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# RFID Technology-based Exploration and SLAM for Search And Rescue

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**Abstract**— Robot search and rescue is a time critical task, i.e. a large terrain has to be explored by multiple robots within a short amount of time. The efficiency of exploration depends mainly on the coordination between the robots and hence on the reliability of communication, which considerably suffers under the hostile conditions encountered after a disaster. Furthermore, rescue robots have to generate a map of the environment which has to be sufficiently accurate for reporting the locations of victims to human task forces. Basically, the robots have to solve autonomously in real-time the problem of Simultaneous Localization and Mapping (SLAM).

This paper proposes a novel method for real-time exploration and SLAM based on RFID tags that are autonomously distributed in the environment. We utilized the algorithm of Lu and Milios [8] for calculating globally consistent maps from detected RFID tags. Furthermore we show how RFID tags can be used for coordinating the exploration of multiple robots.

Results from experiments conducted in the simulation and on a robot show that our approach allows the computationally efficient construction of a map within harsh environments, and coordinated exploration of a team of robots.

## I. INTRODUCTION

Robot search and rescue is a time critical task, i.e. a large terrain has to be explored by multiple robots within a short amount of time. The efficiency of exploration depends mainly on the coordination between these robots and hence on the reliability of communication, which considerably suffers under the hostile conditions encountered after a disaster.

Furthermore, rescue robots have to generate a map of the environment which has to be sufficiently accurate for reporting the locations of victims to human task forces. Basically, the robots have to solve autonomously in real-time the problem of Simultaneous Localization and Mapping (SLAM), consisting of a continuous state estimation problem and a discrete data association problem. The state estimation problem, on the one hand, is hard due to the extremely unreliable odometry measurements usually found on robots operating within harsh environments. The data association problem, i.e. to recognize locations from the data, on the other hand, is challenging due to the unstructured environment, i.e. arbitrarily colored and shaped debris from building collapse and fire.

The system introduced in this paper is capable of fully autonomous SLAM in real-time within test arenas of the National Institute of Standards and Technology (NIST) [6]. The system tackles the problem of state estimation with a Kalman filter, integrating data from scanmatching and odometry. In particular, we have developed a robot with over-constrained

odometry, i.e. four shaft-encoders instead of two, for the detection of slippage of the wheels. The problem of data association is solved by the active distribution and recognition of RFID tags. RFID tags have a worldwide unique number, and thus offer an elegant way to label and to recognize locations within harsh environments. Their size is already below  $0.5mm$ , as shown by the  $\mu$ -chip from *Htatchi* [12], and their price is lower than 13 Cents [1].

Besides the solution of the data association problem, the RFID-technology based approach comes with three further advantages: Firstly, in a multi-robot exploration scenario, maps from many robots can easily be merged to one consistent map by utilizing found correspondences from RFID tags registered on those maps. Secondly, RFID tags that have been put into the environment can be used in a straightforward manner by humans to follow routes towards victim location, i.e. they do not need to localize themselves within a metric map. Thirdly, RFID tags can be used by human task forces to store additional user data, such as the number of victims located in a room or an indication of a hazardous area.

The basic idea behind the proposed RFID-based SLAM is to build successively a graph  $G = (V, E)$  consisting of vertices  $V$  and edges  $E$ , where each vertex represents an RFID tag, and each edge  $(V_i, V_j) \in E$  represents an estimate of the relative displacement  $(\Delta x, \Delta y)^T$  with covariance matrix  $\Sigma_{(\Delta x, \Delta y)}$  between the two RFID tags associated with the two vertices  $V_i$  and  $V_j$ , respectively. The relative displacement between two tags is estimated by a Kalman filter, which integrates pose corrections from the robot's odometry, an Inertia Measurement Unit (IMU), and laser-based scan-matching. RFID tags are actively deployed by the robot at adequate locations, i.e. locations that are likely to be passed. We utilized the algorithm of Lu and Milios [8] for calculating globally consistent maps from the RFID graph.

