

Human-Aware Robot Motion Planning with Velocity Constraints

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ABSTRACT

This paper addresses the issue of how high-speed robots may move among humans such that the robots complete their tasks efficiently while the humans in the environment feel safe and comfortable. It describes the Segway robotic platform used for this research and then discusses the three primary research areas needed to develop the human-aware motion planner. First, it is necessary to conduct experiments with humans to develop human aware velocity constraints as a function of the distance of the robot from a human. Next, these velocity constraints must be used to plan the robot motion in real time. Finally, practical implementation of this motion planner requires the ability to robustly detect humans using the available vision sensors. The approach taken to each of these problems is described in this paper along with preliminary results.

KEYWORDS: Human aware motion planning, human response, human detection.

1. INTRODUCTION

An emerging and growing area of robotic research is *human-robot interaction* (HRI) [1, 2]. A major aim of HRI research is to ensure that robots can serve and interact with humans in ways that feel natural, non-threatening, and even enjoyable to humans. Most research in HRI [3, 4] focuses on direct, cognitive interaction between humans and robots. However, non-cognitive and indirect interaction is also of great importance. For example, recognize that in human interactions, unwritten social norms dictate how we move around each other in crowds and how we approach each

other physically for direct interaction. These norms may vary slightly based on culture, but they certainly exist globally. As one specific illustration, notice that even when a human is in a rush to reach a destination, he or she is generally careful not to approach someone who is moving in the opposite direction in a manner that will give that person concern that a collision is possible. Humans also have learned to stop at a ‘respectable’ distance from another human when approaching them for direct interaction.

The research presented here is in the general area of what has been called *human-aware motion planning* [5, 6, 7]. Although this research may be viewed as a subset of motion planning research [8, 9], the key difference in human-aware planning is that humans are not treated as simply objects in the environment. Instead, the planning acknowledges the psychological dimensions of the human ‘objects’ and hence treats them differently than non-human objects in the environment.

Most research in human-aware planning is being conducted in Laboratoire d’Analyse et d’Architecture des Systemes (LAAS) in France [6, 7, 10]. Their research focuses primarily on planning in indoor environments using two criteria: safety and visibility. The first criterion focuses on ensuring safety by controlling the distance between the robot and humans. The second criterion aims to improve human comfort by encouraging the robot to stay in the humans’ field of view. The overall system has been implemented on a robot called Rackhma, a B21r robot from iRobot. The planner is essentially a standard A* path planner that is not capable of planning for velocity constraints or taking into account either the kinematics or dynamics of the vehicle. Rackhma only moves in indoor environments at low speeds less than

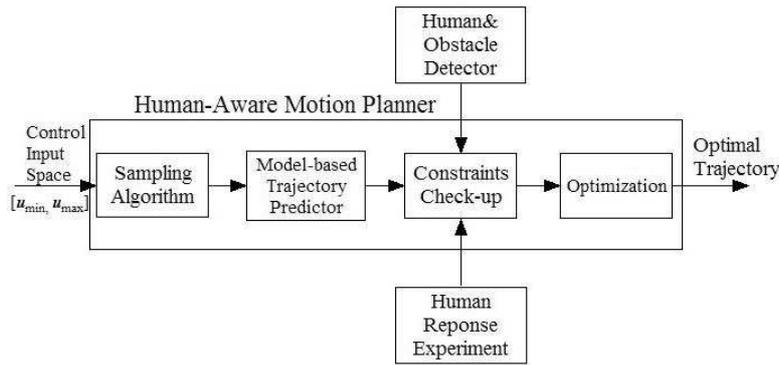


Figure 1. System Elements for the Human-Aware Motion Planner

1m/s.

In contrast, this paper focuses on high speed robots operating in outdoor environments or large indoor environments. It describes the Segway robotic platform used for this research and then discusses the three primary research areas needed to develop the human-aware motion planner. First, it is necessary to conduct experiments with humans to develop human aware velocity constraints as a function of the distance of the robot from a human. Next, these velocity constraints must be used to plan the robot motion in real time. Finally, practical implementation of this motion planner requires the ability to robustly detect humans using the available vision sensors. The approach taken to each of these problems is described in this paper along with preliminary results.

