having perfect information about the position of people at all times, is common in the state of the art research in this area[ref][ref] **[DV] must add references**, where the main focus is on the planning itself. However, moving to real applications, poses serious challenges in terms of noisy perception information and high uncertainties, that need to be addressed and modelled in a human-aware approach.

Unlike other works which choose to ignore this very important aspect of the uncertainty in perception, we propose a model which computes the uncertainty of the location and orientation of the people in an environment. We aim to study, how this factor should influences the social costs used by the path planner and how taking this into account the resulting trajectories will be improved in terms of social acceptability.

[DV] Core idea for last para In this work, we have developed a human aware navigation method incorporating uncertainty in perception. By using an FMM based social navigation planner and a DWA based social navigation planner, we compare how a global and local planning strategy can be used for human aware navigation. We explore the benefits of each strategy in a stochastic environment with varying uncertainty about the location of the people in the environment.

[DV] Use all you need from below for the FMM and DWA para. but all details should be pushed to background. Introduction should be crisp and clear.

The remainder of this article is organized as follows. In section **??** we introduce the related works in this area. Section **??** explains the probabilistic perception model and Section **??** explains the model of social navigation incorporating the uncertianity from perception. The robotic platform [20] used in our tests, and the experimental setup will be explained in detail in section V. In section VI-A, we show the results of our simulations and real robot experiments and finally, section VII concludes this work.

II. Literature

[DV] Place our work. Use this section as a narrative to place our work among the available works on human aware navigation. By the end of this section it should be clear how and why our work is relavant. Coarse overview : Broadly summarize the works on human aware navigation historically. Then come to introducing FMM and its use in human aware navigation. One para about local planning (DWA) and its applicability in human aware navigation. One para about people tracking works and probabilsitc model. FMM has been proven to be successful in real domestic spaces with high complexity [10]. However, we add a social component to the aforementioned method by augmenting it with social costmaps —based on proxemics principles [11]— around individual people which correspond to speedmaps for the FMM method. There have previously been a number of research papers which have address social path planning [8], [12] using FMM.

The work of [12] a theoretical framework for introduced sub-problems of social path planning is presented and an extended mode for engaging groups of people is proposed by using a special version of fast marching square planning method [13]. Nonetheless, the information about humans are considered to be given and noiseless, while only simulations have been used to show the effectiveness of the proposed method for static people. We are interested in investigating the same problem in real-world scenarios with the challenges that exist therein. Particularly, in the case of moving people, while the perception is subject to uncertainty. We believe that uncertainty of perception in social robotics, is an important topic which to our knowledge, has not been the subject of many notable studies. There is a dedicated chapter in [14] on local planning with uncertainty, however this is not considered in a social context. The sources of uncertainty in [14] are the position of the robot and the obstacles, and the partially known motion of moving obstacles and perception of people and the uncertainty in person and group detection and tracking has not been investigated.

Another interesting aspect of human-aware navigation problem which should be deeply investigated is knowing how to decide when to replan. As a perquisite, We have studied whether accounting for social costs in the local planner can be effective. In basic navigation, the global path planner, provides a plan and local planner deals with dynamic obstacles and collision avoidance for making it possible to reach the goal. It is common to have social path planners considerate of people's presence and activities, but this is seldom taken into account for local path planners. Of course, this reactive short horizon control does not exactly have a social nature but it is interesting to see, how accounting for social costs in this low level is reflected on the higher level navigational behavior of the robot. By delegating part of the work to the local planner, the cost of global planning which is much larger than the local planning can be reduced. However, for the best behavior, a hybrid approach that adopts the use of social planners on both level is more effective.

III. Perception model

Presence of humans in an environment should be properly perceived by a robot as a requirement for a socially-aware path planner that takes into consideration individual humans and possible social interactions taking place in the environment. This information can be obtained by an external source such as an overhead camera or can be attained using on-board sensors of the robot. Different perception sources for person detection and tracking, have different levels of uncertainty and accuracy in their detections, and are affected by various elements such as the movement of the robot, movement of the person, complexity of the environment in terms of occlusions, etc. while, there exist trackers able to perform this task with cm-level accuracy, others have a much larger uncertainty associated to them.

