

# Experimental Evaluation of Some Indoor Exploration Strategies

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Abstract: A key capability of any indoor service robot is to explore arbitrary, unknown environments in order to record a complete and correct map in minimal time. Such a map is a prerequisite of common tasks like surveillance, transportation as well as search and rescue. In recent years a series of solutions has been proposed by the authors: a dynamic enhancement of the frontier-based approach, ground plan-based exploration and a hybrid combination of both. This paper evaluates the performance of each of these strategies within an everyday office scenario in simulation and reality and discusses their pros and cons.

## 1 INTRODUCTION

In order to perform a service task like surveillance or transportation efficiently, a robot needs an accurate map of its working space. Ideally, the robot should be able to derive this map autonomously, so it can adapt to a priori unknown environments without user intervention. Feasible SLAM solutions exist for map construction. But calculating a trajectory, that allows to record a complete and correct map in minimal time, is still an open problem. In the past, three solutions have been developed by the authors of this paper, all following the cyclic next best viewing pose (NBV) approach of (Amigoni, 2005). Each iteration consists of three steps: map update, NBV calculation and target approach. The strategies mainly differ in the type of map and the sophistication of the NBV computation.

Subject of this paper is to evaluate and compare the power of these approaches in a daily office scenario, both under well-defined conditions in simulation and in a real office scenario with dynamic changes (doors, people). Nota bene, the focus is on the performance of the *proposed* solutions in a *typical* application environment, especially on the differences between simulation and reality as well as between the three strategies. In contrast, an analysis of their effectiveness in different environmental layouts and a comparison to competitive state of the art approaches is subject of ongoing research.

Section 2 presents important state of the art solutions regarding indoor exploration. The sophistication of the respective approaches is condensed for putting the strategies under study into context. Since each of

them has been published previously, only their main ideas and features are introduced in section 3. The experimental evaluation is described in section 4, and the findings are condensed in section 5.

## 2 STATE OF THE ART

(Yamauchi, 1997) has developed one of the most famous approaches: NBVs are derived from the frontiers between unknown space and regions already known as free in an occupancy grid map. The one that maximizes expected information gain, i. e. frontier length, is selected in Greedy manner. (Oriolo, 2004) describes a far simpler strategy based on random motions. (Freda, 2005) biases the random motion towards the free frontiers of the known space.

(González-Baños, 1999) and (González-Baños, 2002) create polygonal maps of the environment based on the concept of the *safe region*, i. e. the areas already known as traversable. NBVs are sampled everywhere within these areas and scored by weighting expected information gain and travel cost. (Surmann, 2003) uses polygonal 2D maps on several horizontal height levels in order to generate a 3D model of the working space. Within each map, NBVs are calculated along the frontiers, and the most promising one regarding information gain is selected greedily.

(Makarenko, 2002) has defined the problem of automatically mapping an unknown environment formally as *integrated exploration*. Accordingly, three tasks have to be performed at the same time: mapping, localization and navigation. Hence, three cri-

teria are evaluated simultaneously as a weighted sum: information gain, travel cost and *localizability*. NBVs are either taken from the frontiers or from locations with a high chance of relocalization. (Amigoni, 2004) and (Amigoni, 2005) propose NBV exploration as a common solution: first the current map is updated; then a series of viewpoints is generated and the most promising one is selected via a scoring function; finally this position is approached. In contrast to the previously used *ad hoc* functions, where determining feasible weights is an open problem, here the entropy of information gain and of travel cost is calculated based on information theory. Whereas (Amigoni, 2004) balances these two criteria, (Amigoni, 2005) performs a multi-objective optimization using also localization (map overlap) for calculating the Pareto-optimal viewpoint candidate as NBV. As a further extension, (Basilico, 2011) applies multi-criteria decision making (MCDM) and fuzzy functions for an online adaptation of the exploration criteria, e. g. information gain, travel cost and either chance of establishing a wireless link to a fixed base station or chance of reaching a charging station.

Beside the sophistication of the NBV scoring, the kind of mapped features and the strategy of map evaluation influences the exploration performance. (Wurm, 2008) proposes to segment the already known map according to the structure of the environment, e. g. into different rooms, and to perform a segment-wise exploration. Assigning to each robot a different segment yields a very efficient coordination of multiple robots. Similarly, (Schmidt, 2006) combines reactive behaviors for exploring the current room and deliberative behaviors for switching between rooms. The trajectory is continuously adapted to the changes of the map. (Maffei, 2014) also performs an online adaptation by regarding exploration as a boundary value problem in a potential field: obstacles have high potential, unknown regions a low value and already visited areas a variable one. Revisiting known areas supports relocalization. Distortions are added to balance relocalization and information gain.