Moreover, we show how the distributed RFID tags can be utilized for efficient multi-robot exploration. State of the art approaches assume that the relative position between robots is inherently known or provided at startup and that at some point in time the robots will be able to communicate their maps [3], [16]. However, in a rescue scenario, robots are not necessarily deployed within the same time and at the same location, they might even be from different teams. Moreover, they might also not be able to communicate at all, depending on the structure of the area that has to be explored.

In RFID-based exploration, trajectories and maps of heterogeneous robots can easily be combined since the data

association problem is solved. We show how to make use of the additional capacity of RFID tags for coordinating the exploration of multiple robots. This is achieved by storing locations of the robot's current trajectory and exploration targets relatively to the location of the tag. If other robots read this information from the tag, they are able to optimize their target selection without being within communication range.

The remainder of this paper is structured as follows. In Section II we give an overview on existing work. In Section III we introduce the robot hardware including a novel mechanism for the deployment of RFID tags. The RFID-based SLAM approach is described in Section IV, and the RFID-based exploration approach is described in Section V. Finally, we provide results from simulation and real world experiments in Section VI and conclude in Section VII.

## II. RELATED WORK

Hähnel and colleagues [5] demonstrated successfully how RFID tags can be used to improve the localization of a mobile robot, given the location of RFID tags within a map. In contrast to our system, which actively distributes tags and requires them to be situated beneath the robot, their system detects tags that are fixed in the environment. Their approach deals with the problem of localizing a robot within a map previously learned from laser range data, whereas the work presented in this paper describes a solution that performs RFID-based mapping and localization simultaneously while exploring an unknown environment.

Balch and Arkin [2] showed that their *grazing task*, i.e. to completely cover a terrain, can be carried out by multiple robots without communication, as long as the robots mark their trajectories within the terrain. They did neither describe how to mark the trajectories physically nor how they can be detected reliably.

Svennebring and Koenig [14] proposed an approach for terrain coverage that has been evaluated within a real scenario. They have basically shown that multi-robot terrain coverage is feasible without robot localization and an exchange of maps. Their current approach requires robots to continuously mark their traveled trajectory<sup>1</sup>, which is not desirable or possible in every kind of situation. However, we are confident that their *node counting* method could also be combined with our approach.

Zlot and his colleagues describe a system for multi-robot exploration based on a market economy approach [16]. As shown by conducted experiments, their system turned out to be robust. However, it requires from robots to be able to communicate, at least at some point in time, in order to exchange their bids for exploration targets and maps. Furthermore, their approach requires that robots localize themselves within the same coordinate system in order to share information on regions that have already been explored. This is seldom the case, for example, if robots start exploration from different locations in space and time or if localization fails at all.

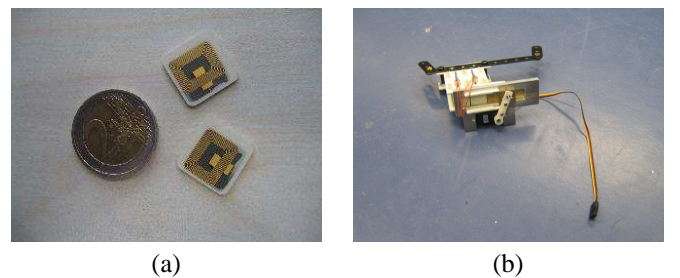
Burgard and colleagues [3] contributed a system for multi-robot localization based on frontier cell exploration [15]. In

<sup>1</sup>In their example, robots use a crayon to mark a paper sheet covering the ground.

contrast to former work [13], their latest system does not require a central server for the distribution of map pieces and exploration tasks. Instead, this information is dynamically distributed by any group of robots that are within communication range. Robots are, at least partially, required to communicate in order to exchange maps of explored regions and to negotiate exploration targets. Furthermore, the approach also builds upon the assumption that robots continuously know their relative locations among each other, which can only be achieved if all robots begin their operation from locations where their range scans are overlapping and if the user informs the system about the initial displacement. Our approach does generally not require robots to be within communication range, since RFID tags are used for indirect communication. However, if robots are within range, they might exchange their information on RFID tags in order to accelerate the exploration. Here, also the unique location description given by a RFID tag simplifies the fusion of data between different robots.