We use networked cameras to track the location of the people in the environment. Omnidirectional cameras[ref] were chosen because: (1) they are less obtrusive, and can be left in the environment with less risk of making people feel uncomfortable about being watched; (2) they provide a global view of the area, with less risk of occlusion than elevated side-view cameras and with more flexibility as to their positioning; (3) we can reduce the number of cameras needed in the environment, which has benefits in terms of equipment cost, installation cost and computational load of the perception algorithms.

A. *Probabilistic model*

We are interested in the underlying *state* of the environment which is the location of the people. The *detectors* used to estimate these state variables have associated noise due to various state factors such as occlusion, lighting conditions, different posture of people, motion of the robot and the people. Coupled with this, there is also stochasticity in the state transitions, which makes it hard to compute an exact estimate of the location of the people. A principled approach to solve this problem, is to compute a *belief* (posterior distribution) over the states using recursive Bayesian estimation. We first describe the state representation of the system and then explain the tracking model formally.

1) Detector: The background based detector proposed in [ref] is a very effective probabilistic method, which allows the automatic evaluation of the number of people in the scene and the detection of those peoples location. This method has the following advantages: (1) It can incorporate prior knowledge, including which areas in the scene can contain people and how probable it is for people to be in those locations; a probability distribution over the number of people in the scene; a probabilistic model of how close together people tend to walk; etc. (2) The complexity of the algorithm depends linearly on the number of people in the scene. When many people are present in the frame, detecting all of them requires more than 1/25th of a second with our current implementation of the algorithm, although it still requires far less than a second. Further optimisations could easily improve this performance. (3) The method is robust to changes in illumination, shadows and occlusions. We have adapted it to adjust to a non-static background automatically.

2) State representation: For tracking the people in the environment, we use an occupancy grid based approach. The environment is discretized into G cells. Each cell is of size 25cm by 25cm. The size of cells have been chosen in such a way that each cell can occupy atmost one person at any time. The occupancy of each cell is denoted by X_i where $i \in G$. The occupancy of all the cells at time t is the state of the word $\mathbf{X}_t$. At every time instance t, the observations from the detector for each cell i is given by O_i. The set of observations for the whole state is denoted by $\mathbf{O}_t$

3) Tracking model: Let $\mathbf{X}_t$ be the state of the environment at time t.

$$P(\mathbf{X}_t|\mathbf{O}_t) = \frac{P(\mathbf{O}_t|\mathbf{X}_t)P(\mathbf{X}_t|\mathbf{X}_{t-1})}{P(\mathbf{X}_{t-1})} \tag{1}$$

Where, $P(\mathbf{O}_t|\mathbf{X}_t)$ is the likelihood of the state given all our observations (detector outputs). Computation of this likelihood is best performed by using a learnt model of how the detectors perform for different states.

$P(\mathbf{X}_t|\mathbf{X}_{t-1})$ is the *transition model* which models the evolution of the state variables. For a multi person natural environment, an exact analytical model is intractable. So we choose to ignore this aspect of the environment and attribute it to the uncertainty we have in the state estimation. We assume that people move randomly and that there is an equal probability of motion in any direction.

In a multi person environment, the state space is extremely complex so as to compute exactly this probability distribution over the states. We use an MCMC based sampling algorithm to approximately compute the belief. In the next section we explain the implementation details of our probabilistic model for person detection and tracking.

Although, the detector is a modelled probabilistically, we still need to We learn from data, the distribution $P(\mathbf{O}|\mathbf{X})$ for the detector. Given, the labelled location of the people in a data set, we learn the uncertainity in our observations for all the locations and configurations of the state space.

