R2D2 Reloaded:
Dynamic Video Projection
on a Mobile Service Robot

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Abstract—In this paper, we present a holistic approach to enable mobile robots using video projection in a situation aware and dynamic way. Therefore, we show how to autonomously detect wall segments that are suitable to be used as projection target in a dynamic environment. We derive several quality measures to score the wall segments found in the local environment and show how these scores can be used by a particle swarm optimization to find the best local projection position for the mobile robot. Furthermore, it is demonstrated how the presented approach can be used to display directions in an orientation training task for stroke patients while the robot is following them.

I. INTRODUCTION

User interaction plays a very important role for mobile service robots. It should be possible to use them easily and to get a real benefit from the offered service. However, current generations of these robots do have some shortcomings in presenting information in an appropriate and easily understandable manner. The idea of using video presenters on a mobile robot states back to the first Star Wars films and can help to improve the intelligibility of the information provided by the robot [1]. This is especially true for our tour robots Konrad and Suse that are used to tour people around in our multi-story faculty building [2]. In order to increase the acceptance of the tour guide scenario, the robots should not only talk to the user and give information on the on-board display, but also make use of walls next to the exhibit to display information. Since the exhibits can change over time, it will be beneficial if the robot can optimize its position and the wall used for projection depending on the local surroundings and the location of the current audience.

Another field of application addresses our research project ROREAS (Robotic Rehabilitation Assistant for Stroke Patients) [3], which aims 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 patients during their walking and orientation exercises, practicing both mobility and spatial orientation skills. In one of the more advanced stages of the orientation training, the patient should walk around the building on its own while the robot follows, observes and only intervenes if the patient fails to find the right way to a given destination. However, instead of just talking to the patient, the
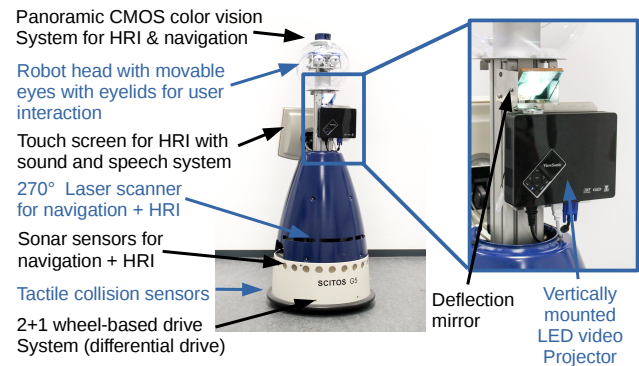

Fig. 1: Robot platform with mounted LED video projector and deflection mirror.

robot can use its video projector to display arrows on the walls in front of the patient to guide him once he had lost orientation.

Fig. 1 shows the experimental platform used for our research. It is equipped with interaction devices, mainly a touch-display, as well as a couple of additional sensors enabling autonomous navigation and perception of people and obstacles in the robots environment. In addition to this regular setup, the test platform has been equipped with a LED video projector (ViewSonic PLED-W500). The projector is mounted together with a deflection mirror in a vertical position below the robot head to guarantee minimum space requirements. It does deliver 500 lumens of brightness at a maximum power consumption of 120 W, which is of course questionable for the desired field of application. However, current generations of small LED based projectors have already doubled or tripled brightness and can easily replace our projector used for demonstration purposes.

To deal with the different problems arising from the dynamic projector position optimization the paper is structured as follows: After a brief overview of related work and the presentation of the prerequisites of our work we give a detailed overview of our proposed method and the involved score functions in Sec. IV. Afterwards, we show how the motion planning of the robot can be extended to prefer motion trajectories with good projection properties in Sec. V. After that, experimental results are presented in Sec. VI.

