

# ”Go ahead, please”: Recognition and Resolution of Conflict Situations in Narrow Passages for Polite Mobile Robot Navigation

Thanh Q. Trinh, Christof Schroeter, Jens Kessler, and Horst-Michael Gross

Neuroinformatics and Cognitive Robotics Lab, Ilmenau University of Technology,  
Ilmenau, Germany  
`quang-thanh.trinh@tu-ilmenau.de`

**Abstract.** For a mobile assistive robot operating in a human-populated environment, a polite navigation is an important requirement for the social acceptance. When operating in a confined environment, narrow passages can lead to deadlock situations with persons. In our approach we distinguish two types of deadlock situations at narrow passages, in which the robot lets the conflicting person pass, and either waits in a non-disturbing waiting position, or forms a queue with that person. Forthcoming deadlock situations are captured by a set of qualitative features. As part of these features, we detect narrow passages with a raycasting approach and predict the movement of persons. In contrast to numerical features, the qualitative description forms a more compact human-understandable space allowing to employ a rule-based decision tree to classify the considered situation types. To determine a non-disturbing waiting position, a multi-criteria optimization approach is used together with the Particle Swarm Optimization as solver. In field tests, we evaluated our approach for deadlock recognition in a hospital environment with narrow corridors.

**Keywords:** Human-aware navigation, socially assistive robotics, situation understanding, polite navigation

## 1 Introduction and Motivation

In the ongoing research project ROREAS (Robotic Rehabilitation Assistant for Stroke Patients) [10], we aim at developing a robotic rehabilitation assistant for walking and orientation exercising in self-training during clinical stroke follow-up care. The robotic rehab assistant is to accompany inpatients during their walking and orientation exercises, practicing both mobility and spatial orientation skills. The test site is a complex U-shaped rehabilitation center and accommodates more than 400 patients. The operational environment is highly dynamic. Patients and staff working in the patients’ rooms are moving in the corridors and in the public areas, many of them using walking aids. Moreover, beds, supply and cleaning carts, or wheel-chairs are occupying the hallways, resulting in more or less restricted space conditions at some times.

The self-training is mostly performed on the corridors. Due to the structure of the building or objects standing in the hallways, some parts have limited lateral space, forming a narrow passage which permits movement only in one direction at

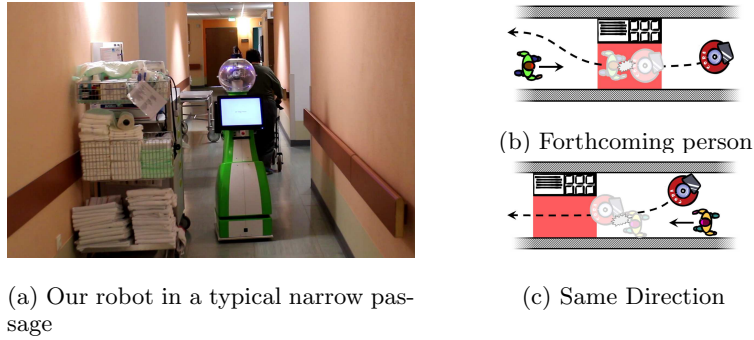


Fig. 1: Our robot in a typical narrow passage at our test site, the m&i rehabilitation center in Bad Liebenstein, and schematic depiction of the considered conflicting situations caused by narrow passages.

a time (Fig. 1(a)). Moving in such a restricted space imposes deadlocks in narrow passages. Since a polite and attentive navigation is an important requirement for an assistive robot, these situations must be predicted to trigger a proactive reaction of the robot. In this work, we distinguish two types of deadlocks: (i) deadlocks caused by a forthcoming person and (ii) deadlocks occurring when the robot and a person are entering the narrow passage in the same direction. In Fig. 1(b)(c) schematic examples of these situations with a narrow passage typical to the operation area are depicted. Both cases have different resolution strategies, but basically result in a "give way" behavior. To be more specific, in case of type (i) deadlocks, the robot is driving to a waiting position to give way to the forthcoming person, whereas type (ii) deadlocks are resolved by forming a queue and following the person through the narrow passage.