4) MCMC sampling: Markov chain monte carlo is a widely used sampling algorithm for estimation of complex posterior distribution[ref]. It has been gaining popularity in multi-target tracking applications. Compared to traditional particle filters, MCMC based sampling leads to far less sample impoverishment[ref] and thus leads to a much better estimate of the state over time.

The core idea is to generate samples from a markov chain. We then evaluate the samples using a *proposal distribution* and accept or reject the samples based on an *acceptance probability*. The MCMC sampler creates hypothesis of the location of the people in the grids. Each sample is an estimate of the occupancy of all the cells taken collectively.

In our case, we use the occupancy of the grids as hypothesis. Each cell can either be occupied or not occupied. Initially we start from a random distribution of occupancy. Then we generate samples using the following moves:

1. *Birth-Death proposals* We randomly select a cell, and flip the sample state of the cell. If the cell was occupied we generate a proposal which makes the cell unoccupied and vice-versa.

2. *Move proposals* In this case, we select an occupied cell and randomly move the occupancy to one of the 8 connected neighbours.

Once the proposal sample is generated, we evaluate the orignal sample and the proposed sample with reference to a proposal distribution. In our case, we use a learnt observation model of the detector output as the proposal distribution. We fold in the detector output $\mathbf{O}_t$ while evaluating the proposals using the proposal distribution. every proposal is a hypothesis of the state $\mathbf{X}_t$. Evaluating the proposals will give us an acceptance probability. If the acceptance probability is greater than 1 we accept the sample unconditionally. If the acceptance probability is less than 1, we randomly sample from a uniform distribution and then accept or reject the sample if the acceptance probability is greater than the sampled value of uniform distribution. Formally, The acceptance probability is computed as:

$$Acc(x|x^{'}) = \min\left\{\left(\frac{P(\mathbf{O}|x)}{P(\mathbf{O}|x^{'})}\right), 1\right\} \quad (2)$$

Where x is the proposed sample of state $\mathbf{X}$, and $x^{'}$ is the initial sample.

If the sample is accepted, we use the currently proposed sample as the initial sample for the next step of the MCMC sampling. If rejected, we still add the sample to our set of hypothesis, but start sampling again from the old sample.

IV. Human aware Navigation Model

[DV] Sections 3 and 4 can be used to explain our model. First the perception and then the human aware navigation model. Don't spend too much time explaining the background of these methods. Make that brief and explain more on our approaches. It is a bit confusing when you split social path planning and navigation. I feel its better to have it under the same section. We have one Human aware navigation model which could have a subsection for social cost and such and another for navigation(FMM,DWA). Human-aware navigation focuses on the interaction dynamics between humans and robots that occur as a result of navigation [2]. In the literature, we can find several strategies for comfort ranging from appropriate approaching strategy [15], maintaining appropriate distance [4], control strategies to avoid being noisy [16] and use of planning for avoiding interference [17].

In this work we focus on the principle of proxemics which is the most common in the literature of human-aware navigation, with social costs encoded as costmaps similar to [8]. The personal space around a human can be defined as the mixture of two Gaussian functions, one for the front and another one for the rear part of the area surrounding the person. A Gaussian function ϕ, centred on p with covariance matrix Σ, is defined as follows:

$$\phi(q) = e^{(-\frac{1}{2}(q-p)\Sigma^{-1}(q-p))} \quad (3)$$

q indicates the position of a point and Σ is:

$$\Sigma = \begin{pmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{pmatrix} \quad (4)$$

σ_x and σ_y are used to modulate the shape of the Gaussian and are traditionally chosen in a way to respect the personal space of a person as indicated by the proxemics principle. Getting closer to a person, will cause an increase in the value of the function, and hence the social cost associated to that position will increase.

If the center of the costmap, which indicates the position of the person in not deterministically known, the costmap can not correctly model the social costs and hence the social path planning could fail in finding an appropriate socially compliant path. This problem becomes much more critical in real applications where robustness is vital for succeeding under different conditions.