II. RELATED WORK

Several methods can be found, that are dealing with aspects of the problem we have described above. The largest group has been emerged during the last few years and tries to integrate a video projector onto a guide robot. One example is given in [4]. The authors are using a pan and tiltable video projector to display addition information of exhibits onto the wall. Furthermore, the projector is used to create buttons on the ground, that can be activated by means of the user's feet. In [5] a guide robot is used to augment a guiding tour by projecting directly onto various exhibits in order to highlight the parts explained but also to simulate ancient computer models by projecting directly onto a switched off monitor. The authors of [6] are using the humanoid robot NAO to project information on walls in a home environment. However, the robot position as well as the projection surface are predefined in this approach. Two examples of methods that do combine video projection with gesture detection are given in [7], [8].

Since the surfaces used for projection are predefined in all the methods stated above, none of these tries to find an optimal projection surface in the local environment dynamically. Most of the methods do even rely on fixed and predefined robot positions that are aligned perpendicular to the wall.

A closely related research field is the optimal observation pose problem, since it can be regarded as the inverse problem. The authors in [9] try to find an optimal position for the unobtrusive observation of a user. Although the optimization criteria used are different, the optimization is very similar and is also performed using a particle swarm. A survey of approaches to the view finding problem can be found in [10].

The aspect of projecting images while driving has gained even less attention. One method that deals with that problem is explained in [11]. However, it also relies on predefined markers on the projection surface and uses visual servoing.

Current methods for camera based projection calibration rely on predefined patterns that are displayed during an initialization phase [12], [13]. Since the robot changes its pose relative to the projection surface once it is moving, a closed loop algorithm, as used by other methods for projection, correction cannot be applied in our scenarios.

III. PREREQUISITES

In order to build and explain the projector position optimization, we rely on different components that are not in the scope of this paper.

First, we are using MIRA [14] as software framework in order to combine all the different modules in an easy and efficient way. The integrated transformation framework of MIRA enables stepping back and forth between the various coordinate frames (robot frame, map frame, person frame) easily.

Second, we also need to take the user position, view, and walking direction into account. To reliably track people in the local environment of the robot, we are using the probabilistic multi-hypotheses people detection and tracking system developed in our lab over the last eight years [15]. It is based on a 7D Kalman filter that tracks the position, velocity,

and upper body orientation of the respective persons assuming an uncertain random acceleration. The tracker processes the detections of different, asynchronous observation modules - namely a 2D laser-based leg detector, a face detector, a motion detector, and an upper-body shape detector. The leg detector in its initial version is based on the boosted classifier approach of [16]. The face detection system utilizes the well-known face detector of Viola & Jones [17]. Finally, we apply an upper body shape detector based on Histograms of Oriented Gradients (HOG) [18]. A detailed description of the person detector and tracker and the tracking results of comparing evaluation studies on different data sets with increasing difficulty is given in [15].

Third, we utilize mapping and localization algorithms proven to work robust during several years [3]. These algorithms include the generation of a local map (8x8 meters in our application) covering the local surroundings seen by the robot so far.

IV. FINDING OPTIMAL PROJECTION SURFACE AND POSITION

The problem of finding an optimal projection position can be divided into two tasks. First, the detection of walls in the local surrounding that are candidates for a projection target. Second, we need to take the user and the robot position into account to score the wall candidates in order to obtain the best projection surface. Three aspects are of importance during scoring. The wall needs to be visible to the user and should show an appropriate distance and view angle. Furthermore, it should be possible to project onto the wall. Therefore, it should show a suitable brightness and color and should not have any dominant structure (no signs or posters should cover the wall). Moreover, the wall should be in range of the projector, which again sets requirements on the distance and angle of the wall. The person visibility and wall structure related demands do not depend on the current robot position, therefore, we refer to these requirements as *robot position independent score functions* in the remainder of this paper. In turn the other requirements are *robot position dependent*.

