in: Proc. Autonomous Mobile Systems (AMS 2012), Stuttgart, Germany, Informatik aktuell, pp. 59-67, Springer Verlag 2012

Using a Spatio-Temporal FastMarching Planner to Politely Avoid Moving Persons

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Abstract. When mobile robots operate in home environments, a robot should consider the inhabitants while moving around. In this work, an approach is presented, which at the one hand predicts the movements of a person in a very simple way, and on the other hand uses the predicted movement to plan a motion path of the robot. We deploy a potential field approach to predict the person's movement trajectory and use an modified Fast Marching planner to access a time-variable cost function for the planning process. The goal of our development is an early avoiding behavior of the robot, when the robot passes a person. This should increase the acceptance of the robot, and signal a "busy"-behavior. We show the feasibility of the presented approach in some first simulation results.

1 Introduction

If mobile robots are used in everyday life, the acceptance of these robots is important, especially, when the users are non-expert users. As experiments show [14], users expect human-like behaviors from technical devices like mobile robots. Normally, the scenario of human-robot interaction is investigated, when the robot and its human user want to interact in a dialog with each other, as for example in [5,6]. In the work presented here, we want to emphasize the case of human-robot interaction, when the robot does *not* want to interact with a person. For example, when the robot is on a tour to collect food orders, or the robot has to drive to its charging station, an interaction with a passing person is not wanted. In such cases, the robot has to signal its busy state. The spatial configuration of non-interaction was investigated by Hall [7] in the theory of the personal space. In our work, this spatial distance is used to signal non-interaction. We want the robot during the path planning phase, to take the predicted motion of an observed person into account, and plan a non-intrusive path towards a predefined goal which keeps the robot out of the interaction distance to signal busy behavior.

Related work: In the COGNIRON project [3] a proof of the validity of the personal space could be given. In robotics, the personal space is used regularly in tasks such as approaching a person [11,18] and also path planning [17]. The method of Sisbot[17] is only defined in an static environment, and cannot deal

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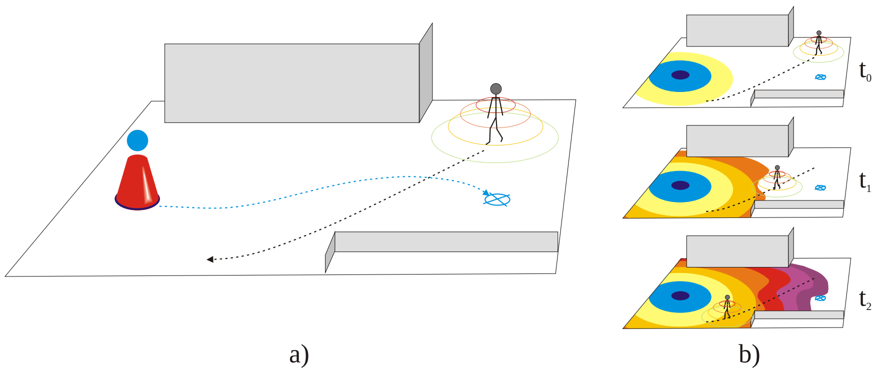

Fig. 1. The idea of the presented approach: the robot should be able to politely pass a moving person. To do so, the person's path is predicted (see a)) and the personal space of the person is used in a spatio-temporal planning process to compute a feasible path. In b), a planning wave is propagated from the robot origin towards the goal (blue cross). This wavefront is deformed from the obstacles as well as from the moving personal space from the predicted trajectory.