When a deadlock situation with a forthcoming person is predicted, the robot needs to wait until the narrow passage has been cleared. In the wait state, the robot should position itself in a non-obstructive manner aside. This has a twofold effect: First, in an already restricted environment, the position to be chosen should not hinder the movement of the person and ease the deadlock elimination. Second, the movement to a waiting position signals the approaching person the intention of the robot to give way. Additionally, the narrow passage must be observable from the robot's waiting position, since it must be able to recognize when the narrow passage is free to be entered. In our approach, we formulate the problem of finding a suited waiting position as a multi-criteria optimization problem and use a Particle Swarm Optimization (PSO) [16] as solver.

The main contributions of this paper are: (a) a new approach for detecting narrow passages by means of qualitative features capturing the spatial relationships of conflicting situations, (b) an efficient method for predicting space conflicts in narrow passages, (c) a fast approach for finding non-obstructive waiting positions based on multi-criteria optimization, in order to support the conflict resolution.

## 2 Related Work

The recognition and handling of deadlock situations in narrow passages has been explicitly taken into account in [3]. In this approach however, deadlock situations

are only recognized and handled in a reactive manner, when the path is blocked by a person standing in a narrow passage. For a rehab center with patients having reduced mobility and using walking aids, a more predictive recognition is necessary to proactively avoid deadlocks.

In our approach, a set of qualitative spatial features is used to recognize deadlocks. Such a qualitative description is also used in [12] to evaluate the movements of a robot and a person. Particularly, the Qualitative Trajectory Calculus is utilized. In [14] and [24], Inverse Reinforcement Learning is employed to learn a navigation behavior in crowds based on features capturing the environment. However, narrow passages are not explicitly described.

To assess the situation from a set of situation describing features, the relationships between them must be described. The techniques for finding these relationships belong to the field of Data Fusion (DF). In the robotic field, only few papers on DF for situation assessment have been published so far. A general framework for situation assessment is described in [1]. Situations are learned with an extensible Markov Model from a set of feature sequences describing the environment. In contrast to the robotics research, the field of Advanced Driver Assistance Systems provides a wider range of publications dealing with situation understanding. The common applications are the recognition of a driver's driving maneuvers, driving behaviors at intersections, and the recognition of unusual driving behaviors. For situation assessment, often Hidden Markov Models [21], Bayesian Networks [19][9], and rule-based techniques [20] are used.

So far, only explicit recognition techniques have been mentioned. In the robotics field, there also exists a category of implicit techniques. The main subject of these techniques are the usage of spatiotemporal planners and the incorporation of long-term human motion predictions to avoid deadlocks. Although the deadlock problem can be solved with this approach, there is still a need for situation assessment, when a human-robot communication is required to interact with the person when a deadlock situation occurs. Since implicit techniques aim at generating collision free trajectories, deadlock situations are not explicitly recognized. The implicit techniques can be distinguished by the used planning algorithms and human motion prediction methods. The most widely used planners are  $A^*$  [13][2] and Rapidly-Exploring Random Trees [18][23]. Human motion prediction methods can be categorized into learning-based and reasoning-based [17] ones. Learning-based approaches learn a predictor from a given training set of trajectories [2], whereas reasoning-based approaches make predictions based on a given motion model for the person [7].

Since our focus lies in the application of qualitative features for describing deadlock situations and an efficient collision prediction method for narrow passages, we only use a simple linear motion prediction and a rule-based approach for situation assessment. However, our field experiments demonstrate that these methods result in a relatively good recognition performance for this hospital environment.