Finally, several comparative studies analyze the pros and cons of existing approaches in order to derive hints for future improvements. (Amigoni, 2008) reports that a Greedy selection of NBVs based on information gain performs better than a random choice, and balancing utility and travel cost is even more efficient. However, a significant difference between an *ad hoc* function (González-Baños, 2002) and a scoring measure based on information theory (Amigoni, 2004) could not be approved. In contrast to that, (Holz, 2011) has demonstrated that balancing two criteria (González-Baños, 2002) is not always better

than a simple Greedy approach choosing the closest frontier and that a sound design of the viewing pose candidate (vp) evaluation function like MCDM (Basilico, 2011) pays off. Furthermore, a continuous re-evaluation of the selected NBV based on online map updates and a segmentation of the working space have been proposed for increasing exploration efficiency. In this regard, (Amigoni, 2013) has analyzed the influence of the frequency of map updates (perception) and of NBV selection (decision) on the exploration performance. As a result, a frequency-based approach with online updates outperforms the classic event-based scheme (updates only at an NBV), especially in unstructured environments, but the frequencies have to be adapted to the computational effort of the continuous re-evaluation.

The strategies discussed in this paper rely on a continuously updated 2.5D grid map, but on a discrete NBV selection. Hence, the target is not changed once it has been determined, and either it is reached in a reasonable time span or marked as inaccessible. The trajectory is adapted online to new map information and dynamic changes (people walking around, doors opened or closed) during NBV approach. Thus it may leave the areas that are known at the moment of the target selection. This yields a more flexible approach than those of (Yamauchi, 1997) and (González-Baños, 2002). Vps are sampled along frontiers or within polygonal maps of floor and ceiling, derived from a 3D reconstruction of the working space similar to (Surmann, 2003). The scoring function is designed as weighted sum as in (Makarenko, 2002) and balances information gain, travel cost and dispersion of NBVs. Localization is delegated to a continuously operating particle filter and therefore no issue for the scoring. The focus is on examining how the developed approaches perform in a real world application, what the benefit of evaluating 3D features is, how the strategies cope with dynamic changes and how a combination of a sophisticated strategy with a fallback to a simple, but always working approach influences the reliability of the exploration process.

### 3 EXPLORATION STRATEGIES

The three exploration approaches under observation have been presented in preceding papers. For a better understanding, the main ideas and key features are summarized in the following. Common base is an indoor robot, shown in figure 1. It is equipped with a differential drive, a planar laser scanner at the front and the back, a circumferential belt of ultrasonic sensors and a 3D laser scanner.

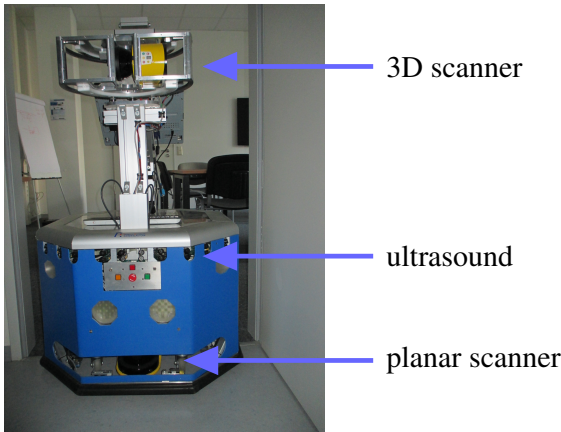


Figure 1: Robot and sensors used for exploration.

Figure 2 presents the common concept for all three strategies. Hardware abstraction, SLAM and navigation are shared. On the lowest level, distance measurements are fused into local obstacle memories and overlaid sector maps as virtual sensors. Besides, abstract motion commands are transformed into control values for the differential drive. Localization is based on odometry plus continuous pose corrections via DP-SLAM (Eliazar, 2003). Mapping constructs a

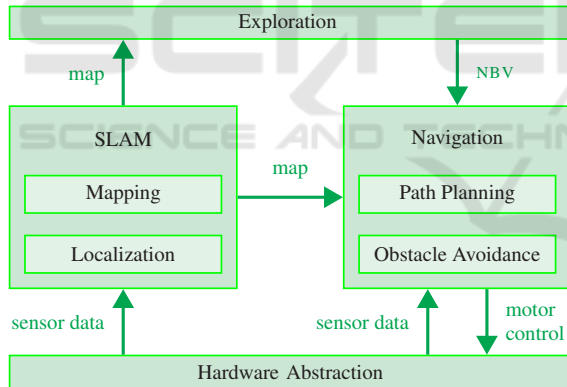


Figure 2: Concept of integrated exploration.

