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ARTICLE:
Human-Aware Navigation using External Omnidirectional Cameras

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Abstract – If robots are to invade our homes and offices, they will have to interact more naturally with humans. Natural interaction will certainly include the ability of robots to plan their motion, accounting for the social norms enforced. In this paper we propose a novel solution for Human-Aware Navigation resorting to external omnidirectional static cameras, used to implement a vision-based person tracking system. The proposed solution was tested in a typical domestic indoor scenario in four different experiments. The results show that the robot is able to cope with human-aware constraints, defined after common proxemics rules.

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Human-Aware Navigation using External Omnidirectional Cameras ⋆

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Abstract. If robots are to invade our homes and offices, they will have to interact more naturally with humans. Natural interaction will certainly include the ability of robots to plan their motion, accounting for the social norms enforced. In this paper we propose a novel solution for Human-Aware Navigation resorting to external omnidirectional static cameras, used to implement a vision-based person tracking system. The proposed solution was tested in a typical domestic indoor scenario in four different experiments. The results show that the robot is able to cope with human-aware constraints, defined after common proxemics rules.

1 Introduction

In the last few years, robotics is becoming focused on Human-Robot Interaction and on its role in social environments. When people think of a robot interacting with a person, what comes to mind is a robot that can speak with her or hand over some object. However, the motion itself is of great importance in a social context (e.g. when a robot is requested to fetch an item), or simply when a normal navigation behavior needs to be adjusted according to proxemics rules, so it does not disturb people. The study of robot navigation in the presence of people is called Human-Aware Navigation.

Most approaches in the literature used only sensors on-board the robot. Even though those sensors bring the advantage of context-independence, most robust people tracking methods are based on computer vision and computationally expensive. Hence not suited for on-board computational devices [2]. In this paper, a Networked Robot Systems have been used to overcome the limitations of on-board sensing. Particularly, external omnidirectional fisheye cameras were mounted on the ceiling. This setup ensures a broader perception of the environment, capable of seeing both humans and robots at the same time. In addition, an increase in processing power is achieved (computational effort can be distributed through external devices), which gives the robot extra computation time that can be used in other tasks (e.g finding objects).

In 2007, Sisbot et al. [19] proposed the Human-Aware Navigation Planner (HANP). Their work is focused on human comfort, which is addressed by three criteria: preventing personal space invasions; navigating in the humans' field of view (FOV); and preventing sudden appearances in the FOV of humans. Those criteria are modeled as cost functions in a 2D cost-map and path planning is performed with A^*. Even though HANP accounts for replanning if people move, it does not adapt their personal space during the motion. With that in mind, two extensions to HANP were proposed:

- a prediction cost function which, by increasing the cost in front of a moving human, decreases the probability of the robot entering that area [11];
- the concept of compatible paths, which says that two paths are compatible if both agents can follow their paths (reaching the goal position), without any deadlocks [10].

Kirby at [8] proposed a new solution, which differ from HANP on the considered constraints and their formulation. Instead of focusing simply on human comfort, constraints concerning social rules (e.g. overtake people from the left) and low-level human navigation behavior (e.g. face direction of movement) are also taken into account.

Another important issue related with human comfort, in a social context, is the interference with humans interacting with other humans and/or objects. This issue is tackled in [16] where, besides considering proxemics and the back space of a person, a constraint is included to model the space between interacting entities.