This paper is organized as follows. Section 2 describes the elements of the overall system, including the detailed approaches. Section 3 presents the preliminary results. Section 4 gives conclusions.

2. OVERALL SYSTEM AND APPROACHES

The research focuses on development and experimental implementation of the three major areas of velocity-constrained, human-aware motion planning: 1) the response of humans to robot to yield human-aware velocities constraints, 2) robot motion planning with human-aware constraints to provide velocity-constrained optimal trajectories, and 3) human detection and tracking using robot-mounted vision sensors to obtain human position and velocity. Fig. 1 illustrates the overall motion planning system. Since experimentation is integral to this research, the robotic platform upon which the experiments are based and the environment

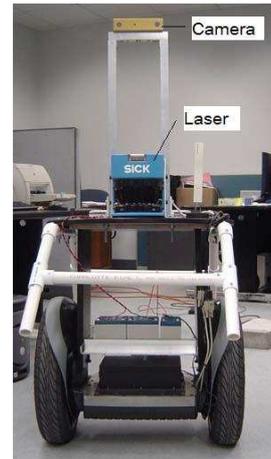


Figure 2. The Indoor-Outdoor Segway RMP 200 Robot System

in which some of these experiments are undertaken is first described.

2.1 Experimental Platform and Environment

The robot needed in this research has these primary requirements: It must be both large and fast enough to provide a substantial possible threat to a human, and it must be capable of moving efficiently in outdoor environments. To satisfy these the robotic platform chosen is the indoor-outdoor Segway RMP 200, which has a height of about 5 ft (the top of the Bumblebee camera) and is capable of moving at speeds up to 10 mph. This Segway has already been equipped with the necessary control software and sensors. In particular, Player/Stage [11] was chosen as the robotic device control software, and as shown in Fig. 2, it has been equipped with a SICK laser range finder and a Bumblebee stereo camera. Additional sensors are the wheel encoder and an inertial navigation unit provided with the Segway platform.

The experiment is set up in an outdoor grass field in the midst of trailer buildings. Additional objects, such as cars and boxes, can be added to the environment to increase its complexity. This is particularly important for the human detection task, since it is desired to show human detection in unstructured and complex environments.

2.2 Measuring and Modeling Human Response to Robot Motion

Human response to approach by robots has not been well studied. There are several factors which should be considered in developing an approach to measure such responses.

First, there are no generally accepted societal rules of interaction between humans and robots because robots are currently not widely deployed and the ones that are deployed (e.g., Roomba) generally lack adaptive response to humans. Secondly, although anthropomorphism has shown some indication of benefit to facilitating interaction between people and machines [12, 13, 14, 15, 16], anthropomorphic features cannot be assured in robotic design because of engineering limitations. Thirdly, the conditions under which the interaction occurs and the characteristics of the human user(s) could influence the interaction. Finally, the proposed experimentation is expected to involve student subjects who are novices with respect to robotic interaction and whose interactivity will be limited in time during the experimentation effort.

Because of these unknowns and lack of widespread deployment of robots in society, the approach taken here to assessing and measuring interactions is based more on perceptual than cognitive factors. The first experiments, described in Section 3 consider humans in static positions in free space, although they are allowed to move if they feel threatened.

Each of the experiments enables the robot to approach or travel in the vicinity of a human at a set velocity with a set minimum interaction distance (i.e., the closest distance that the robot approaches the human). For a given scenario the human response is measured using a subset of the following metrics: 1) the human’s response to a questionnaire regarding his or her comfort level, 2) physical movement, and 3) heart rate.

2.3 Motion Planning with Position and Velocity Constraints

The A* and D* algorithms [9] provide optimal solutions to path planning with and without dynamic obstacles; however, these algorithms are not able to solve motion planning with velocity constraints. To develop computationally tractable motion planning algorithms, sampling based methods have been proposed and developed [8, 9]. These methods use probabilistic sampling (i.e., discretization) to effectively reduce the solution space, and hence reduce the size of the underlying optimization problem. In these algorithms if the configuration space includes the vehicle velocities, then velocity constraints, such as those associated with human-aware planning, are essentially treated as obstacles in this higher dimensional configuration space. Rapidly exploring random trees (RRTs) [9] were developed as an incremental sampling method that yields good results in practice without any parameter tuning. The major limitation of RRTs, as well as all traditional sampling-based motion planners, is that they sample in the state space. The second limitation is that this methodology requires the solution

or approximation of a two-point boundary value problem (BVP). The complexity of the BVP increases significantly with the use of more realistic system models and higher dimension configuration spaces.