2.5D occupancy grid map, filled with distance measurements of all laser scanners. The SLAM unit facilitates online map updates, while the robot is moving. Obstacle avoidance is realized by a network of anti-collision, keep distance and evasion behaviors according to the iB2C methodology (Proetzsch, 2010). The behaviors evaluate the sector maps for analyzing the free space around the robot and compute abstract motor control commands. The navigation unit guides the robot to an NBV computed by the explorer. This goal approach uses A\* for planning an initial path. It is transformed into an elastic band that performs a continuous free space analysis and adapts the path according to the online map updates (Quinlan, 1993).

Consequently, the three approaches differ in the strategy for calculating the series of NBVs. The dynamic frontier-based approach only evaluates the occupancy grid map, whereas the ground plan-based and the hybrid approach record the layout of floor and ceiling for deriving better vp candidates.

$$\begin{aligned}
 \text{SCORE}(vp_i) = & \lambda_i \cdot \text{information gain}(vp_i) \\
 & + \lambda_u \cdot \text{unknown cells}(vp_i) \\
 & - \lambda_c \cdot \text{cost}(vp_i) \\
 & - \lambda_o \cdot \text{occupied cells}(vp_i) \\
 & - \lambda_{dp} \cdot \text{distance to past nbv}(vp_i) \\
 & - \lambda_{du} \cdot \text{distance to unreachable nbv}(vp_i)
 \end{aligned}
 \tag{1}$$

In order to determine the NBV at a particular exploration step, a set  $VP = \{vp_i\}$  of viewing pose candidates is generated, and the best one is calculated via the scoring function (1). This function is the same for all three approaches regarding its layout as weighted sum and its parameters  $\lambda$ , but the contributing factors are calculated differently for each strategy based on the features that are recorded in the respective map.

Advantages of a vp are expected information gain according to the particular strategy and number of unknown cells at vp in the occupancy grid map. Disadvantages are path cost, number of occupied grid cells at vp as well as distance to past and unreachable NBVs. The last two factors guarantee an efficient dispersion of NBVs. First, the robot has to keep off previously visited areas, at least as long as there are promising vps in unknown regions. Even more important is to stay away from NBVs that could not be reached in the past, because these give a hint for an unknown, but attractive area that cannot be mapped, e.g. a neighboring room only visible through a window. Hence the last factor avoids deadlocks. All values are calculated in relation to the respective optimum, that is minimum for dispersion and maximum for all other factors, i.e. they are normalized to  $[0, 1]$ . The set of scoring weights  $\lambda = (\lambda_i, \lambda_u, \lambda_c, \lambda_o, \lambda_{dp}, \lambda_{du})$  defines the exploration “mood”, e.g. curiosity or guardedness. Reasonable values have been determined via comprehensive experiments (sec. 4.1).

An important issue of any exploration strategy is the termination criterion. The challenge is to decide whether the accessible areas have been mapped exhaustively. Especially in real world scenarios, the robot may not be able to approach some visible places closely enough due to narrow space or a door closed casually. For this purpose, any NBV, that cannot be reached in a certain period of time, is recorded as unreachable, and new vp candidates, that are close to such one, get a high penalty. On the other hand, the expected information gain decreases over time since

the remaining unknown areas shrink. Hence, the algorithm stops when the score of the vp candidates at a certain exploration step indicates, that there are no rewarding targets left.

**Dynamic Frontier-based Exploration.** (Wettach, 2010) has extended the frontier-based strategy of (Yamauchi, 1997) by a continuous localization and the option to leave the safe region while approaching the NBV. This facilitates online map updates even in unknown areas and reduces detours. Vp candidates are derived from the center of the free frontiers. Expected information gain is calculated as length of the respective frontier. Unknown and occupied cells are calculated within a circular area with a predefined radius around the vp. Path cost is given by the A\* planner. The distances to past and unreachable NBVs are computed via the Euclidean norm.