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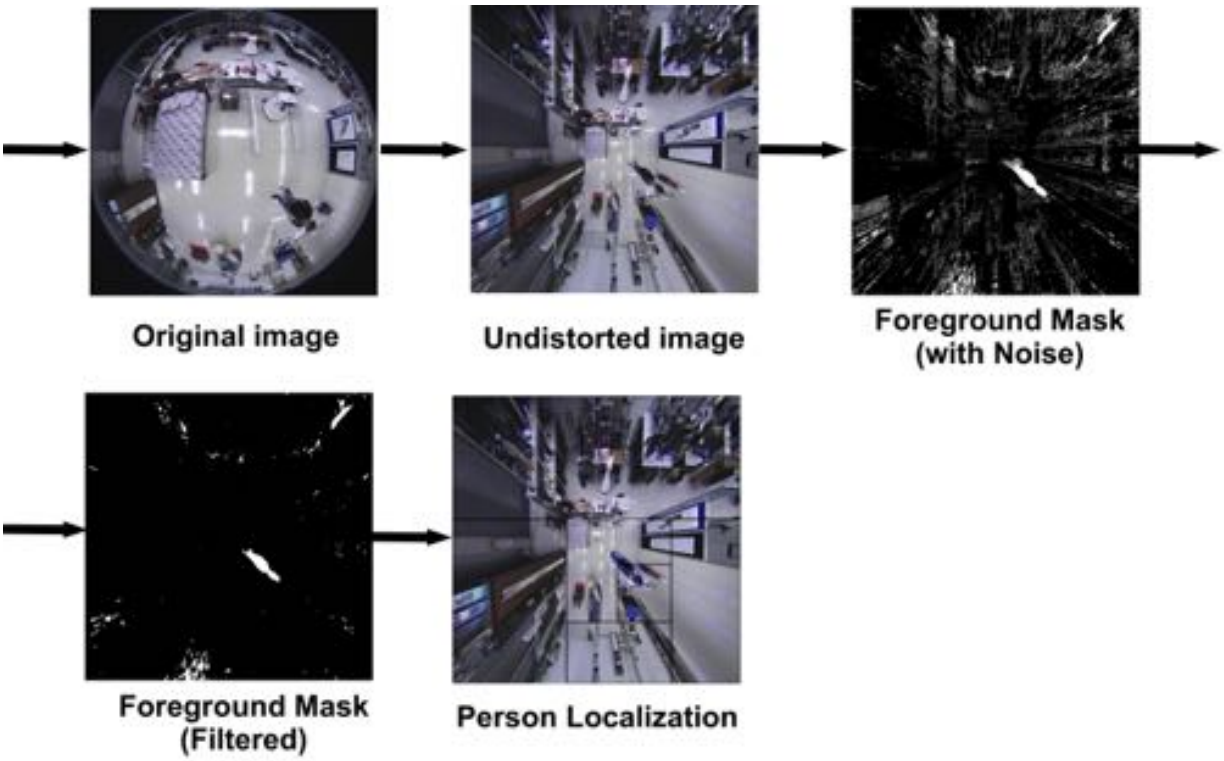


Fig. 1. Representation of the steps used for detecting people. The first picture corresponds to the original image (distorted image). The second is the undistorted image. Third and fourth correspond to background subtraction and foreground filtering steps, respectively. The last image corresponds to the final detection (the blue ellipse identifies the person on the image).

Other important work was presented in [15], a framework for planning a smooth path through a set of milestones. Those are added, deleted and/or modified, based on the static and dynamic components of the environment.

In 2013, Kruse et al. [12] defined the three goals for Human-Aware Navigation as: human comfort (e.g. space that people keep from each other in different contexts, known as the theory of proxemics [6], and velocity that robots navigate close to humans [18]); respect social rules; and mimic low-level human behavior.

In this paper, we propose a solution for Human-Aware Navigation resorting external cameras, for person state estimation. A cost-map is computed by combining several constraints associated with Human-Aware Navigation. Each time the robot receives a new goal, it computes a path on that cost-map. When compared with state-of-the-art approaches, the main contributions are:

- the use of static external camera sensors, increasing the field of view (allowing to see the robots and people at the same time and not requiring the re-estimation of the camera pose, thus eliminating one cause of error), Sec 2; and
- standardization of human-aware constraints (collection of a set of constraints from different state-of-the-art methods and reformulation of some of them), Sec. 3.

The solution was tested in simulated and realist scenarios in four different experiments. The results (Sec. 4) show that the proposed solution fulfills the respective goals.

2 Vision-Based Person Tracking

One of the most important steps of Human-Aware Navigation is person tracking. That problem is solved by a vision-based tracking system, consisting of two steps: people detection, including posture (identify if people are seated,

standing or if it is just noise, e.g. a robot); and person tracking with a Kalman Filter. The goal is to get a setup that is capable of seeing both the robot and people, at same time. For that purpose, omnidirectional fisheye cameras mounted on the ceiling are used.

2.1 People Detection Including Posture

The goal of the detector is to be as fast as possible, for a good real-time tracker. With this is mind, our solution first finds blobs of interests on the image; associates these blobs to posture states (also filters some errors due to noise); and finally tracks those blobs in the world frame.