This research uses a recently developed sampling based planning approach called *Sampling Based Model Predictive Control (SBMPC)* [17]. This method was derived by applying the concept of sampling within the paradigm of model predictive control (MPC) [18, 19, 20, 21]. SBMPC may be seen as a “fast” version of MPC, which was originally developed for relatively slow processes in the petroleum and chemical industries and is well known to have difficulties in computing control inputs in real time for processes with fast dynamics (e.g., robots). SBMPC differs from traditional sampling based methods in that it replaces the potentially costly BVP of these methods with integration by sampling in the system control input space. This also has the effect of eliminating the need for the NN search due to the fact that the sampled input is applied directly to a current node.

Table 1. Simulation Parameters

Sampling Time	1.0s
Subsampling Time	0.1s
No. of Samples per Expansion	25
Velocity: u_1 (m/s)	$[-2.0 \ 2.0]$
Steering Rate: u_2 (rad/s)	$[-\pi/2 \ \pi/2]$

To illustrate the capability of SBMPC, consider its use with a kinematic model of an Ackerman steered vehicle. The two inputs to the model are the forward velocity and the steering rate, which determine the position and orientation of the vehicle. The SBMPC algorithm was applied to randomly generated scenarios with 50 obstacles of various sizes. The velocity and steering rate were constrained as indicated in Table 1. One sample is shown in Fig. 3. The thin segments represent all the trajectories that were evaluated while the thicker line represents the calculated trajectory. The smoothness of the trajectory indicates how the steering rate constraint limits the maneuverability of the vehicle, forcing it to make wider turns than would occur without this constraint.

2.4 Human Recognition Using Vision Sensors

Different detection methods have been proposed and used based on different “human” models, i.e., what constitutes a human in terms of available features from sensor inputs. Since faces are the most prominent features of humans, human detection can be based on face detection (see [22] for a recent survey). This method is particularly attractive be-

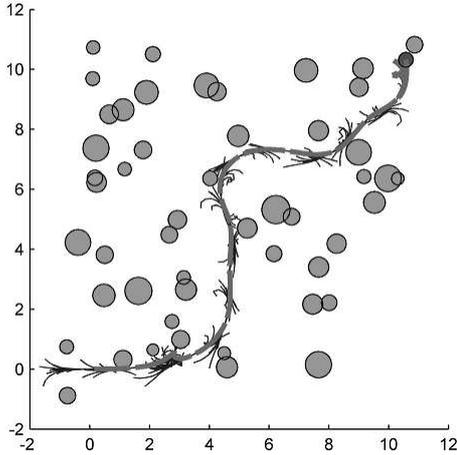


Figure 3. A sample SMBPC trajectory in a random cluttered environments (from a start point (0, 0) to a goal point (10, 10))

cause frontal and profile faces can be detected in real-time [23] using a typical laptop computer. Facial-based detection has been used and demonstrated in experimental human robot interaction systems [24]. Clearly, this method of human detection should not be relied on as the sole method of detection since humans that are not facing a robot cannot be detected. Human detection can also be based on shape, motion, and other features. In [25], size and shape constraints of pedestrians are used to segment candidate regions based on disparity edges from stereo inputs, and a neural network is used for pedestrian recognition. In [26], human motion is detected using the difference between image frames.

Outside the context of mobile robots, detecting and tracking people has also been widely studied, especially for video surveillance applications (see [27, 28, 29, 30] for recent surveys). However, most methods are not applicable directly to human-robot interaction systems due to the real-time constraints, limited availability of sensors, and lack of robustness in performance.

In order to enable robots to interact with humans robustly, humans in the vicinity of robots must be detected and tracked in real-time and their positions and velocities must be accurately estimated. In this research, the problem of detecting and tracking humans is decomposed as follows: 1) robust estimation of 3D point clouds of the environment, including ground surface detection, and 2) detection of candidate regions of humans.