**Ground Plan-based Exploration.** (Wettach, 2012) calculates NBVs from the differences between floor and ceiling: space visible at the floor, but hidden at the ceiling is usually caused by open doors; free space in the ceiling, that is blocked on the floor, marks inaccessible regions that deserve a closer look, e. g. due to furniture or a closed door with skylight. At each NBV a 3D point cloud is collected via a 360° panorama scan, and the main structures of the environment are extracted by RANSAC-based plane fitting. This way the ground plan of floor and ceiling is reconstructed and recorded as polygonal maps. Vps are derived as center of the difference polygons, and expected information gain is calculated as polygon area. All other scoring factors are computed from the grid map as for the frontier-based approach.

**Hybrid Exploration.** In extreme situations the ground plan approach may fail: unobstructed areas like corridors do not provide significant differences between floor and ceiling and thus no valid vp candidates; in narrow places like door frames a panorama scan may not be performed safely due to the protruding 3D scanner. (Wettach, 2014) has developed a hybrid strategy, that evaluates the ground plans whenever possible and that uses the frontier information as a fallback. Expected information gain is either computed from the difference polygons or from the frontier length, whereas all other contributing factors of the scoring function (1) are derived from the grid map.

## 4 EXPERIMENTAL EVALUATION

The exploration strategies have been evaluated in a simulated office scenario, shown in figure 3, as well as in its real world counterpart. It consists of an

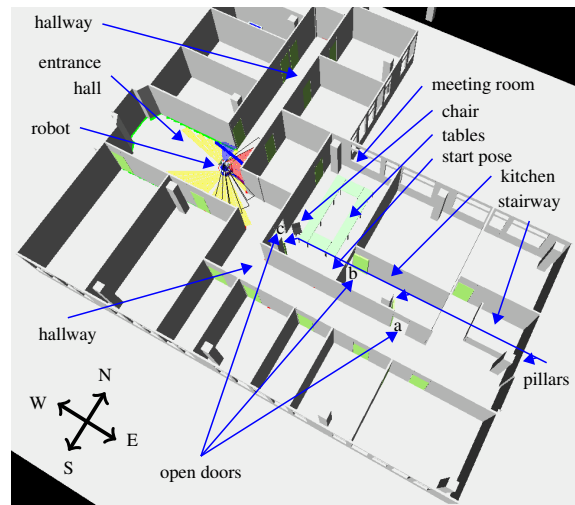


Figure 3: Simulated office scene (from (Wettach, 2014)). Open doors are marked with labels a, b, c.

L-shaped hallway with an open entrance hall in between and adjacent offices on each side. Since the tests took place at common business hours, the office rooms have been made inaccessible order to limit the complexity of the experiments. Challenges are represented by a meeting room, equipped with tables and chairs, as well as by a small kitchen. The respective doors have been kept statically open. Figure 1 shows the robot passing the door (b) from meeting room to kitchen. Obviously, changing the room is a critical operation due to the dimensions of doors and robot. Besides, both rooms can be left via opposite doors, yielding a potential loop as trial for the DP-SLAM unit. The descending stairway at the south-east end of the corridor represents a negative obstacle in reality and is modeled by half-height walls in simulation. The virtual model serves as ground truth, because it has been built based on the construction plan of the building. Naturally, the real scenario contains additional difficulties: the kitchen is equipped with a table and a dresser; there are environmental dynamics, e. g. people walking around, doors casually opened and closed; sometimes doors closed in simulation stay partially open, so the robot can look into but not enter the neighboring room, which yields a big challenge for the deadlock prevention (see figures 8, 9, and 10).

### 4.1 Impact of the Scoring Weights

In order to show the impact of the weights  $\lambda$  in function (1), two different sets  $\lambda_1 = (5, 1, 15, 1, 8, 50)$  and  $\lambda_2 = (20, 10, 12, 5, 8, 50)$  are compared via a test run of the dynamic frontier-based exploration in simulation. In both sets, deadlock prevention is most im-

portant in order to cope with traps of attractive, but inaccessible areas like the stairway in the south corridor.  $\lambda_1$  then focuses on the path cost in order to avoid oscillations between opposite borders of the known space, i. e. to exploit locality. The distance to past NBVs serves as a counterpart in order to achieve a reasonable dispersion of NBVs. Expected information gain is slightly less important. For putting the focus on these four criteria, the unknown and the occupied grid cells in the vicinity of a vp have least influence.