### 3 Robot Platform ROREAS

Our robot has a relatively small size of 45 x 55 cm footprint and a height of 1.5 m (Fig. 1(a)). The drive system is a differential drive with a castor on the rear and

allows a maximum driving speed of up to 1.4 m/s. The robot's sensory system consists of two SICK laser range finders, three Asus RGB-D cameras, and a panoramic color vision system mounted on the top of the head. For person perception, we utilize a probabilistic multi-hypotheses and multi-cue tracking system based on a 7D Kalman filter [25]. It tracks the position, velocity and upper body orientation of multiple persons. As detection modules, we are using a face detector, a motion detector, and an upper-body shape detector. Additionally, generic distance-invariant laser-scan features are used to detect legs and persons with mobility aids (i.e. crutches, walkers and wheelchairs) [26]. With these detection modules we are able to track persons up to a distance of 8 m. To safely navigate in dynamic environments, the positions of obstacles need to be determined. To this end, we use a generic mapping system which is able to process 2D laser-scan and 3D information of the robot's surroundings [5]. The navigation system consists of a Dynamic Window Approach (DWA) [8] guided with an  $E^*$  planner [22]. Furthermore, multiple DWA objectives are utilized to respect the personal space of bystanders and to achieve a right-hand traffic behavior. The complete robotic system was developed with MIRA [6]. For a more detailed overview of our robot system see [10].

## 4 Deadlock Recognition

The deadlock recognition is formulated as classification problem. As argued before, we distinguish two types of conflict situations depending on the movement intention of the person (Fig. 1(b)(c)). Both situations have different resolution strategies. In case of a deadlock with a forthcoming person, the robot drives to a non-disturbing waiting position aside. These situations are labeled as *Waiting*. In case of a deadlock with a person moving in the same direction as the robot, a queue is formed with the person. These situations are labeled as *Queuing*. Using the resolution strategies as class labels and adding the class *Proceeding* for uncritical situations, the deadlock recognition problem can be formulated as a classification problem over situations. In finding a classifier  $C : \mathcal{S} \rightarrow \{\textit{Waiting}, \textit{Queuing}, \textit{Proceeding}\}$  with  $\mathcal{S}$  as the set of all situations, we can recognize the considered deadlock situations. Our recognition approach can be described as a sequential processing chain consisting of four distinct steps: (1) the detection of the narrow passage, (2) the extraction of qualitative spatial features describing the situation around the narrow passage, (3) the prediction of space conflict, and (4) the classification of the considered situations. In all the processing steps we assume a planar operational space.

### 4.1 Narrow Passage Detection

Narrow passages are detected by first calculating normals perpendicular to the planned path for a finite set of points sampled from the path (Fig. 2). The normals are determined analytically. To this end, we utilize a spline interpolation scheme to derive a trajectory  $\pi : \mathbb{R} \rightarrow \mathbb{R}^2$  parametrized over the path's arc length. For each normal, rays are cast in the navigation map until hitting an obstacle in the 2D occupancy map. The total length of the resulting rays indicate

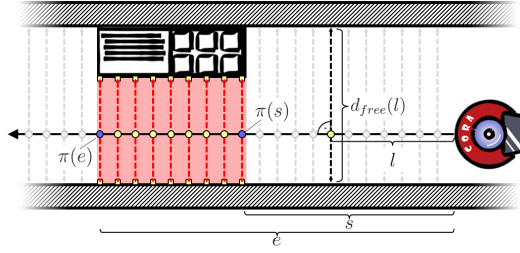


Fig. 2: The narrow passage detection. The circles depict the sample points on the robot's path for which a ray perpendicular to path is cast.  $\pi$  is the trajectory of the path parametrized over arc length. The highlighted path points  $\pi(s)$  and  $\pi(e)$  are the start and end point of the narrow passage with  $s$  and  $e$  as their corresponding arc length. Thus the arc length interval of the narrow passage is  $\mathbf{N} = [s, e]$ . The quadratic points are the boundary points of the narrow passage's polygon. The polygon itself is marked red.

how much free lateral space is available at a given path point. With these distances, a narrow passage can be described as a continuous path section given by an arc length interval  $\mathbf{N} \subset \mathbb{R}$ , where the section's maximum distance is smaller than a given threshold. Another useful form for reasoning about the spatial relationship around the narrow passage is its bounding polygon. To construct the polygon, the sampled path points in the narrow passage, which were used to calculate the normals, are translated along their cast rays to get the points on the polygon's boundary.