Each time a new image is received, the respective undistorted image is computed (the method/model used is proposed at [17]). Moving objects in the scene are detected using background subtraction. In addition, since resulting foreground is very noisy, morphological operations are employed (opening and closing). Blobs are then extracted and, from the resulting contours, those with an area bigger than a threshold are fitted onto an ellipse (in our experiments we used 3000 pixels as threshold). In addition, one needs to ensure that the localization only takes into account fully detected people, i.e., the fitted ellipses cover people shapes from head to toe. As a result, ellipses that have none of the limits of its major axis inside a predefined interest region are discarded. An example of the application of each step is shown in Fig. 1.

Regarding person posture classification, let us assume that a person's silhouette looks similar when she appears at the same location multiples times (this is verified for different people as long as their heights do not differ much, e.g. children and adults). Using this assumption, a Support Vector Machine (SVM), particularly a C-SVM, [3], was used to classify the fitted ellipses in three possible classes. Those classes are associated with person postures: standing, seated, or noise. Videos of people walking and sitting in the scene were recorded and used for training. The robot was also taken into account in the training, and classified as noise.

For each frame, three features of the ellipses were retrieved:

- (u, v) position of their center on the image;
- size of major axis; and
- size of minor axis.

The features of the ellipses are collected into vectors and classified by the SVM. If ellipses are classified as noise (e.g. a robot), they are discarded. Otherwise, each ellipse is considered to be a person and is going to be localized in the world. Examples of classification using C-SVM are shown in Fig. 2.

The location of a standing person is considered to be her feet. These correspond to the point in the contours closest to the image center. This is true for every point on the image, except when the person is exactly below the camera.

If an ellipse is classified as a sitting person, its center is checked to assess on which of the seating areas the person is (e.g. couch and chairs). If the ellipse is not on any of them, it will be discarded. Otherwise, its position is set to a default for that sitting region. We chose to associate this default position, because feet are often occluded when a person is seated, which will significantly affect the estimation of localization.

To conclude this section, one needs to associate the coordinates of the persons to the world frame (same as the robot). For that, we used the following assumptions:

- cameras are on the ceiling and vertically align with the ground plane (z-axis are aligned);
- only people and the robot are moving on the scene;
- they are all moving on the same plane (floor);

For each detection, we compute the inverse projection of the respective pixel and its 3D coordinates, in the camera reference frame (which can be easily obtained by intersecting the 3D projection ray with the 3D floor plane). Then, a homography is applied to transform coordinates of this point from camera to world coordinate systems, [7], concluding the localization step.

(a) (b)

Fig. 2. Results of people detection (including posture) on zoomed images. Blue ellipse on Fig. (a) means that the classification is standing person (the center of the yellow circle is the point that is assumed to be the feet. Green ellipse on Fig. (b) means that the person is seated. A video of this results is sent as supplementary material.

2.2 Tracking

Let the person state (position and velocity on the ground plane), at time k, be denoted by $\mathbf{x}_k = \left(x_k, y_k, v_k^x, v_k^y\right)$. Taking the position measurements from people detection scheme (described in the previous subsection), one can track the person using a Kalman Filter. The observation equation is

$$\mathbf{z}_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \mathbf{x}_k + \mathbf{v}, \tag{1}$$

where $\mathbf{z}_k$ is the measurement vector, $\mathbf{v} \sim \mathcal{N}(\mathbf{0}, \mathbf{R})$ (normal distribution at $\mathbf{0}$ with covariance matrix equal to $\mathbf{R}$). Humans tend to walk at a constant velocity, [1], hence a constant velocity model was assumed. Then, the state equation is