## III. ROBOT HARDWARE

Due to the specific needs within robot rescue, we completely hand-crafted a 4WD (four wheel drive) differentially steered robot, as depicted in Figure 4. The 4WD drive provides more power to the robot and thus might allow the robot to drive up ramps and to operate on rough terrain. Each wheel is driven by a *Pitman GM9434K332* motor with a *19.7:1* gear ratio and shaft encoders. The redundancy given by four encoders allows to detect heavy slippage or situations in which the robot gets stuck, as we will show in Section IV. In order to reduce the large odometry error that naturally arises from a four-wheeled platform, we utilized an Inertial Measurement Unit (IMU) from *InterSense*. The sensor provides an accurate measurement of the robot's orientation by the three Euler angles *yaw*, *roll*, and *pitch*. Furthermore, the robot is equipped with a *Hokuyo URG-X003* Laser Range Finder (LRF), five *Devantech SRF08* sonar sensors and eight GP2D120 infra red sensors, and a *Thermal-Eye* infrared thermo camera for victim detection.



**Fig. 1.** (a) RFID tags used during the experiments and (b) a novel mechanism for distributing them from a mobile robot

We utilized Ario RFID chips from *Tagsys* (see Figure 1(a)) with a size of  $1.4 \times 1.4\text{cm}$ , 2048Bit RAM, and a response frequency of 13.56MHz. For the detection of the tags we employed a Medio S002 reader, likewise from *Tagsys*, which allows to detect the tags within a range of approximately 30cm while consuming less than 200mA. In order to detect tags lying beneath the robot, the antenna of the reader is mounted in parallel to the ground.

The active distribution of the tags is carried out by a self-constructed actuator (see Figure 1(b)). The device is realized by a magazine of tags, maximally holding around 100 tags, and a metal slider that can be moved by a conventional servo. Each time the mechanism is triggered, the slider moves back and forth while dropping a single tag from the magazine. Experiments showed that due to the small size of a tag, even passing over with a wheel does nearly not change the position of a tag. The mechanism is triggered by the software with respect to the density of tags and the density of obstacles around the robot. The dropping of a tag occurs with higher probability if the tag density is low and the obstacle density on the left and right hand side of the robot is high. Both conditions are estimated with a local evidence grid [10], which is generated from scans matched by the scan matcher described in Section IV.

#### IV. RFID TECHNOLOGY-BASED SLAM

The proposed RFID-based SLAM method requires reliable measurements of the local displacement between two tags. Therefore, a Kalman filter has been utilized, which estimates the robot's pose from both scan matching and odometry-based dead reckoning with respect to the robot's slippage.

Generally, the robot's pose can be modeled by a Gaussian distribution  $N(l, \Sigma_l)$ , where  $l = (\hat{x}, \hat{y}, \hat{\theta})^T$  is the mean and  $\Sigma_l$  a  $3 \times 3$  covariance matrix, expressing uncertainty of the pose [9]. Given the measurement of the robot's motion by the normal distribution  $N(u, \Sigma_u)$ , where  $u = (d, \alpha)$  is the input of traveled distance  $d$  and angle  $\alpha$ , respectively, and  $\Sigma_u$  a  $2 \times 2$  covariance matrix expressing odometry errors, the robot's pose at time  $t$  can be updated as follows:

$$l_t = F(l_{t-1}, d, \alpha) = \begin{pmatrix} \hat{x}_{t-1} + \cos(\hat{\theta}_{t-1})d \\ \hat{y}_{t-1} + \sin(\hat{\theta}_{t-1})d \\ \hat{\theta}_{t-1} + \alpha \end{pmatrix}, \quad (1)$$

$$\Sigma_{l_t} = \nabla F_l \Sigma_{l_{t-1}} \nabla F_l^T + \nabla F_u \Sigma_{u_{t-1}} \nabla F_u^T, \quad (2)$$

where  $F$  describes the update formula, and  $\nabla F_l$  and  $\nabla F_u$  are partial matrices of its Jacobian  $\nabla F$ .