Walls in the local surrounding can be very long, the suitability is likely to fluctuate heavily at different positions. Therefore, we break the walls apart by dividing them into segments, that are scored independently. It would be possible to use a real 3d segmentation for this step. However, it would increase the computational complexity a lot and cause only a slight benefit in our scenario since we are not able to pan or tilt the projector. Therefore, we are using wall segment with fixed width (30 cm in our application as a trade of between computational complexity and spatial resolution) and a fixed height of 1.2 meter (covering the area from 1 meter to 2.2 meter above the ground) during the segmentation phase. A closer look at the requirements and at the application scenario reveals that the overall problem is twofold. The first task is to find the best suited wall segment(s) for a given position of the robot regarding the user's gaze. The second task is more general and comprises of finding the best robot position, so that the best wall segment(s) in the local surrounding can be used for projection (Fig. 2). The second task involves the first one, since we need to evaluate the maximum score for different robot locations and orientations. Since evaluating all possible robot poses in the local neighborhood is way to expensive,
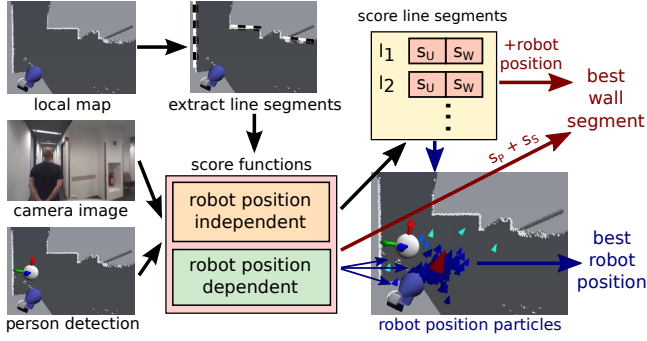
Fig. 2: Overview of process to find the best wall segment (red) and robot position (blue). The robot position independent scores need to be computed only once and can be stored with the segment. The robot position dependent scores need to be recomputed every time the robot pose changes. The image at the bottom right shows the result of a PSO with 200 particles with the best particle colored in red.

we apply a particle swarm optimization (PSO) [19] to find the optimal projection position. Therefore, every particle returns the score of the best segment(s) for projection from this single position.

The two tasks can be applied directly to our two application scenarios. In the guide scenario the PSO approach can be used to find the best location for augmenting the exhibit presentation. In the ROREAS scenario, we are using the extraction of the best wall segment only since the position of the robot is defined by the motion planner of the robot.

The projected image gets distorted if the projector is not aligned perpendicular to the projection wall. Fortunately, the distortion correction is comparably easy for straight walls if the angle between the projector and the wall is known. Since the position and orientation of the wall segment used for projection is known from the optimization, we can compute a homography for image rectification by means of vector geometry. However, the position of the user is also known, and can be used to rectify the image perpendicular to the axis of the users view alternatively. The two rectification methods and the results of a user study of the acceptance and the suitability for displaying directions are given in [20].

In the remainder of this section the wall extraction and the different score functions are explained in more detail.

A. Wall segment extraction

Since our application scenarios are in public environments, they are dominated by vertical and planar walls. Fortunately, this type of wall is also visible for the laser scanner and we can use simple but efficient 2D methods for extracting wall segments, and filter out false positives with the help of a *projection suitability* cost function. Although, 3D-based plane fitting methods can also be executed in real time, they are much more expensive. Nevertheless, their benefit might be justified in more cluttered home environments. For wall extraction we do not rely on a pre-build map, since the clinic environment is likely to change so that walls can be covered by trolleys or

hospital beds. Therefore, we are using the local map containing the local surroundings seen by the robot so far.

A line fitting is performed using a *Random Sample Consensus* (RANSAC) [21] based algorithm on all the points marked as obstacle in the local map. The algorithm searches and returns the line hypothesis with the most points supporting the hypothesis. Removing the supporting points (that also determine the start and endpoint of the line) and repeating the process as long as lines with a specified support can be found, results in the extraction of the best n lines for the local surrounding. These lines are split into smaller line segments with a fixed length (30 cm in our application).

B. Robot position independent cost functions

The first set of cost functions to be discussed are independent of the robot's position and need to be computed only once for every run of the PSO. Please note that we try to use a Gaussian score function whenever possible to help the PSO particles to find a gradient if they are far away from the optimum.