Our goal is to show that the assumption of having perfect information about the state of the human is unrealistic and in real situations when the robot has to deal with uncontrolled environments, the uncertainty in this information can not be ignored. We can think of false negative detections where the robot misses to take on person into consideration, false positive detections where other objects are detected as humans, noisy estimations of position, orientation, velocity of the person, etc. To the best of our knowledge, there does not exit any work on including uncertainty of perception in this problem.

A. Navigation

Global path planning and local path planning are the main components of an autonomous navigation system. We base our navigation method on FMM [10] for global path planning and DWA [19] for obstacle avoidance and more reactive control. However, these planners will be modified to account for social costs and constraints in their planning.

FMM computes the optimal path for the robot for a given destination, according to a potential filed created by the setting of obstacles in an environment based on wave propagation principles. In a constantly changing environment a given plan may no longer be valid over time. So applying FMM continuously is one solution to deal with this dynamicity. However, the frequency of this planning should be reasonable given the computational cost of this global planning method. In our system, social costs are incorporated into the FMM method when computing the optimal path by means of imposing the social costs as virtual obstacles.

In the case of DWA, the method has been modified to include a social component. The inherent reactive nature of this method, given the small window of planning which is required for ensuring collision, may not seem to benefit from human-awareness. However, we believe this is an interesting problem to investigate. We will discuss this in more details in the following section **??**.

B. FMM Based Human-aware Navigation

Talk about social costmaps. Talk about samples of MCMC tracker as position sample.

1) Clustering: We cluster the sample to obtain the center of the Gaussian and the σ values are adaptively computed. Random measurements still get picked and clusters are formed.

Kmeans Clustering: Number of clusters should be known ahead of time. Not a realistic assumption for environments with multiple people. More accurate and closer to reality based on our simulations and real collected data from the probabilistic tracker.

Shifted Means Clustering: Automatically computes the number of clusters. However, is less accurate.

2) Convolution: The conventional 2D Gaussian shape of the social costmap is not longer kept. We compute the convolution of the estimate of the underlying distribution for presence of people in an environment, by the conventional social costmap to get the final social cost for each position of the map. No need to know the number of people, more flexible, easier to discard small probabilities that are random measurements.

Fig. 1. Robot used in our experiments to perform the automatic fingerprinting.

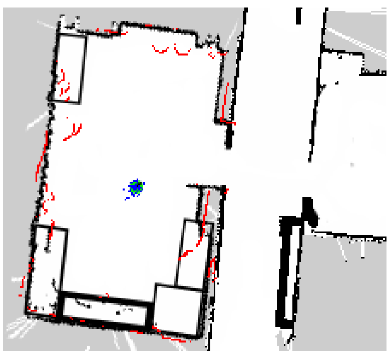

Fig. 2. Graphical view of the robot's position estimation with AMCL. The blue dot is the position estimate, while the red dots represent the measurements of the laser range finders.

C. DWA with Social Factors

Discarding velocity candidates that cause discomfort in social zones due to unsuitable velocities or acceleration. Penalize velocity candidates that cause the robot to move closer into the social zones.

V. Experiments

In this section we will briefly explain our robotic platform, experimental setup and the set of experiments which have been conducted to test our uncertainty-based human-aware navigation system.

A. Robotic Platform

The robotic platform used in this work is shown in Figure 1. This robot is called mBot [20] and is developed within the FP7 European project MOnarCH (Multi-Robot Cognitive Systems Operating in Hospitals [**?**]). It is an omni-directional drive robot with an approximately round footprint of 0.65m in diameter and a height of 0.98m. It is provided with two laser range finders placed in the bottom of it, between the base and the rest of the robot, on both the front and the back for providing full coverage.

Two batteries give it an autonomy of approximately five hours, depending on the usage. The robot has two PCs inside its shell: one manages the sensors, navigation and actuators, while the second one is for other functions such as human-robot interaction functionalities, which are outside our interests for this work.