Apart from deadlock prevention,  $\lambda_2$  emphasizes information gain, followed by path cost in order to exploit locality. Number of unknown grid cells around the target is a second measure of information gain and has slightly less influence, similar to distance to past NBVs as antagonist to locality. Estimated accessibility of the target is least important.

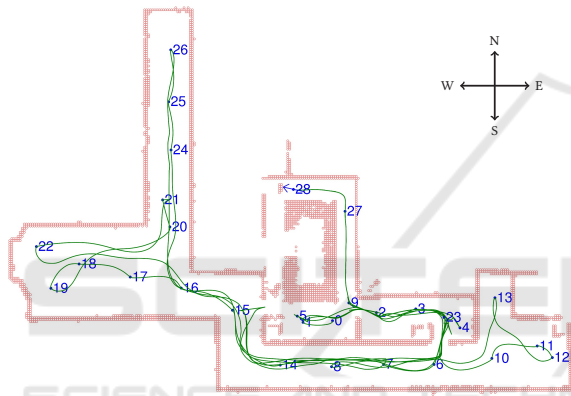


Figure 4: Simulation result of dynamic frontier-based exploration using scoring weights  $\lambda_1 = (5, 1, 15, 1, 8, 50)$ , with occupied grid cells (red), NBVs (blue), trajectory (green) and map orientation (cross hairs).

Table 1: Summary of experimental results.

Run	Comp %	Corr %	$T_{Exp}$ min	$\sum NBVs$ w/o scan	$\ ET\ $ m
fig. 4	<b>6.59</b>	2.79	56.5	29/8	232
fig. 5	14.4	1.87	<b>30</b>	22/2	160
fig. 6	14.5	<b>1.64</b>	37.5	<b>16</b>	<b>99.4</b>
fig. 7	11.5	2.38	53.8	24/5	139.9
fig. 8			<b>51</b>	<b>25/7</b>	<b>208.0</b>
fig. 9			94	33	273.2
fig. 10			83.8	30/5	247.4

Figure 4 shows the test run with  $\lambda_1$ , and figure 5 the one with  $\lambda_2$ . The benchmark values are summarized in table 1 (see sec. 4.2 for a description).  $\lambda_1$  yields significantly more detours than  $\lambda_2$ , i. e. oscillations between meeting room, kitchen and corridor, which leads to a much longer trajectory (232 m vs. 160 m) and exploration time (56.5 min vs. 30 min). At least,  $\lambda_1$  is competitive regarding map complete-

ness and correctness. In sum,  $\lambda_2$  seems more promising due to the reduced execution time. Since here the focus is on evaluating the different strategies depending on environmental conditions,  $\lambda_2$  is used for all subsequent experiments.

## 4.2 Comparison of the Three Strategies

In the following a test run with the robot starting in the meeting room facing to the east is performed for all three exploration strategies, first in simulation, then in the real environment. System parameters like scoring weights, prefiltering of vp candidates and number of replanning operations per NBV are fixed for all runs. The maximum velocity of the robot has been limited to 0.35 m/s. In simulation, the DP-SLAM unit and corresponding pose correction have been switched off in order to examine the power of the approaches without odometry errors.

For comparing the results, a set of benchmarks has been defined. Non-functional criteria are: *robustness* regarding collision avoidance: the robot must not hit any object; *deadlock prevention*: the algorithm has to terminate in finite time; *a priori knowledge*: a grid cell may either be free or occupied, floor and ceiling can be described by a set of polygons; *genuineness of application*: the test has to be performed in an everyday scene. These criteria have been fulfilled equally by each experiment. Functional criteria are map completeness (Comp), map correctness (Corr) and exploration time ( $T_{Exp}$ ), because the goal is to record a complete and correct map in minimal time. Number of NBVs with and without 3D scan and length of the exploration trajectory  $\|ET\|$  are subordinated parameters, indicating how the needed time has been spent. All these values are summarized in table 1.

$T_{Exp}$ ,  $\sum NBVs$  and  $\|ET\|$  are measured directly. Comp is the number of cells missing in the recorded map wrt. a ground truth map (derived from a construction plan) versus total number of cells in the true map (false negatives). Corr is calculated as number of cells in the recorded map that are not present in the true map versus total number of cells in this map (false positives). For reasons of comparability, Comp and Corr are always calculated for the grid map. In reality, these two criteria can only be qualitatively inspected due to significant map inaccuracies arising from SLAM errors.