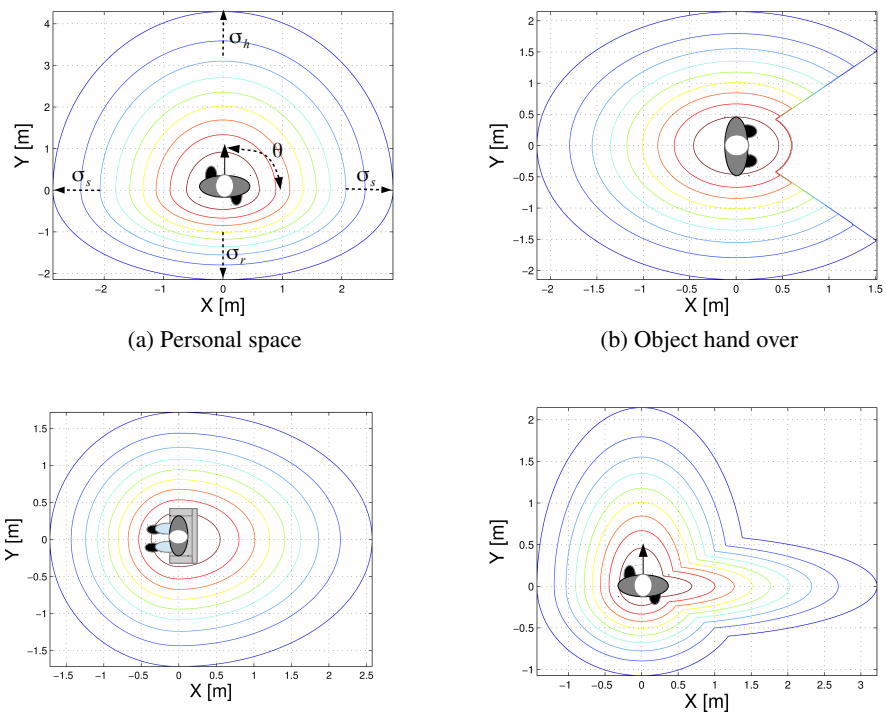
$$\mathbf{x}_k = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{x}_{k-1} + \mathbf{w}, \tag{2}$$

where $\mathbf{w} \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$ and Δt is the time difference between messages received from the people detector. $\mathbf{R}$ and $\mathbf{Q}$ are the measurement and process noise covariance matrices.

For each iteration, there are four possibilities (note that we are assuming that only one person is being tracked):

1. a person is not being tracked;
2. a person is being tracked and a new detection was received;
3. a person is being tracked and more than one detection was received;
4. a person is being tracked and no detection was received.

In the first case, if there is only one detection, the tracker is initialized. Otherwise (none or more than one detection was sent) that message is discarded. For the second case, the filter predicts a new state and then corrects it based on the measurement. If there is more than one detection, the measurement closest to the last estimated state is used to correct the filter's prediction. Finally, if there are no detections the estimated state is the prediction from the filter, without correction.



(a) Personal space

(b) Object hand over

(c) Seated person

(d) Walking person

Fig. 3. Representation of cost functions associated with different people posture: Fig. (a) represents the cost function for the personal space of a person walking in the y direction at 1 [m/s]; Fig. (b) shows the cost function of a person standing, oriented in the x direction, during an object hand over; Fig. (c) represents the cost function for the case were a person is seated; and Fig. (d) shows the total cost function of a walking person, including the social rule of overtaking her by the left and her personal space.

3 Human-Aware Path Planning

To be as Human-Aware as possible, the three goals of the field (namely human comfort; social rules respect; and naturalness) were considered. As a result, following constraints were taken into account:

1. Take least effort path (naturalness);
2. Keep a distance from static obstacles (naturalness);
3. Respect personal spaces (human comfort);
4. Avoid navigating behind sitting humans (human comfort);
5. Do not interfere with human-object interactions (human comfort);
6. Overtake people by the left (social rule);

These constraints are based on previous approaches. However, some of them are reformulated (constraints 4 and 5) in order to be better integrated in our approach and to standardize their formulation. Next, we fully described the formulations used for each constraint.

The first is addressed by the path planner. In this work A^* was used, ensuring a minimum cost path as long as the heuristic is admissible. The total cost of a node is given by the sum of the cost of reaching that node, with the heuristic cost. The latter was considered to be the euclidean distance from the node to the goal position. Since the environment is dynamic, planner computes a path periodically.

The second constraint prevents the robot from passing too close to obstacles. This is solved by attributing a high cost to areas surrounding the obstacles, [4].

The third constraint accounts for personal space. We consider three different situations: when a person is standing; walking; or seated. For the case of a person walking, we used the formulation proposed in [8], which the authors call asymmetric Gaussian

$$f = asymGauss(x, y, \theta, \sigma_h, \sigma_s, \sigma_r), \tag{3}$$

where

- θ - orientation of the function;
- σ_h - variance in the θ direction;
- σ_r - variance in the $\theta - \pi$ direction;
- σ_s - variance in the $\theta \pm \frac{\pi}{2}$ direction.