1) User dependent segment visibility: To check if a segment is visible to the user. The line of sight between the user (defined by its position $\mathbf{p_u}$ and its orientation normal $\mathbf{n_p}$) and the segment i (defined by its position $\mathbf{p_{l_i}}$ and orientation normal $\mathbf{n_{l_i}}$) is free of obstacles. Therefore, we trace the local map between the points $\mathbf{p_u}$ and $\mathbf{p_{l_i}}$ and set the obstacle score s_O to zero if we found an obstacle and to 1 otherwise. For performance reasons we only check the visibility of the center of the segment since we do only use segments lengths of 30 cm. However, if segments are longer or if higher accuracy is required the whole view triangle can be checked for obstacles. Furthermore, we need to take the visual field of the user into account. Therefore, we compute the angle between the line of sight and the person orientation normal as $\alpha_{Segment} = acos((\mathbf{p_u} - \mathbf{p_{l_i}}) \cdot \mathbf{n_p})$. Assuming that the visual field of a human is almost 180° with a central field of 90° we are using a parted Gaussian function $s_{VF}(l_i) = g_{sp}(\alpha_{Segment}, -\pi/4, \pi/4, 0.35, 0.35)$ that returns 1 for the central field and drops of almost reaching zero at 90° on each side.

$$g_{sp}(x, lo, up, s_1, s_2) = \begin{cases} exp(-\frac{(x-lo)^2}{2s_1^2}), x < lo \\ exp(-\frac{(x-up)^2}{2s_2^2}), x > up \\ 1, lo \leq x \leq up \end{cases} \quad (1)$$

The last of the tree sub scores, is the distance score. We suggest preferring segments with a distance between 1.5 m and 4 m using the parted Gaussian $s_D(l_i) = g_{sp}(||\mathbf{p_u} - \mathbf{p_{l_i}}||_2, 1.5, 4.0, 1.0, 1.7)$. Therefore, the resulting score of the user dependent segment visibility s_U becomes: $s_U(l_i) = s_O(l_i) \cdot s_{VF}(l_i) \cdot s_D(l_i)$.

2) Projection suitability: It is important that the wall segments used for projection purpose are of a bright and uniform color and are clear of obstacles.

Using a calibrated camera we can extract the image regions associated with the single segments and analyze them in terms of color and structure. We project the 3D-world position of the segment edges into the image space and extract the gray-scale image region (Fig. 3a). Afterwards, the average image value
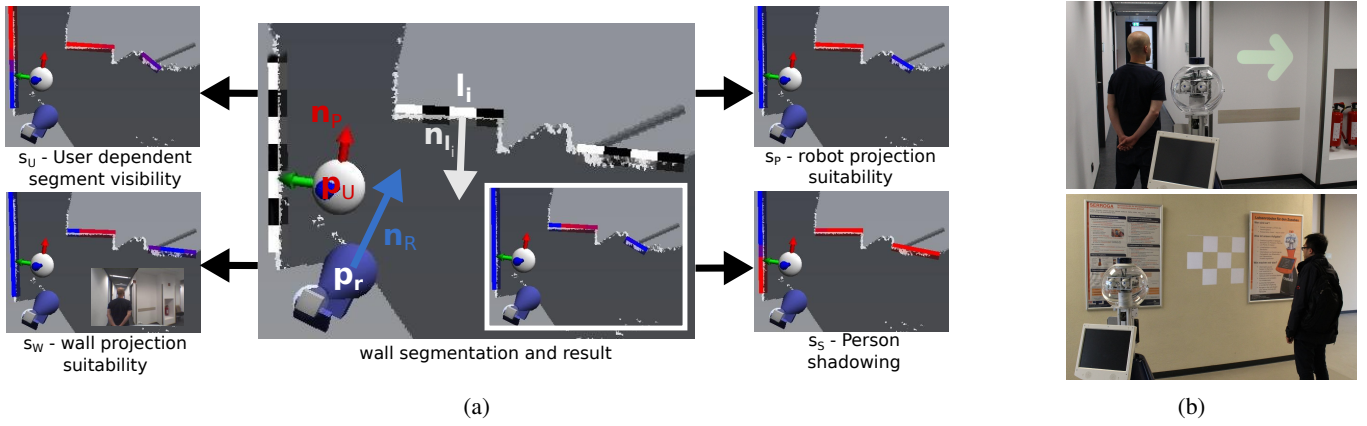
Fig. 3: (a) Results of the different score functions for an exemplary situation. The line segments are color coded according to the result of the score functions with blue being the lowest score. Please note that the line segments do vary slightly since the images were recorded consecutively and the RANSAC algorithm varies due to its random nature. (b) Example image for the wall segment extraction and projection rectification.