## 4.2 Qualitative Spatial Features

The common method to describe spatial relationships is to use geometrical measures. For humans these quantitative measures are a rather unintuitive way for describing spatial relationships. Instead, they use a qualitative abstraction and group similar measurement values to an intuitive representation [12]. For example, a person is more likely to describe another person as standing behind him/her, than to give the exact orientation angle. We use this insight to reduce our geometrical feature space to a more compact space. In this compact space, simple rules are employed to distinguish the considered situations. Thus, we overcome the need for a learning approach to collect a dataset, which must contain many instances of the geometrical features. We use the following features to describe deadlock situations:

**Movement Direction** In Fig. 3(a) an illustration of this feature is depicted. This feature describes the movement direction of a person relative to the movement direction of the robot at either the start or the end of the narrow passage. We distinguish three different directions *Opposite*, *Same* and *Passing*. Additionally, a fourth value *Standing* is introduced for a person with no movement.

**Orientation** This feature represents the position of a person relative to the robot. The feature can take the values in *Front*, *Rear* and *Side*. To determine this feature value, the angle between the robot's movement direction and the connection line of the person to the robot is used. See also Fig. 3(b) for an illustration.

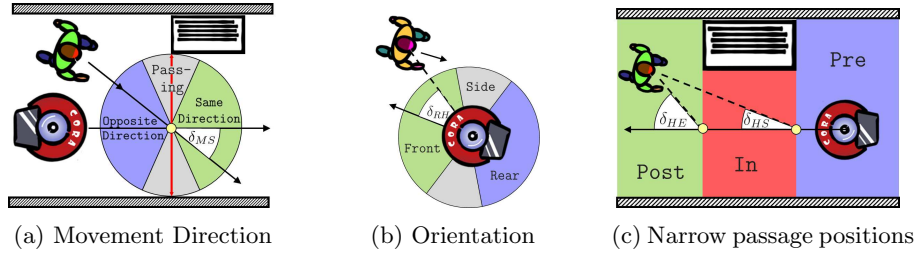


Fig. 3: Qualitative spatial features extracted from the position of the narrow passage, the persons and the robot.

**Narrow Passage Position** Given a narrow passage, this feature describes the positions of the robot or a person relatively to the passage. We define three sub-areas representing the *Pre*-, *Post*- and *In*-area of the narrow passage (Fig. 3(c)). The reference orientation is given by the movement direction of the robot. To determine this feature value for a person, we assume a person to be disc-shaped. The intersection area of the person with the narrow passage’s polygon and the relative orientation to the narrow passage is utilized to reason about the sub-area.

### 4.3 Space Conflict Prediction

A narrow passage can be understood as a rail predefining a movement flow. Persons entering the narrow passage can only move along the given direction. Moreover, a point in the narrow passage can only be occupied by one person or the robot at the same time. Thus, without losing information, we describe the movement of the person and the robot through the narrow passage as a trajectory  $\tau : \mathbb{R} \rightarrow \mathbb{R}$  parametrized over time and having function values in the passage’s arc length interval on the planned path. Using a linear model, the movement of the person through the narrow passage can be predicted. By assuming a linear motion model the trajectory of the robot and the person can be described as linear functions. Thus, predicting space conflicts can be reduced to finding the intersection point of two linear functions.

### 4.4 Situation Classification

For each perceived person we extract the qualitative spatial features and predict possible space conflicts. Thereafter, a decision tree (DT) is used to classify the situation for each person separately. In Fig. 4(a) a coarse view on the DT is depicted. The root of the DT represents common preconditions for the conflicting situations. Only when these conditions are fulfilled, further evaluations are considered. The preconditions consist of the check for the presence of a narrow passage and a space conflict with a person. Furthermore, an evaluation area around the narrow passage is constructed, permitting further evaluations only when the robot and conflicting person stay inside this area. Upon the fulfillment, the evaluation is redirected to the subtrees according to the movement direction of the person. The subtrees for standing persons and persons moving in opposite direction are dedicated for the separation of the *Waiting* class from the *Proceeding* class, whereas the subtree for person moving in the same direction separates