The two on-board PCs, run Ubuntu desktop 12.04 and ROS Hydro. All the software modules that compose the underlying layers of the robotic platform were already implemented at the time of our work since the robot was already used in the context of the MOnarCH project. These modules provide self localization and navigation capabilities, which are exposed through software interfaces to the user-level software.

The robot's self localization feature has fundamental importance in our work. It is based on AMCL (Adaptive Monte Carlo Localization) [**?**], a probabilistic localization algorithm for a robot moving in 2D. AMCL, a variation to the MCL above mentioned, provides an estimate of the position and orientation of the robot by matching the measurements of the laser range finders with a known map of the environment and considering the odometry data.

B. Experimental Setup

People detection and tracking is done by means of an omni-directional overhead camera (explain specifications) with x frames per second. The deterministic tracker outputs results with xx hz and the probabilistic tracker with y hz. (maybe a table for everything here)

C. Scenarios

Experiments are performed inside the robotics lab depicted in where the tracker is operational. Give dimensions of the room and tracker accuracy.

Ground truth position of the robot is given by AMCL with x accuracy and the person stands and walks on physically marked tracks to get the exact precise ground truth.

We study 4 scenarios for each of our human-aware navigation method each being tested 5 times. We start with a single static person and incrementally increase the complexity to 2 moving people in the arena. We should emphasize that uncertainty is affecting the tracking performance and is not very evident from just looking at the environment. The person is not aware of what is happening on the tracker side, but the information given by the tracker greatly affects the behavior of the robot.

Figure shows a snapshot of the setup with two people moving in the arena. For the case of static people we have also done extensive tests using a high fidelity simulator webots [**?**], by 1) emulating the uncertainty of tracking, and 2) replaying real uncertainty and tracking data from real experiments. This was done to simplify the debugging and speeding up the robotic tests.

Since we aim to study the effect of uncertainty and social factors in human-aware navigation we chose a task of point to point navigation for the robot in the vicinity of humans. The complexity of navigation task can be increased and more interesting scenarios in terms of HRI can be investigated but that is outside the scope of our work.

VI. Results and Discussion

[DV] Need to identify one or two scenarios where the uncertainity will help us. Like two people standing close by and the robot not going in between them. In the other case with deterministic tracker, the robot should go in between them.

For each of the scenarios described in section V-C, we have compare the results obtained from the 1)basic navigation method, 2)deterministic human-aware navigation, 3)kmeans clustering human-aware navigation, 4)shifted means clustering human-aware navigation, 5)social cost convolution human-aware navigation for both FMM and DWA. Sample results from simulations for the case of static people, are also depicted in Figure ? for comparing the results of our simulations with reality.

A. Results

Figures Tables of parameters

B. Discussion

Reasoning about the figures.

We expect to see improvements when applying FMM and more so when considering in uncertainty of perception. Convolution method given its higher flexibility and not requiring the number of people in the scenario is expected to give better results.

DWA cant make a noticeable difference in the trajectories, due to the tendency of the robot to take velocity candidate that are tangent to the planned path and small differences in the new positions of the robot that each candidate will cause. However, it does a good job of discarding velocity candidates that result in uncomfortable accelerations or speeds.

VII. Conclusion

A. Future work

By taking the uncertainty of perception into account in a human-aware path planner, the same planning method could easily be reused even when the source of perception changes. As an example while overhead cameras can provide position information of people with good accuracy, when moving to on-board perception for a mobile robot, this accuracy and the associated uncertainty will largely change. This is even more significant, if tracking is done using an ultra-wide-band (UWB) tag. So, for more robustness and effectiveness, a human-aware navigation method, should be able to handle all these situations without undergoing major changes.

modelling the uncertainty in orientation.

Acknowledgements

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[ZT] Deepak I don't know what is wrong with the reference list

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