Robust Estimation of 3D Point Clouds. A BumbleBee stereo camera (shown in Fig. 2) is used along with computer vision algorithms to estimate 3D point clouds. The BumbleBee stereo camera was chosen because the two component cameras are aligned horizontally, and built-in functions are

available to remove radial as well as other types of image distortions. Hence, the resulting component cameras are essentially equivalent to ideal pinhole cameras.

Stereo reconstruction has been widely studied and the algorithms are well understood [31, 32]. The key problem for robust 3D reconstruction is to establish accurate and robust correspondences, i.e., to find the image point in the right image that “corresponds” to a given image point in the left image.

To further improve the accuracy, an efficient sub-pixel matching algorithm is used. Given a left image $f(x, y)$ and a right image $g(x, y)$, the normalized cross correlation at point (x_0, y_0) for a window size $(2M + 1) \times (2N + 1)$ for disparity (u, v) is given by

$$NCC(x_0, y_0, u, v) = \frac{\sum_{i=-M}^{i=M} \sum_{j=-N}^{j=N} \hat{f}(x_0 + i, y_0 + j)g(x_0 + u + i, y_0 + v + j)}{(2 \times M + 1)(2 \times N + 1)\sqrt{\bar{f}(x_0, y_0)\bar{g}(x_0 + u, y_0 + v)}}, \quad (1)$$

where $\hat{f}(x_0 + i, y_0 + j) = f(x_0 + i, y_0 + j) - \bar{f}(x_0, y_0)$, $\bar{f}(x_0, y_0)$ is the local mean, and $\bar{f}(x_0, y_0)$ and $\bar{g}(x_0 + u, y_0 + v)$ are the local variance. Note that normalized cross correlation depends on the alignment, and even sub-pixel misalignment can have a large effect. To overcome this problem, bilinear interpolation is used to create a continuous image for $g(x, y)$. Our prior research has shown that by using integral images [23], NCC can be computed to the sub-pixel accuracy without much additional computation [33].

Candidate Region Detection for Humans. The method initially implemented in [24] is adopted for finding initial candidate regions. A map of the environment is first built with only background objects during a training phase. Background objects are defined to be any non-human objects present in the scene. During typical running phases, candidate regions of humans are estimated by first calculating a height map of the current scene. The height map is formed by obtaining the highest 3D point in a given region. From this, the background scene can be modeled by taking into consideration previous height maps in the image sequence. Human candidate regions can be estimated by finding the height difference in sampled grids of the ground surface between current height maps and the background scene. If the height difference is significant, foreground objects must be present and these regions will be marked as candidate human regions to be later processed by face detection algorithms. If the face detection algorithms return a successful match, The point cloud corresponding to the candidate region is labeled as a human.

The current implementation of our method focuses on face

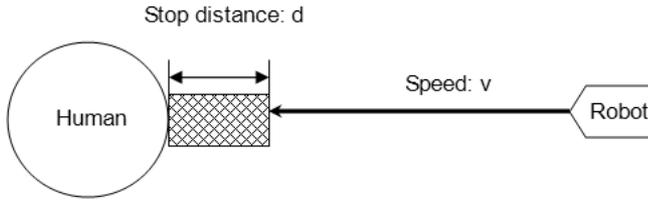


Figure 4. Experimental plan

detection. Further study is being considered on more effective and robust ways of detecting human candidate regions by collecting and modeling human body profiles relative to the ground surface. For example, human bodies have two legs and two feet (almost always close to the ground surface) and they should generate a relatively unique signature if point clouds of certain heights above the ground surface are modeled.

3. EXPERIMENTAL RESULTS

This section shows the preliminary results of human response experiments, the human aware motion planner, and human detection and recognition respectively.

3.1 Preliminary Results of Human Response Experiments

Four sets of experiments to measure human response have been performed. The layout for each set of experiments is given in Fig. 4. In each experiment the Segway robot started at the same position and approached the human subjects in the same direction. The speed v of the robot and the stopping distance d were varied. The parameters of the four sets of experiments are shown in Table 2. The human subjects ranged in age from 20 to 30. The response of the subjects was determined by a video camera and a questionnaire that asked whether the subject felt: 1) safe, 2) slightly unsafe, 3) unsafe, 4) very unsafe.