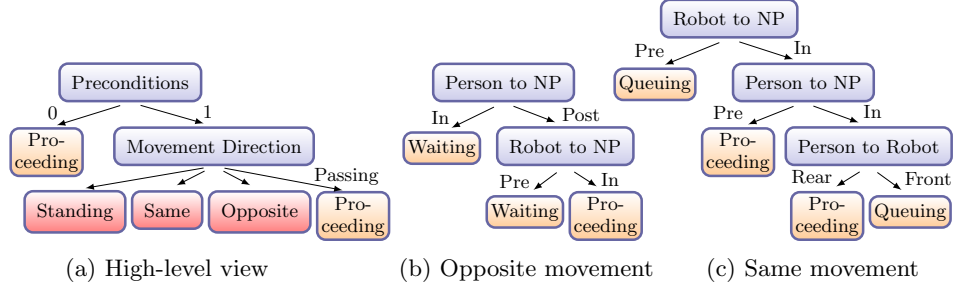


Fig. 4: (a) The high-level view of the decision tree. The orange nodes represent the classification results; the blue nodes are the decision nodes; and the red nodes contain a subtree. (b) The subtrees for persons moving in the opposite direction and (c) same direction to the robot. The decision nodes use the relative position of the robot or persons to the narrow passage (NP) and the relative position of the person to the robot to chose the appropriate class.

*Queuing* from *Proceeding*. The main idea of the subtrees is to use the qualitative spatial features describing the relative positions of the person and robot (Sec. 4.2) for arguing about the class membership. In Fig. 4(b)(c), the subtrees for persons moving in the opposite and the same direction as the robot are depicted.

## 5 Finding Non-Obstructive Waiting Positions

### 5.1 Multi-criteria Optimization

The problem of finding a proper waiting position is formulated as a multi-criteria minimization problem. The search space consists of points  $(\mathbf{x}, \phi)$  with  $\mathbf{x} \in \mathbb{R}^2$  a position in a planar world and  $\phi \in [0..2\pi)$  an orientation defining the robot's viewing direction. The information about the obstruction and the passage's observability of a pose is encoded in the optimization function

$$f(\mathbf{x}, \phi) = \alpha \cdot c_{dist}(\mathbf{x}) + \beta \cdot c_{observe}(\mathbf{x}, \phi) + \gamma \cdot c_{wall}(\mathbf{x}) + \eta \cdot c_{social}(\mathbf{x}) \quad (1)$$

through linear combination of the criteria (i) driving distance to a position  $c_{dist}$ , (ii) observability of the narrow passage  $c_{observe}$ , (iii) distance to walls  $c_{wall}$  and (iv) social distance to persons  $c_{social}$ . Since our criteria are non-linear or non-differentiable, we use the Particle Swarm Optimization to find the minimum.

### 5.2 Optimization Criteria

**Driven Distance** Given the representation of the environment as a grid map, this criterion penalizes positions which are far away from the robot, thus minimizing the time to drive to the selected position. This is important, since the person might get irritated about the robot's intention to wait, if the waiting position is chosen too far. The driven distance to a position is determined with Dijkstra's algorithm [4]. Note, that for unreachable positions, Dijkstra's algorithm results in an infinite distance.

**Observability** This criterion indicates if the narrow passage is observable at a given pose. The robot's field of view is modeled as a cone directed along  $\phi$ . The cone is further refined to incorporate the position of obstacles. The refinement is conducted by casting rays from  $\mathbf{x}$  inside the cone until hitting an obstacle or the cone's boundary is reached. The ending points of those rays are used to form a polygon. The intersection area of this cone and the narrow passage's polygon is used to determine the observability value.

**Distance to Walls** Imagine a robot moving in a hallway and the robot waits in the middle of the hallway. This is a rather unintuitive signal and depending on the width, the person might have to squeeze around the robot. A more intuitive way is to let the robot wait near the walls. This is more explicit and provides the person more free space to pass the robot. To determine the distance to walls a distance transform algorithm [15] is performed on the environment's map. The resulting image allows lookup of the distance to the next wall for each potential waiting position.