with changing environment situations. In [13], a rule based behavior was constructed to pass a person in a feasible distance in straight floors. This behavior only works in floor-like environments and fails in complex situations or environments. Today, there are no further known publications on the topic of politely passing a moving person with respect to the person's distances. However, there are many approaches which concern spatio-temporal path planning, to which our approach belongs to. The most advanced methods operate on planning trees, like lattice graphs [15,12], which are not real-time capable today, or expanding random trees [11,9], which have the problem on reconfiguration by deviating from the given path. In the approach presented here, we use a modified Fast Marching Planner, originally proposed by [16], to include a moving person into the planning process. To the best of our knowledge, there are no comparable works done in this field. A fundamental precondition for spatio-temporal planning is the prediction of the motion trajectory of the recognized person. Here, a large set of prediction algorithms exist, mostly using probability densities, which are build upon a large set of trajectory observations [10,2]. The disadvantage of these approaches is the need of an exhaustive data collection to learn trajectory models. We prefer an out-of-the-box approach, where the trajectory of a person is predicted using the current motion direction and a potential field, presented in [9].

Presented approach: Our approach uses a modified version of the Fast Marching Method, to propagate a wavefront into the environment. The passing times of the wavefront could be afterwards used to extract an optimal path. The passing time of the wavefront is determined by using a physically correct simulation of the wave, which also includes the predicted motion trajectoriy of a person and their personal space. The obstacle and personal space configuration is only

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evaluated inside the wavefront. We use the well known potential field method [9] to predict the trajectory of the moving person. A brief overview of the key idea of the presented approach is shown in figure 1.

2 Prediction of the person's movement trajectory

In this section, the prediction method of the person's movement trajectory is presented. We use a very simple model, also known as potential field, which is also used in [9]. The key idea is, to model the environment as a set of point like electrical charges, which create an electrical field. This field could affect other charges by applying a force towards them. Two forces are modeled to predict the motion trajectory. On the one hand, the pushing forces of the obstacles are used, to avoid collisions, and on the other hand, the pulling force of a virtual target line in front of the person is modeled. The definition of the electrical field is applied to compute the resulting force. For a given set of charges in positions $\boldsymbol{x_i}$, the field at a position $\boldsymbol{x}$ is defined as:

$$\boldsymbol{E}(\boldsymbol{x}) = \sum_{i=0}^{n} Q_i^- \cdot \frac{\boldsymbol{x} - \boldsymbol{x_i}}{|\boldsymbol{x} - \boldsymbol{x_i}|^3} \tag{1}$$

The resulting force is also influenced by the virtual target of the person, which is defined by a tangential line towards the current motion direction at a defined distance. The force could be also calculated as shown in equation 1, and results in a pulling force towards the current motion direction of the person. So, the resulting force is defined as follows:

$$\boldsymbol{F}(\boldsymbol{x}) = Q^-(\boldsymbol{E}_{obs}(\boldsymbol{x}) + \boldsymbol{E}_{target}(\boldsymbol{x})) \tag{2}$$

The idea of predicting the trajectory is, to iteratively simulate the movement by considering the force $\boldsymbol{F}(\boldsymbol{x_j})$ in the currently predicted position $\boldsymbol{x_j}$ for the time interval Δt. If the motion of a charged particle within the resulting force field should be processed, the well known momentum equation could be formulated: $\boldsymbol{v}_{t+1} = \boldsymbol{v}_t + \boldsymbol{F}/m \cdot \Delta t$. Here, m denotes the mass of the charged particle, and $\boldsymbol{v}_i$ denotes the speed at time i. It could be seen, that the mass influences the update of the speed. Since a collision free path of the person should be constructed, the mass is set to zero and only an approximation of the momentum equation is used to update the current person speed:

$$\boldsymbol{v}_{t+1} = |\boldsymbol{v}_t| \cdot \frac{\boldsymbol{F}}{|\boldsymbol{F}|} \cdot \Delta t \tag{3}$$

The predicted, piecewise linear person's path is used for the robot's motion planning.