is derived. This value should not be too close to white, as ceiling light might outshine the projected image, nor should it be to dark or have any extreme color cast. Therefore, we are using a Gaussian function aiming at an average gray value of 2/3 of the maximum possible gray value (255) to compute brightness subscore $s_B(l_i) = Gauss(Avg(l_i), \mu = 170, \sigma^2 = 50)$. The structure of the segment is analyzed by computing the magnitude of the Sobel-filtered image region in x and y direction. Since the segments can become unsuitable for projection even if the magnitude is far away from the maximum value, we use a low threshold for the score function that allows a maximum average gradient magnitude of 40: $s_G(l_i) = max(0, 1.0 - AvgMag(l_i)/40)$. Thus, the resulting wall projection suitability score is $s_W(l_i) = s_B(l_i) \cdot s_G(l_i)$.

The drawback of this approach is that not all the segments are visible to the camera and that they can be shadowed by persons and thus yields wrong scores. To avoid this problem, the module stores a local segment history (same 8x8 meter environment as the local map). If segments are shadowed by persons (details on how to detect shadowing are given in the Sec. IV-C2), the suitability score is not updated. The same applies if a segment is currently used for projection, since the projector changes the score of the segment. If the score cannot be obtained, we take the score from a similar segment in the history buffer.

C. Robot position dependent cost functions

The second group of cost functions depends on the robot pose and therefore needs to be computed for every single robot pose hypothesis.

1) Robot projection suitability: This cost function is mostly related to the limitations of the video projector and combines three different sub scores. First, similar to the person visibility function, the line of sight between $\mathbf{p_r}$ and $\mathbf{p_{l_i}}$ needs to be free of obstacles (s_O). Second, the projector offers only a limited aperture angle, therefore segments that cannot be covered by the projector need to get a very low score. We compute the angle between segment normal and robot

with $\alpha_{Robot} = acos((\mathbf{p_r} - \mathbf{p_{s_i}}) \cdot \mathbf{n_r})$ and combine it with the parted Gaussian to match the projector opening angle of 60°: $s_{PA}(l_i) = g_{sp}(\alpha_{Segment}, -\pi/6, \pi/6, 0.05, 0.05)$. The last subscore regards the distance between projector and wall. Since the projector has only limited brightness and the focus is fixed, the projector needs to stay within a certain distance range to offer acceptable projections. Therefore, we select the optimum distance to be within 1.4 and 2 meter and let the score drop on both ends: $s_D(l_i) = g_{sp}(||\mathbf{p_r} - \mathbf{p_{l_i}}||, 1.4, 2, 0.5, 1.5)$. Again, the combined score s_P becomes $s_P(l_i) = s_O(l_i) \cdot s_{PA}(l_i) \cdot s_D(l_i)$.