As illustrated by the two subjects in Figs. 5(a) and 5(b), at the higher robot speed, some of the subjects actually showed visible concern for their safety by moving as the robot approached. However, as illustrated by the two subjects in Figs. 5(c) and 5(d), at the slower speeds the subjects always stayed in their original position. The results of the final evaluation are shown in the last column of Table 2. The results clearly show that the robot needs to be human-aware when approaching a person. Fig. 6 shows the extracted velocity constraints for the above experiments. The straight line is a least square fit.

Table 2. Results of Initial Human Response Experiments

Experiment	v (m/s)	d (m)	No. of Subjects	Average Response
1	4.5	0.5	5	Slightly Unsafe
2	4.5	1.0	5	Slightly Unsafe
3	2.0	0.5	5	Safe
4	2.0	1.0	5	Safe



(a) Experiment 1



(b) Experiment 2



(c) Experiment 3



(d) Experiment 4

Figure 5. (a) and (b), in which the robot moved at relatively high speed, the subjects often moved as the robot approached. (c) and (d), in which the robot moved at a much slower speed, the subjects always remained stationary as the robot approached.

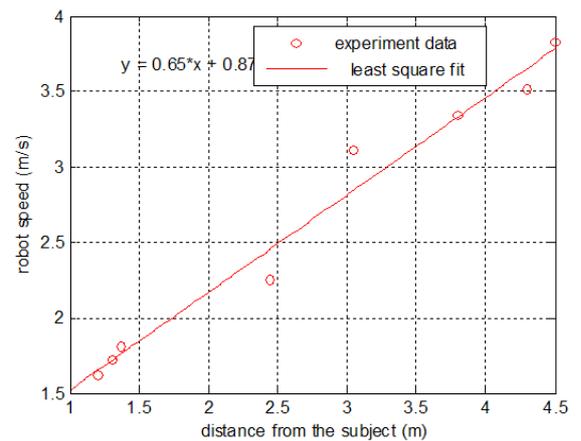


Figure 6. Distance-Dependent Velocity Constraints

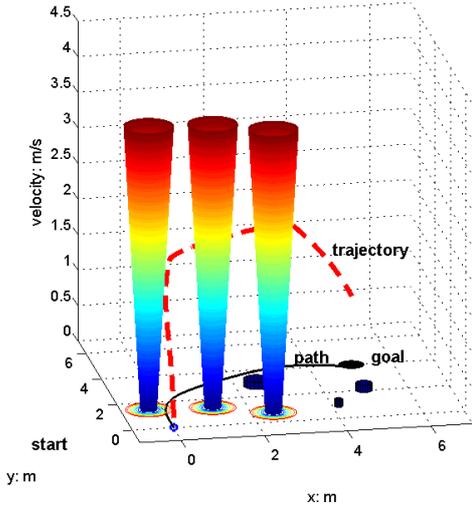


Figure 7. Result 1 of SBMPC Planning with Human-Aware Constraints

3.2 Preliminary Results of Human Aware Motion Planner

SBMPC has been simulated in Matlab by using some assumed human-aware constraints and a kinematic model of the differentially steered Segway robot. For this model the control inputs are the linear acceleration a and the angular acceleration α . The output are the robot position and orientation in the inertial frame.

The human-aware constraint associated with each human was assumed to be the position-dependent velocity constraint, given by

$$v(r) = \begin{cases} 0 & , r \leq r_0 \\ kr & , r_0 < r \leq r_{max} \end{cases} , \quad (2)$$

where $k > 0$ is a constant scaling factor, r_0 is the radius of a human-centered circle that the robot is not allowed to enter, and r_{max} is the radius of a larger circle outside of which the robot does not need to constrain its velocity. The constraints of (2) require the robot to decrease its velocity as it approaches a human.

Figs. 7 and 8 show the results of the motion planner. In these figures, the large cones correspond to the velocity constraints around humans, while the small cylinders are simply static obstacles. The solid lines connecting the start and the goal are the actual paths of the robot. The dashed lines connecting the start and the goal are the trajectories of the robot.