3 The Adapted Fast Marching Planner

As stated before, we use the Fast Marching Method approach from Setian [16] for robot path planning. It is executed on a regular grid, where each grid cell

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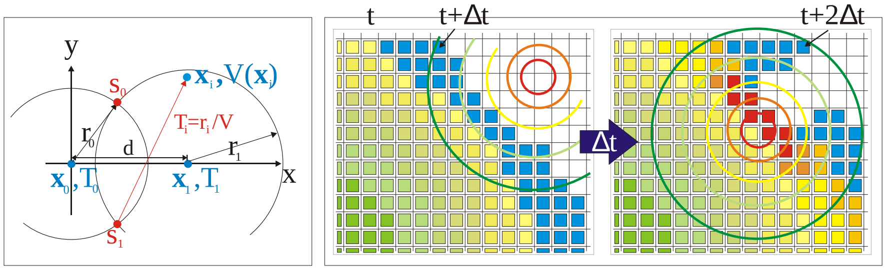

a) b1) b2)

Fig. 2. In image a), the details of the interpolation of one cell element of the wavefront are shown. Blue values are initially known, while black values are computed. The red values describe the final step of interpolation, where from the virtual wave sources s_0 or s_1 the passing time of the wavefront is calculated. On the right side b) a full simulation step is shown. Note, that only the blue elements of the wavefront investigating the current speed configuration. The wavefront is only updated with the current speed configuration until the elements reach the simulation time $t + \Delta t$, shown in b1). Afterwards, the speed configuration is updated to $t + \Delta t$ and the propagation of the wave is simulated until $t + 2\Delta t$ is reached (see b2)).

contains a cost value that physically reflects a speed, at which a virtual wavefront is able to travel through this cell. Near zero values are assigned to obstacle cells, whereas high values are assigned to free space. The advantage of this method is, that all positive real values can be applied to the map cells, while in most common planning approaches [4,8] only binary values could be used. The main benefit of the standard Fast Marching Method is the ability, to construct monotonical raising functions with *any* configuration of positive speed values, which is essential for a path planning algorithm. The Fast Marching Method calculates a solution of the so called Eikonal equation $\boldsymbol{v}(\boldsymbol{x}) \cdot |\Delta T(\boldsymbol{x})| = 1$, which describes the evolution of a closed curve in time T, reacting on the different speeds $\boldsymbol{v}(\boldsymbol{x})$ at the positions $\boldsymbol{x}$. In most cases, the solution could not be found in closed form. Fast Marching proposes a numerical solution to this problem. The wave starts from a single point and spreads to neighboring points by expanding grid cells, which are currently part of the wavefront. The neighbors are added to an open list, sorted by the interpolated travel times. The elements of the open list with the smallest traveling time values are expanded and deleted sequentially from the list, until no expandable cells remain. The key idea of the interpolation of one cell is shown in figure 2. The two neighboring cells with the smallest travel times are used to calculate the two possible sources of the wavefront section. The most distant source is used to calculate the passing time with the current speed of the wave within the interpolated cell. The mathematical details are described in [16].

3.1 Adaptation for Predicted Motions

Our main idea is, to evaluate the speed, the waveform can travel through a cell element *at the time*, the cell is reached by the wavefront. This is the key element, changed within the standard Fast Marching approach. To adapt the interpolation method from static cell speeds $\boldsymbol{v}(\boldsymbol{x})$ to time variant traveling speeds of $v(\boldsymbol{x_i}, t)$, a number of changes are necessary. First, the planning direction is reversed. Normally, a path from the target position to the current robot's position is planned. Since the traveling times of the wave have a physical meaning, in our case the robots's position at passing time, the path is planned from the robot towards the goal. Second, the fusion process of the static environment with the person's trajectory is the fundamental change in wavefront propagation. The system starts from a time t_0 and updates the prediction of the person movement *as well as* the propagation of the wavefront in time intervals Δt. This means for the n-th planning step, that only those wavefront cells are expanded, whose travel times are smaller than $t_o + n \cdot \Delta t$, and only for these cells, the dynamic speed function $v(\boldsymbol{x_i}, t_0 + n \cdot \Delta t)$ is evaluated.