If the robot operates on varying ground, for example, concrete or steel sporadically covered with newspapers and cardboard (see Figure 4 (a)), or if it is very likely that the robot gets stuck within obstacles, odometry errors are not normally distributed, as required by localization methods. In order to detect wheel slippage, we over-constrained the odometry by measuring from four separated shaft encoders, one for each wheel. From these four encoders we recorded data while the robot was driving on varying ground, and labeled the data set with the classes  $C = (\text{slippage}, \text{normal})$ . This data was taken to learn a decision tree with the inputs  $I = (\Delta v_{Left}, \Delta v_{Right}, \Delta v_{Front}, \Delta v_{Rear})$ , representing the velocity differences of the four wheels, respectively. As depicted in Figure 2, the trained classifier reliably detects this slippage from the velocity differences. Given the detection of slippage, the odometry measurement of traveled distance  $d$  is set to zero and the robot's pose updated according to Equation 2, however, with a modified covariance matrix  $\Sigma_u$

that reflects the higher uncertainty in translation. Note that we do not reflect uncertainty in rotation since the traveled angle  $\alpha$  is measured by the IMU and thus not influenced by slippage of the wheels.

Additionally, the robot's pose is estimated by an incremental scan matching technique [4]. The technique determines from a sequence of previous scan observations  $o_t, o_{t-1}, \dots, o_{t-\Delta t}$  subsequently for each time point  $t$  an estimate of the robot's pose  $k_t$ . This is carried out by incrementally building a local grid map from the  $\Delta t$  most recent scans and estimating the new pose  $k_t$  of the robot by maximizing the likelihood of the scan alignment of the scan  $o_t$  at pose  $k_t$ . The robot pose  $N(l_t, \Sigma_{l_t})$  is fused with the pose of the scanmatcher  $N(k_t, \Sigma_{k_t})$  by:

$$l_{t+1} = (\Sigma_{l_t}^{-1} + \Sigma_{k_t}^{-1})^{-1} (\Sigma_{l_t}^{-1} l_t + \Sigma_{k_t}^{-1} k_t) \quad (3)$$

$$\Sigma_{l_{t+1}} = (\Sigma_{l_t}^{-1} + \Sigma_{k_t}^{-1})^{-1} \quad (4)$$

In contrast to the widely used *LMS200* range finder, which measures distances up to 80 meters, the LRF utilized in our system has a range limit of four meters, leading in some environments to a large number of *far readings*, i.e. measurements at maximum range. A large number of far readings, however, leads to failures of the utilized scanmatcher. Since these errors are not normally distributed, we ignore scans if the number of far readings goes above a given threshold  $N_{far} > \Theta$  and update the robot's pose by odometry estimates only <sup>2</sup>.

With the described technique the robot is able to track continuously its pose. However, the quality of its pose estimate will decrease according to the length of the traveled trajectory. We tackle this problem by actively distributing unique RFID tags into the environment, i.e. placing them automatically on the ground, and by utilizing the correspondences of these tags on the robots trajectory for calculating globally consistent maps according to the method introduced by Lu and Milios [8]. Suppose the robot distributes  $n$  RFID tags at unknown locations  $l_1, l_2, \dots, l_n$ , with distance  $d_{ij} = (\Delta x_{ij}, \Delta y_{ij}, \Delta \theta_{ij})$  between  $l_i$  and  $l_j$ . In order to determine the estimated distance  $\hat{d}_{ij}$  with corresponding covariance matrix  $\Sigma_{ij}$  between  $l_i$  and  $l_j$ , the previously described Kalman filter is utilized. However, if the robot passes a tag  $l_i$ , we reset the Kalman Filter in order to estimate the *relative* distance  $\hat{d}_{ij}$  to subsequent tag  $l_j$  on the robot's trajectory.