A graphical representation of these parameters is shown in Fig. 3(a). Then personal space of a walking person was modulated as

$$f_1 = asymGauss(x, y, \theta_p, \beta, \frac{2}{3}\beta, \frac{1}{2}\beta), \text{ where } \beta = \max(v, 0.8), \tag{4}$$

where θ_p is the person's orientation and v her speed. A graphical representation of the person walking along y–axis direction with a velocity of 1 [m/s] is presented in Fig. 3(a).

Regarding a walking person, it makes sense for personal space in front to be larger than in the back (to ensure the robot does not pass in front of the person, decreasing risk of collision). On the other hand, if a person is standing and we consider personal space defined using previous formulation, the robot may pass behind too close the person, causing discomfort. Thus, for this case we suggest that personal space be modulated as a circular Gaussian,

$$f_2 = e^{-\left(\frac{(x-xp)^2}{2\sigma_x^2} + \frac{(y-yp)^2}{2\sigma_y^2}\right)}, \tag{5}$$

where (x_p, y_p) is the person position, σ_x and σ_x are the standard deviation in the x and y direction respectively. This formulation was also considered for a seated person.

If an object hand over is required, the robot should be able to enter the personal space, to be at "arm's length". However, the robot cannot be allowed to enter from a random direction, instead it should only be allowed to approach a person from the front, [9]. Thus, our solution is to open the region in front of the person 45 degrees, to a distance of 0.6[m]. Personal space, in a hand over scenario, is depicted in Figure 3(b). Constraint 4 concerns preventing discomfort from passing behind a seated person. We reformulated this problem with an asymmetric Gaussian

$$f_3 = asymGauss(x, y, \theta_p - pi, 1.2, 0.8, 0.006). \tag{6}$$

The fifth constraint prevents the robot from interfering with a person interacting with an object. It is represented by an interaction set modelled as a circle

$$f_4 = \begin{cases} \alpha & \text{if} \quad (x - x_c)^2 + (y - y_c)^2 \leq r \\ 0 & \text{otherwise} \end{cases}. \tag{7}$$

Its center is the middle position of the interacting entities, (x_c, y_c), and the radius r is half the distance between the entities (only one-on-one interactions are considered). α is an importance factor, which varies from 0 to 1. Constraint 6 represents the social rule of overtaking people by the left (considered only for walking persons). This constraint is also represented using an asymmetric Gaussian

$$f_5 = asymGauss(x, y, \theta_p - \frac{\pi}{2}, 1.5, 0.3, 0.0075), \tag{8}$$

For the three possible postures of a person (standing, seated and walking), there are two where more than one cost function is applied and they must be combined. Since the main goal of the framework is to maximize the comfort of the humans, the cost functions are combined by taking the maximum cost value attributed to each point in space. The first case of multiple cost functions affecting the same space, is a seated person, which personal space is given by