## 4.3 Simulation Experiments

Figure 5 shows the result of the **dynamic frontier-based exploration** in simulation. First, meeting room and kitchen are explored (vp 0-2), followed by the

south corridor (3-9). At positions 10, 11 time-consuming oscillations back to distant, previously visited areas occur. Eventually, the robot explores the entrance area and north corridor (12-20), before returning to the last open frontier at the staircase (21). A panorama scan took 30 s on average, i. e. 10 min in total for 20 NBVs (no scan at vp 1, 21 due to close obstacles).  $T_{Exp} = 30$  min is the minimum over all test runs.  $\|ET\| = 160$  m yields a minimum travel time of 7 min 37 s (at maximum velocity). The time penalty of 12 min arises from slow-downs in narrow passages. Obviously, the robot never passed door (c) between meeting room and corridor (cf. fig. 3), because this passage is most challenging due to tables and a chair opposite to the door leaf. Besides, the meeting room could not be recorded completely, leading to a significant Comp errors. At least Corr is quite competitive.

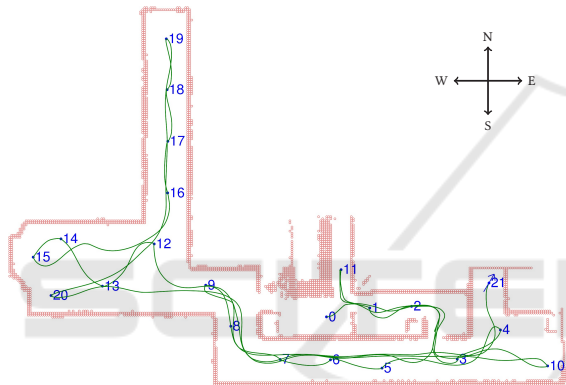


Figure 5: Simulation result of dynamic frontier-based exploration using scoring weights  $\lambda_2 = (20, 10, 12, 5, 8, 50)$ , with occupied grid cells (red), NBVs (blue), trajectory (green) and map orientation (cross hairs).

The test run for the **ground plan-based exploration** is given in figure 6. Apart from some difficulties at the beginning (0, 1), the trajectory is a straightforward loop through the whole working space, close to how a person would explore the environment. Accordingly,  $\|ET\| = 99.4$  m and 16 NBVs are minimal over all test runs. Each scan took about 60 s, due to the time needed for updating the polygonal maps, resulting in a slight increase of  $T_{Exp} = 37.5$  min. This yields 16 min for the scans, a minimum travel time of 4 min 44 s and a time penalty of 17 min for slow-downs. Comp and Corr are similar to the previous run. However, meeting room and staircase area are now almost completely covered.

Figure 7 reveals that the **hybrid strategy** performs significantly worse. Meeting room, kitchen and south corridor are explored quickly (0-7). But then a couple of oscillations occurs by moving back to the meeting room (8, 9), to the staircase (10, 11) and to the kitchen (12-14). Afterwards, the remainder of the

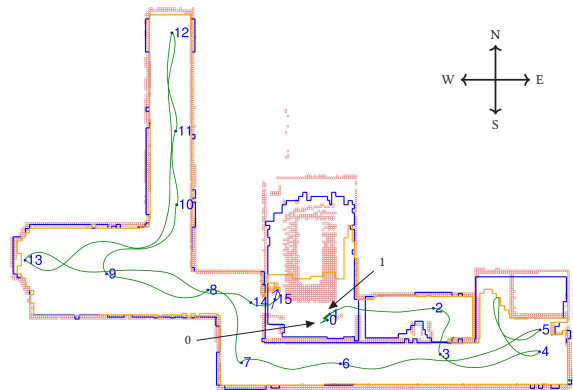


Figure 6: Simulation result of ground plan-based exploration, with ground plan of floor (orange) and ceiling (blue).