The dynamic speed function consists of two parts: the static part $v_{st}(\boldsymbol{x}_i)$ from the obstacle configuration with the free parameters $v_{max}, d_{max}, d_{min}$, and a dynamic part $v_{dyn}(\boldsymbol{x_i}, t_0 + n \cdot \Delta t)$, defined by the predicted motion trajectory of the person and their corresponding personal space, represented by the width σ:

$$v_{st}(\boldsymbol{x}_i) = \begin{cases} v_{max} \cdot \frac{d(\boldsymbol{x_i}) - d_{min}}{d_{max} - d_{min}} & , if\ d(\boldsymbol{x_i}) \leq d_{max} \\ v_{max} & , else \end{cases} \tag{4}$$

$$v_{dyn}(\boldsymbol{x}_i, t_0 + n \cdot \Delta t) = 1 - exp\left(-\frac{|\boldsymbol{x}_i - \boldsymbol{x}_p(t_0 + n \cdot \Delta t)|^2}{2\pi\sigma_p^2}\right) \tag{5}$$

Here, $d(\boldsymbol{x_i})$ is the distance to the next obstacle cell, described by the distance transform of the map, and $\boldsymbol{x}_p(t_0 + n \cdot \Delta t)$ is the predicted position of the person at the current simulation time. The fusion is done by a simple minimum operation:

$$v(\boldsymbol{x_i}, t_0 + n \cdot \Delta t) = min(v_{st}(\boldsymbol{x_i}), v_{dyn}(\boldsymbol{x}_i, t_0 + n \cdot \Delta t)) \tag{6}$$

3.2 Following the Calculated Path

The planning is complete, if the wavefront has reached the predefined target cell. Note, that our approach also calculates *when* the target is reached. Each cell, passed by the wavefront, contains the passing time. The driving path is calculated by performing a gradient descent from the target cell towards the robot's original position. The robot has to follow this path as good as possible with the defined speeds, calculated during the planning process. If the person deviates to much from the predicted path in space and time, a replanning has to be performed. This is triggered, if the three dimensional Euclidean distance $|(x_p^{pred} - x_p^{obs}), (y_p^{pred} - y_p^{obs}), (t^{pred} - t^{obs})|$ is above a certain threshold.

4 Experiments and Results

During the simulation experiments, two scenarios with different characteristics were evaluated. In the first scenario, a person moves on a straight line in the

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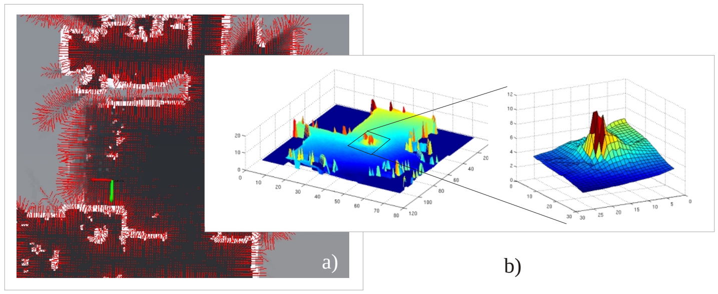

Fig. 3. In a), an example of the force field is shown, which is used for motion prediction. In b) the function of the passing times of the wave is depicted. From this function, the resulting path is created by gradient descent. It can be seen, that the traveling time raises significantly, when the wavefront intersects the personal space of the person. A detailed view of that part of the function is shown on the right.

Simulation Step	Δt**=3s**	Δt**=1.5s**	Δt**=0.5s**	Δt**=0.2s**
t_{avg}	75ms	75ms	75ms	89.2ms
Speed factor	13	13	13	11

Table 1. Overview of the achieved computation time results for different time steps Δt for person position prediction. Here, t_{avg} is the average computation time per iteration step. On larger time steps up to 0.5 seconds the system is able to predict and plan 13 times faster than real time. Only on small simulation steps, this factor begins to lower. In test runs, a simulation time of 0.5 seconds is chosen.