$$f_6 = \max(f_2, f_3), \tag{9}$$

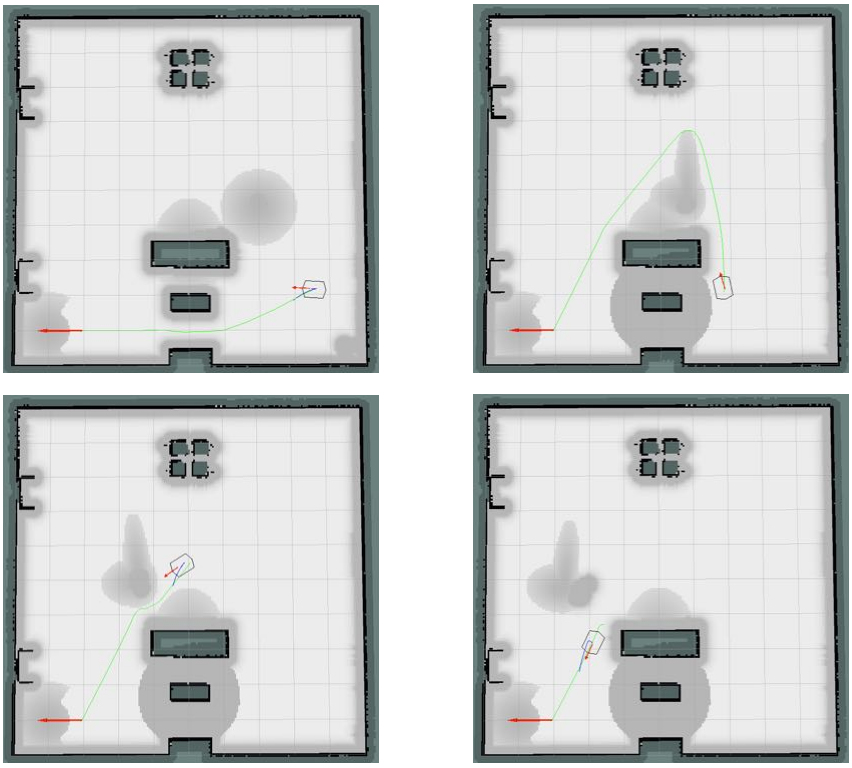


Fig. 4. Evaluation of the proposed navigation system using simulated environments. The environment was created using Gazebo and results are shown in rviz (ROS package). The robot is requested to hand over an object to a person who across the room. However it needs to pass between a seated person and a TV. As it starts moving the TV is turned on. To prevent interference, the robot replans around that area. However, there is yet another person, who is walking behind the couch, who must be taken into account.

this cost function is depicted in Fig. 3(c). The second case concerns a walking person, where the personal space must be combined with the respective social rule (a person should be overtaken by the left),

$$f_7 = \max\left(f_1, f_5\right). \tag{10}$$

A graphical representation of this cost function is shown in Fig. 3(d).

4 Experiments

To evaluate the proposed framework, five experiments were defined. They were conducted both on simulation, Sec. 4.1, and using a mobile platform [14], in a typical domestic indoor scenario, with fisheye omnidirectional cameras on the ceiling, Sec. 4.2.

The proposed system was implemented as an extension of ROS navigation stack, [4]. The cost functions described in the previous section were implemented as plug-ins to the cost-map layered structure [13]. The trajectory controller used was the Trajectory Rollout algorithm, [5]. The implementation of computer vision algorithm was based on OpenCV. Based on the frame rate of the vision-based person tracker, a frequency of 1 [Hz] was used for replanning the paths.

The simulation environment was Gazebo. For the vision-based person tracking, a computer with an Intel Core i5-2430M, with 6GB of RAM (external CPU) was used. For navigation components (reconfiguring cost-maps, path path planning, and trajectory execution), we used an Intel Core i7-3770T with 8GB of RAM (on-board CPU).

The experiments performed were:

Experiment 1: The robot is navigating in free space and a standing person appears on the robot's path. The goal is to see if the robot is able to replan its path, without violating personal space.

Experiment 2: The robot is navigating when encounters a slow walking person, which it must overtake. The goal is to verify if it respects constraints 3 and 6, Sec. 3.

Experiment 3: A person is seated on a couch, watching TV, and the robot wants to go across the room. The goal is to test if the robot respects constraints 4 and 5, Sec. 3.

Experiment 4: The robot navigates towards a person, to hand over some object. The goal is to verify the modification of the personal space, constraint 3, Sec. 3.

Experiment 5: Combines the setup of Experiments 2, 3, and 4. The robot is requested to hand over some object to a person across the room. As it starts moving, the TV is turned on, and the robot replans its path. However, another person is going across the room behind the seated person, who must be overtaken for it to reach its goal.

Next, we present experiments results using both simulated and realistic environments. Videos of the experiments can be seen at `http://tinyurl.com/HANEOCExp` (youtube playlist).

4.1 Results on a Simulated Environment

The goal of these experiments (1 to 4) is to evaluate the proposed navigation system (note that some of the proposed constraints were reformulated and thus needed to be evaluated). The experiments were conducted in a simulated room with some furniture. Three people were placed in the environment, one sitting on a couch and the other two standing. For the first experiment, there were no people in the environment at first, only after the robot started moving, a person was added in its path. Several runs of each experiment were conducted to ensure the robot's behaviour was the desired. During those runs the trajectory controller parameters were fine tuned. Finally, an experiment integrating all the cost functions was conceived (Experiment 5).