2) Person shadowing: Segments that, according to the robot position, are shadowed by or next to a person should not be used for projection for two reasons. First, it makes a proper projection impossible if the person is blocking the projected image. Second, a person can be dazzled. Therefore, we penalize segments, when the angle between the line of sights of the segment and all person hypothesis p_i is too low: $alpha_{min} = \min_{\forall p_i}(acos((\mathbf{p_r} - \mathbf{p_i}) \cdot (\mathbf{p_r} - \mathbf{l_i})))$ $s_S(l_i) = 1.0 - Gauss(\alpha_{min}, \mu = 0, \sigma^2 = 0.1)$.

D. Selecting the best wall segment for projection

To find the best wall segment for a given robot position $\mathbf{p_r}$ and orientation $\mathbf{n_r}$ the robot position dependent (s_P, s_S) and independent score functions (s_U, s_W) have to be computed. Afterwards, the scores of the different functions are multiplied for every segment independently. We use multiplication for this step since the different constraints cannot compensate each other. Segments that are below a certain threshold will be rejected and removed, leaving only segments that are feasible for projection. In a final step, adjacent wall segments get merged, whereby the score of the new segment is the sum of its sub-segments. This guarantees that large segments are preferred but requires a proper choice of the segment threshold in order to combine only segments that are suited for projection. During our experiments a threshold of 0.2 works reasonable well. Finally, the segment with the highest score is returned as the best segment for projection for the current robot and user positions.

V. Optimizing robot trajectories for projection while driving

The orientation training in the clinic environment requires the robot to project information onto walls while driving. This is a challenging task from the path planning perspective, since it involves finding a path which also delivers a high projection score. However, the projection score depends to a very large extent on the person position, which can only be predicted on a local scale. Furthermore, the E* path planner [22] used for metric path planning does not take the robot orientation into account, which is crucial for the score computation since we cannot pan/tilt the projector. However, path planning on a global scale is only subsidiary in the orientation training scenario in which local navigation is of much more importance. This local motion planning is performed by the dynamic window approach (DWA) [23] that samples the possible velocity commands of the robot within a certain prediction time window and scores them by means of various navigation objectives (e.g. distance to obstacles, follow a path, follow a person with a given distance,...) [3], [24].

The prediction time of the dynamic window varies between 2 and 5 seconds, depending on the robot's velocity and in our implementation generates 40 alternative robot trajectories with different rotation and translation velocity. In order to let the robot prefer trajectories suitable for video projection, we added a new objective. This objective scores the end points of the predicted trajectories according to Sec. IV-D. Please note that we also need the prediction of the person tracker for this step, since we need to predict the person position according to the prediction time length of the evaluated trajectory. Therefore, even the robot position independent score functions need to be recomputed for different prediction lengths since the user position changes and needs to be predicted according to the current trajectory. The obtained score is returned to the DWA motion planner in order to prefer trajectories with a high projection score. This substitutes the PSO used in the static case of position optimization.

VI. Experiments

Experiments have been conducted with the actual robot platform in our faculty building and using a robot simulator.

We have tested the extraction of suitable wall segments and the projection rectification for various exhibits and situations in our lab. Results for two situations are given in Fig. 3b. For every location the local surrounding (8x8 m) of the robot and the user position was taken into account. The algorithm was able to generate a rectified projection on wall segments that are of good visibility to the user. However, the position optimization tends to generate positions with acute projection angle as these positions are good in terms of user visibility and maximum projection distance. If maximum projector brightness is an issue, we recommend integrating an additional module for rating the robot to wall angle.

The trajectory optimization has been tested in the robot simulator that imitates the drive behavior and the laser range finder of the real robot platform. Furthermore, we generated noisy person trajectories that were feed as detections into the person tracker in order to obtain user position and velocity. Please note that the projection suitability cost function is not
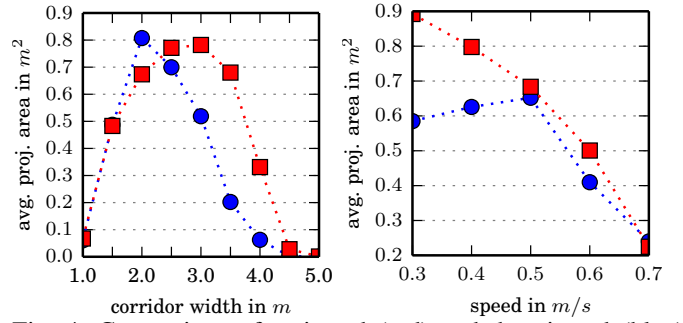