narrow space of our living lab, and the robot has to plan a path which crosses this line. In the second scenario, the person meets the robot in a wide corridor. The person moves also in a straight line and the robot should approach a goal by driving in the opposite direction. Both scenarios are based on real world map data of our lab. The map is 15m x 100m and has a map resolution of 10cm per cell. Person detection and tracking is done by using a laser-based leg detector, based on the approach of Arras [1]. The resulting planning functions and the associated cell speeds, are shown in figure 4 for both scenarios. It can be seen, that in both cases the personal space of the moving person slows down the wavefront and guides the wavefront around the person. To provide a practical system, the robot should be able to plan a path much faster than real time. In fact, it must be possible to plan the path in a fraction of a second for multiple seconds beforehand. Otherwise, the predicted trajectory becomes invalid, since the person has moved to far until the robot starts driving. For the experiments a Core 2 Duo mobile processor with 2.1 GHz was used by using only one core. Table 1 shows the results of the runtime investigation for multiple simulation intervals Δt. In average, the method is capable of simulating 13 times faster than real time. The simulation step time of 0.5 seconds is used for our experiments, since this time provides maximal accuracy by providing still good performance. The simulation and planning of ten seconds of motion can be done in 770 milliseconds.

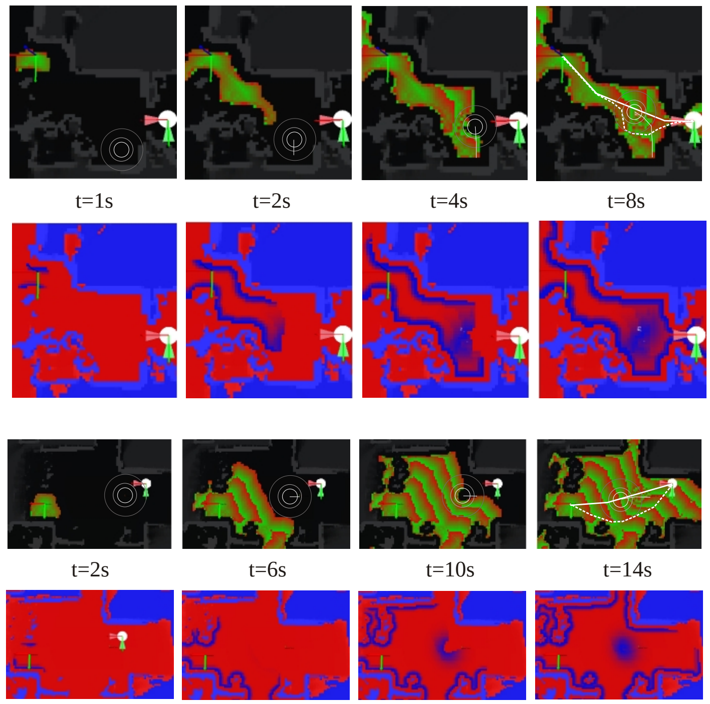

Fig. 4. Propagation of the planning wave for both scenarios. The predicted personal space is shown by multiple bright circles. The wavefront travels through the room until the target is reached and avoids the personal space. Finally, with gradient descent a path is extracted from the wave's passing times. The final path is shown as a dashed line, whereas the planned path without a person is shown as a solid line. Note, that every two seconds in simulation time, the color of the wavefront changes from red to green. Below the traveling time function the used cell speeds are shown, which are calculated when the wavefront passes the cells. Blue corresponds to slow traveling speeds, while red corresponds to high traveling speeds.

5 Conclusion and future work

In this work, an approach for spatio-temporal path planning with regard of one moving person is shown. Up to this stage, the problem of re-planning is only addressed when the person deviates from the predicted path. Here, the behavior of the robot has to be investigated in further experiments with complex situations. Especially, when multiple persons move around the environment, a more sophisticated prediction method has to be used. We plan to use either a statistical model, or a model based on social forces.

Acknowledgment

This work was financed by the project AAL-2009-2-049 "Adaptable Ambient Living Assistant" (ALIAS) co-funded by the European Commission and the Federal Ministry of Education and Research (BMBF) in the Ambient Assisted Living (AAL) program.

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