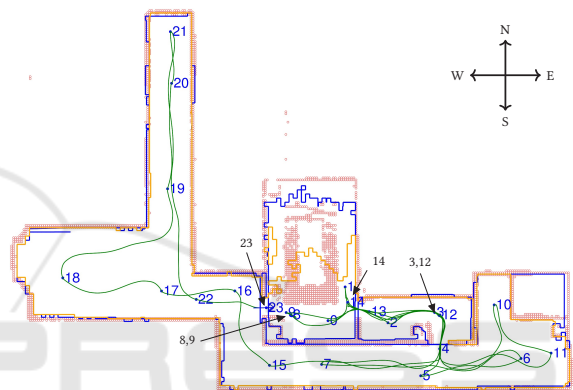


Figure 7: Simulation result of hybrid exploration.

south corridor, entrance area and north hallway are explored (15-22), before the meeting room is reentered from the west (23). Apart from the oscillations, the trajectory represents the same basic loop as in the previous run.  $T_{Exp} = 53.8$  min is fairly poor and the number of NBVs is significantly increased to 24 (no scan at vp 1, 4, 9, 14, 23, due to close obstacles). At least  $\|ET\| = 139.9$  m is better than for the frontier approach. This yields a minimum travel time of 6 min 40 s, 19 min for the scans and 28 min for slow-downs, i. e. more than 50%. As indicated by the accumulation of NBVs, this time penalty is caused by narrow passages in the meeting room and kitchen. However, Comp and Corr are competitive, i. e. errors are only slightly increased, and completeness is significantly better.

#### 4.4 Real World Experiments

In the real office scenario, the experiments are affected by environmental dynamics beyond control, e. g. actuated doors and people walking around. Besides, the SLAM unit does not provide a common reference frame, i. e. the pose of the robot while record-

ing the initial map defines its orientation. Therefore, it is indicated by cross hairs for better comparability.

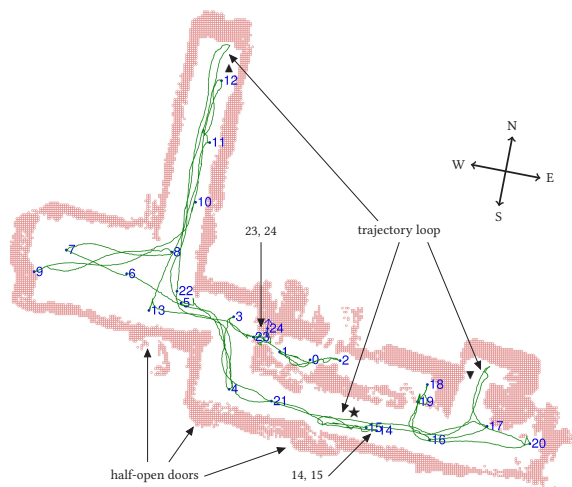


Figure 8: Real world result of dynamic frontier-based exploration.

Figure 8 shows how the **dynamic frontier-based strategy** guides the robot from the meeting room (vp 0-2) through the west door (c) into the corridor (3-4), entrance area (5-9) and north hallway (10-12). On the way back to the south corridor, it is attracted by some half-open doors (13-15), resulting in a local trajectory loop  $\star$ , until the deadlock prevention intervenes. While exploring the remainder of the corridor and the kitchen (16-20), small navigation problems occur ( $\blacktriangledown$ ). Finally, the robot tries to get back to the meeting room at NBVs 23, 24 via intermediate scans (21, 22). Here, the planner searches for an alternative to door (c), as the loop to the north corridor  $\blacktriangle$  indicates. Despite the challenges of the real world,  $T_{Exp} = 51$  min and 25 NBVs are quite competitive, at least compared to the hybrid exploration in simulation. The average time needed for a scan and map update was 45 s, which yields 13.5 min in total (no scan at vp 2, 9, 13, 18, 19, 22 and 23).  $\|ET\| = 208$  m is significantly increased compared to the simulation results. This means a minimum travel time of 9 min 54 s and a time penalty of about 27.5 min for slow-downs.

During the **ground plan-based exploration**, shown in figure 9, the robot needs 5 NBVs (0, 1, 3-5) plus a side trip to the kitchen (2), before it manages to leave the meeting room via the west door. The accumulation of NBVs 1, 4 and 3, 5 arises from the inability to reach the original targets. Afterwards, entrance hall (6-9), north (10-12) and south corridor (14, 15, 17-21) are explored quickly, only disturbed by an additional scan (13) due to the adjacent half-open door and an oscillation (16). After recording the rest of the kitchen (22, 23), the map is rather complete. From