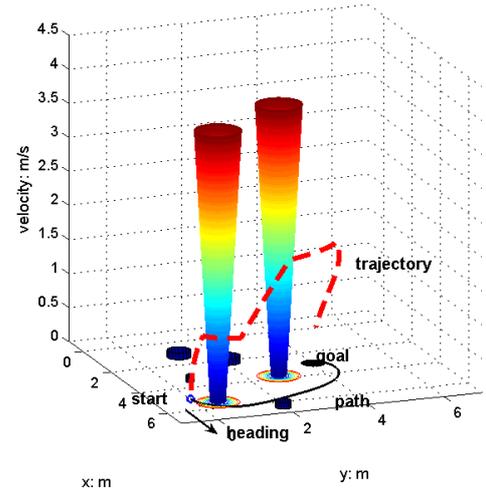


Figure 8. Result 2 of SBMPC Planning with Human-Aware Constraints

3.3 Preliminary Results of Human Detect and Recognition

Fig. 9(a) and (b) shows the respective left and right rectified images from the BumbleBee camera. The image pair is used to find corresponding points and estimate the robust 3D point cloud shown in Figure 9(c). This point cloud is then analyzed in order to find a candidate region. The candidate region is determined by finding the 3D points that do not belong to the background. These points are shown in Figure 9(d).

Face detection examples are shown in Figure 10(a) and (b). The face detection algorithm implemented here is part of the OpenCV computer vision open source library. Figure 10(a) shows successful face detection from a frontal view, and figure 10(b) shows detection of a profile (side) view.

4. CONCLUSIONS

A human-aware motion planner that is fundamentally concerned with how high-speed robots may move among humans such that the robots complete their tasks efficiently while the humans in the environment feel safe and comfortable has been presented. Human's safety and comfort are quantified to be distance-dependent velocities by measuring human's emotions and physical motion through human response experiments. The overall system includes three major parts: 1) human response experiments to mathematically find out the human preference constraints to the robot; 2) a sampling-based model predictive control algorithm used to plan an optimal trajectory with consideration

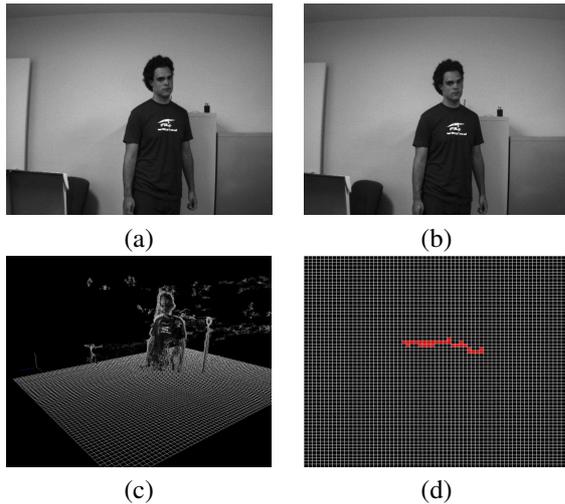


Figure 9. (a) and (b) A stereo image pair from the BumbleBee camera, (c) the reconstructed 3D point cloud using a standard normalized cross correlation matching algorithm, and (d) the estimated human candidate regions

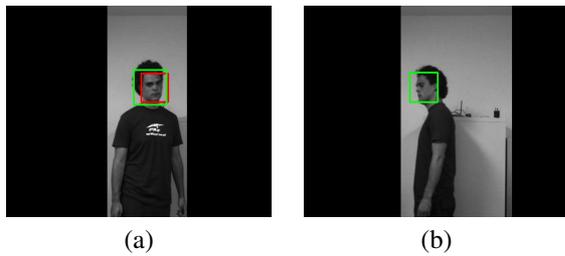


Figure 10. Two Separate Examples of Face Detection Results on Candidate Regions

of human-aware velocity constraints; and 3) a human detection algorithm used to accurately locate humans and obtain humans' velocities. Currently, each aspect has been successfully simulated or implemented separately. Future work will integrate these three aspects to develop and implement a complete human-aware motion planning system for the Segway RMP 200 robot.

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