When the robot receives the action, the personal space of the target opens in front, and the robot starts moving. However, the TV is turned on, as the robot is reaching the area between a seated person and the TV. Since the importance given to the interaction area was 1 the area was marked as forbidden and the robot needs to replan around. Meanwhile another person is walking slowly behind the seated person, thus the robot plans a path to overtake her. A dark grey area continues on the map after the person started moving. This is were the person was before and it was marked as an obstacle, which is cleared as soon as the robot understands from the laser scans that the obstacle is no longer there. Since the robot could only pass on the person's right, the path is longer (to satisfy Constraint 6). Given the longer path the robot is not able to overtake the person, so it passes behind her when there is enough space behind the person. Finally passing the moving person the robot is free to reach its goal. Pictures of the run in question are presented in Fig. 4.

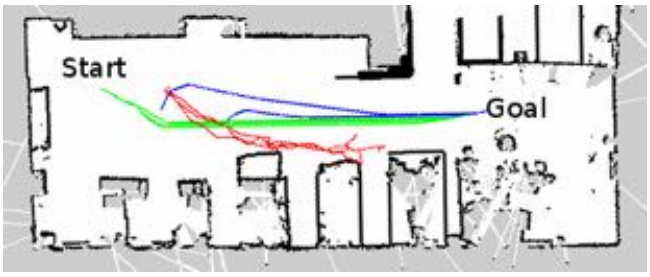
4.2 Real Experiments in an Indoor Domestic Scenario

In this subsection, we validate the complete framework using real experiments, in a typical indoor domestic scenarios. Experiments 1 and 4 were performed 10 times, with fixed start and goal positions. The computed paths and the position of the person in each run are presented in Fig. 5(a) and 5(d), respectively. Experiment 3 was performed 10 times with the TV off and 10 times with the TV on. The paths were recorded and plotted in Fig. 5(c). Finally, Experiment 2 was performed 3 times. The results are shown in Fig. 5(b).

Throughout the experiments, the robot displayed a similar behaviour to the simulation in terms of trajectory execution in most cases. However, the parameters of the cost functions (4), (5), (6), and (8) needed to be adjusted. The values presented previously were derived empirically, taking into account: the values in the literature; the space restrictions of the real scenario, and our intuition of comfort distances. Even though the final distances are similar to previous works, an effort should be made to further validate those parameters, by conducting user studies.

Computational performance of the overall system is mainly constrained by the performance of the vision-based person tracker. When a person is moving slowly, standing and/or seated, the system is able to keep track of the person, as can be seen by the high repeatability of the execution of Experiments 1, 3 and 4. However, for a person walking at faster pace, the system may not show the same performance, Fig. 5(b). As the person moves faster and faster, the vision system may take longer to estimate the person state (position and velocity) than she takes to take another step, thus the

(a) Results for Experiment 1. Green lines represent paths computed before the person entered the scene. Blue lines represent the final path (which was replaned when person interfere with robots path). Person location is represented by red circles.



(b) Results for Experiment 2. Paths computed before the person started walking are in green. Blue lines show the paths computed after the person started walking. The estimated person's path is shown as red.

(c) Results for Experiment 3. Green lines show robot's final paths computed with TV off. Blue lines show the final robot's paths with TV on. Red circles identify person location.

(d) Results for Experiment 4. Green lines show robot's paths to reach the person for object hand over. Person location in each run are shown in red circles.

Fig. 5. Results of the real experiments in a realistic domestic indoor scenario, using a mobile robot, [14].

estimate may be delayed when compared with the true position of the person. The limiting factor in the vision-based tracker is the slow background subtraction step (high resolution images were used).

5 Conclusions

This work addresses the problem of Human-Aware Navigation for a robot in a social context. The proposed framework combines a networked robotics environment, with specific motion constraints representing the human-aware concerns. A new framework was presented, which increases the field of view by using external omnidirectional cameras and attempts to standardize human-aware constraints. Five experiments were conducted in simulation and four in a real scenario to assess the system performance. On simulation, the navigation was shown to satisfy all human-aware constraints. Regarding the real experiments, when adding the people detector and tracking, successful experiments were also achieved, even though a limitation was identified.

As future work, we are planning on fusing data from external and on-board cameras, and extend the tracking system to account for multiple people. Finally, conduct user studies to evaluate how people feel about the robot and validate cost functions parameters.

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