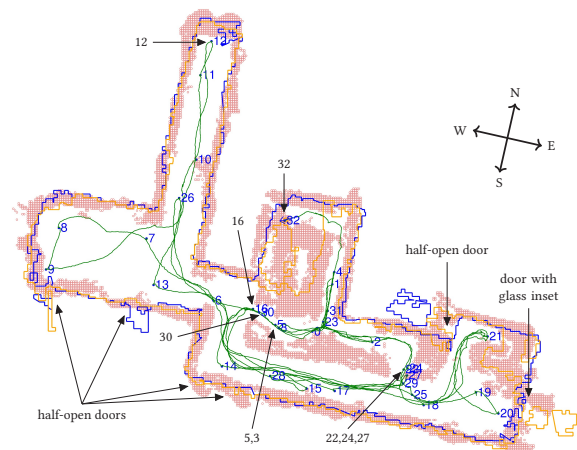


Figure 9: Real world result of ground plan-based exploration.

the following 9 vps, only the last one (32) provides new information, whereas the intermediate oscillations reveal severe navigation problems due to environmental dynamics. At least the strategy is robust enough to prevent deadlocks and to terminate in finite time. Correspondingly, 33 NBVs,  $T_{Exp} = 94$  min and  $\|ET\| = 273.2$  m are the worst of all runs. Each scan took about 81 s, i. e. 44 min 33 s in total, the minimum travel time is 13 min and the penalty for slow-downs 36.5 min.

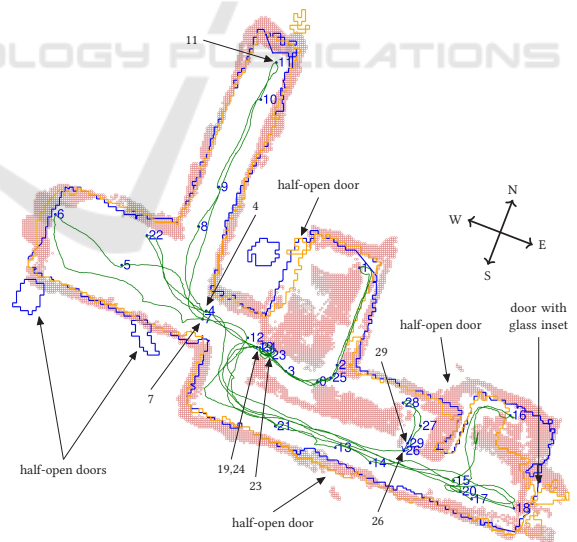


Figure 10: Real world result of hybrid exploration.

As shown in figure 10, the **hybrid strategy** manages to explore the whole meeting room rapidly via NBVs 0-3, followed by the entrance (4-6), north (8-11) and south corridor (12-18), with only one intermediate scan (7) due to the adjacent half-open door. The oscillations between door (c) (19, 23, 24), south cor-

ridor (20, 21) and entrance (22) are caused by the inability to enter the kitchen via the west door (25). Finally, the robot drives back to door (a) and completes the map (26-29).  $T_{Exp} = 83.8\text{min}$ ,  $\|ET\| = 247.4\text{m}$  and 30 NBVs represent a slightly better performance than in the previous run. The total scan time is 33 min 45 s (no scan at vp 2, 16, 19, 25, 29), the minimum travel time is 12 min and the time penalty for slow-downs 38 min.

In sum, table 1 shows that the dynamic frontier-based approach is always the fastest due to the time needed to construct the ground plans for the other two strategies. However, these two produce significantly more complete maps, especially regarding the meeting room, both in simulation and reality. All three procedures need notably more time, more NBVs and a longer trajectory for the real world scenario. They all manage to avoid deadlocks and to create a suitable map within a reasonable amount of time. All in all, in simulation the ground plan-based approach provides the best trade-off between needed time and map quality, whereas in reality the hybrid approach is most promising.

## 5 CONCLUSION

The paper has analyzed the performance of three NBV exploration strategies, based on representative test runs in a simulated office scene and in its real world counterpart. They all use the same weighted sum of influence factors for scoring vps, online map updates and adaptation of the exploration trajectory. They differ in the kind of mapped features (2.5D grid map vs. ground plan of floor and ceiling) and corresponding estimation of information gain (frontier length vs. area of difference polygons). The dynamic frontier-based approach yields always the fastest, but incomplete results, whereas the best trade-off between needed time and map quality is provided by the ground plan-based procedure in simulation and by the hybrid strategy in reality.

Future work concentrates on a comparison with state of the art approaches and on analyzing the influence of the layout of the environment on the results, in order to check that the strategies work in general. Other topics are to find a generally optimal set of scoring weights and to improve and evaluate the room-wise exploration approach of (Schmidt, 2006) in obstructed real world scenarios.

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