Fig. 4: Comparison of activated (red) and deactivated (blue) projection objective for different corridor widths (left) and different person speeds (right).
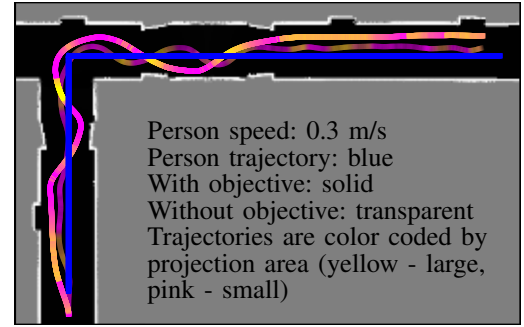

Fig. 5: Visualization of trajectories for "Turn" scenario. The robot starts driving off-center in order to gain a better view on wall segments in front of the user if the presented objective is activated.

enabled in the simulator tests. Since the objective is aiming at the optimization of the combined score of the best segment, an independent measure for benchmarking the algorithm has been applied. Therefore, the average size of the rectified image on the wall was computed for every test setup and was compared to the results for the activated and deactivated projection objective. Furthermore, we have averaged the results of 5 independent trials for every setup to smooth the value variations introduced by the noisy sensor readings and person tracking.

In the first setup we analyzed how the approach performs in a corridor scenario with variable width. Therefore, the simulated person hypothesis is moving 50 meter in the center of a straight aisle at a fixed speed of 0.5 m/s while the navigation algorithms are configured to follow the person at a distance between 0.5 and 1 meter. The results for different corridor widths between 1 and 5 meter are given in Fig. 4. As one would expect, the additional objective cannot generate a benefit if the corridor width is below 2 meter due to the lack of free navigation space. However, with increasing corridor width, the approach with enabled projection objective can greatly improve the average projection area along the path. It has to be noted that the conventional approach outperforms the objective for a corridor with of 2 meter. This effect is caused by the fact that the navigation algorithms tend to undulate behind the person (also visible in Fig. 5) generating slightly better results for that specific corridor width.

The second setup addresses the evaluation of different walking speeds of the person. Since the maximum speed of the

simulated robot is 1.0 m/s, we vary the person speed between 0.3 and 0.7 m/s in a corridor scenario with a right turn (Fig. 5). Is becomes obvious that the objective works best if the difference between the maximum robot speed and the person speed is high (Fig. 5). However, if the difference is low the robot needs to drive straight behind the person in order to follow with the desired distance.

The last setup is identical to the last but the wall at the right side of the trajectory is replaced by open space. Since the normal behavior of the navigation algorithms is keeping a large distance to obstacles, the robot drives to far away from the wall in that cases and lead to an average projection area 0.22 m^2. Once the objective is enabled, it drives slightly off-center between the user and the wall yielding an average projection area of 0.65 m^2.

The presented approach is real-time capable and can provide score values for the DWA approach with an update frequency of 4 Hz for 40 trajectories on the robot (which is the normal update rate for our DWA approach).

VII. CONCLUSION AND FUTURE WORK

This paper describes a method that takes the user position into account in order to dynamically extract wall segments that are suitable for video projection. Furthermore, we showed how to embed the scoring of the wall segment extraction into a PSO framework in order to obtain the best projection position for the robot in the local surrounding.

The experiments given showed that the presented method is able to improve results for the desired application scenarios and is real time capable.

Continuing our work, we need to further investigate if the user adaptive projection correction [20] is beneficial in the person follow scenario. Furthermore, the work presented so far is designed to work with one user only. Therefore, we want to find out if and how the method can be extended to work with multiple users at a time.

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