**Social Distance** Every person has a social distance s/he keeps to others when s/he has no intention of interaction [11]. Assuming that a person is represented as a disc-shape and has the position  $\mathbf{x}_h$ , the social distance of a person is modeled as a Gaussian centered at  $\mathbf{x}_h$ . Then for a position  $\mathbf{x}$ , the social distance criterion is the summed function values of all the perceived persons' Gaussian evaluated at  $\mathbf{x}$ .

## 6 Experimental Results of Field Tests and Outlook

In extensive field tests we evaluated our approach for deadlock recognition in the "m&i Fachklinik" rehabilitation center in Bad Liebenstein with our robot platform. The tests were conducted over two days. During the tests, we let the robot autonomously drive between different goals and floors of the building. For evaluation, an external observer accompanied the robot and manually counted the decisions taken by our approach, but always from far distance to prevent any distraction. In total, a distance of 4,700 m was traveled. During the first 4,000 m, only bystanders were crossing the robot's way. These bystanders were staff members, patients, or guests, which randomly occurred on the hallway and had no knowledge about the robot's deadlock recognition. In this test run, we observed that most bystanders were considerate towards the robot and let it first pass. Only some bystanders took the initiative resulting in the robot to give way. Hence during the remaining 700 m, we additionally informed two test subjects with normal mobility about the deadlock recognition, but without insight to the technical details, and instructed them to actively obstruct the robot by crossing its way. Thus, we obtained more variability in the deadlock situations and a better assessment of the overall robustness. How they crossed the robot's way were up to the test subjects. Each bystander or test subject which crossed the robot's way in a 2 m radius was considered as potential source of a deadlock and contributed to one instance in the confusion matrix shown in Table 1.

### 6.1 Discussion and Future Works

In total 157 persons were potential sources of deadlocks. From these 157 persons, 35 persons caused deadlock situations at narrow passages with further division in

		Predicted class		
		Proceeding	Queueing	Waiting
Ground Truth	Proceeding	96	19	7
	Queueing	0	12	3
	Waiting	1	1	18

Table 1: The confusion matrix containing the experimental results. Each instance in a row correspond to one situation class actually occurred during the experiments. The columns correspond to the predictions made by our approach.

15 queueing and 20 waiting situations. Out of these 35 deadlock situations only one was misclassified as uncritical situation (true positive rate of 97 %). From these 34 correctly classified deadlock situations, 30 were assigned to the correct deadlock type (accuracy of 88 %). However, 26 of 122 uncritical situations were classified as deadlocks (false positive rate of 21 %).

The performance of the deadlock recognition strongly depends on the accuracy of the situation describing features which in turn depends on the person tracker, the narrow passage detection, and the space conflict prediction. Analysis of the false positives revealed that 19 of 26 false positives are caused by false detections of the person tracker. In these cases, the deadlock recognition assumed to have a conflicting situation with a person, even though there was no person present at all. The remaining 7 false positives were caused by dynamic obstacles, e.g. moving persons or objects moved by persons. If a dynamic obstacle causes a narrow passage, the narrow passage itself also has a movement. Since the narrow passage detection uses the navigation map which currently is not yet able to distinguish dynamic obstacles, this movement could not be considered in the space conflict prediction and leads to false predictions. Surprisingly, the linear motion model used in the space conflict prediction and neglecting the uncertainty in the qualitative spatial features only have little influence on the recognition performance. This can be explained by the structure of the test site which mainly consists of long and narrow corridors. In this environment, the movement and space is already restricted. Thus, a simple linear motion model leads to good predictions, and the extracted features have only little uncertainty.

In future works, we are going to reduce the false positive rate by improving the person tracker and the narrow passage detection. To be applicable for complex environments, a more elaborate motion prediction and the consideration of the uncertainty in the recognition process is needed. Furthermore, the human perception about the robot's behavior need to be evaluated more specifically to get better insights to the courtesy of the robot. These evaluations should also be conducted over a longer time period, when the bystanders get used to the robot and renounce to act courteously in front of deadlocks.

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