Our goal is now to estimate locations  $l_i$  that best explain the measured distances  $\hat{d}_{ij}$  and covariances  $\Sigma_{ij}$ . This can be achieved with the maximum likelihood concept by minimizing the following Mahalanobis-distance:

$$W = \sum_{ij} (d_{ij} - \hat{d}_{ij})^T \Sigma_{ij}^{-1} (d_{ij} - \hat{d}_{ij}), \quad (5)$$

where the summation goes over all measured distances and  $d_{ij}$  is the true distance between  $l_i$  and  $l_j$ . Note if we assume the robot's orientation to be measured by the IMU (whose error does not accumulate), we do not need to consider the orientation  $\theta$  within the  $d_{ij}$  in Equation 5, and hence the optimization problem can be solved linearly by calculating

<sup>2</sup>From a series of experiments we determined  $\Theta = 140$ .

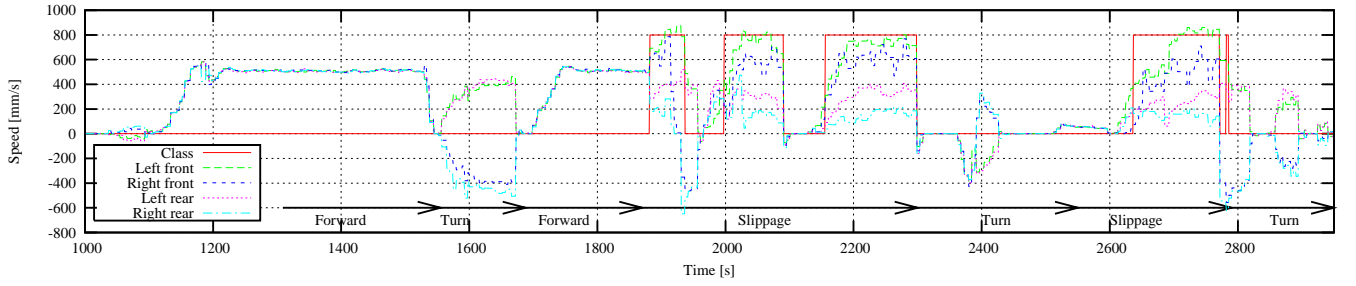


Fig. 2. Odometry measurements of a 4WD robot. The black arrows show the true situation and the red line the automatic classification into *slippage* (800) and *normal* (0).

$d_{ij} = l_i - l_j$ . However, if we also want to improve the estimate of the orientation, the  $d_{ij}$  have to be linearized. It can easily be shown that the optimization problem in Equation 5 can be solved as long as the covariances  $\Sigma_{ij}$  are invertible [8].

Furthermore, it is necessary to account for the spacial extend of the antenna utilized for the RFID tag detection. We use an antenna with an extend of approximately  $20 \times 3\text{cm}$ , mounted parallel to the ground. The measurement uncertainty of the location of a RFID tag within this area is modelled by covariance matrix  $\Sigma_{l_i}$ , which reflects the shape of the antenna and orientation of the robot, i.e. it has a low uncertainty into the robot's direction, and a high uncertainty orthogonal to it.

## V. RFID TECHNOLOGY-BASED EXPLORATION

Efficiency of multi-robot exploration is usually measured by the ratio between the explored area and the distance traveled by the robots [16]. This efficiency can only be maximized if robots know about the past and future exploration targets of the other robots. The proposed method enables an exchange of this information via programmable RFID tags.

We assume that a *single* robot explores the environment, based on the concept of “frontier cell” exploration [15]. A cell is considered as frontier cell if it has already been explored but also neighbors an unexplored cell. Each robot maintains a set  $F_r$  of frontier cells with respect to its observations, e.g. by removing cells coming into the field of view of its sensors and by adding cells that are at the border, respectively. According to the work of Burgard and his colleagues [3], exploration targets are selected by

$$f' = \underset{f \in F_r}{\operatorname{argmax}} (U(f) - \alpha \cdot C(f)), \quad (6)$$

where  $U(f)$  denotes the utility function,  $C(f)$  denotes the costs for traveling from the robot's current location to the frontier cell  $f$ , and  $\alpha$  regulates the trade-off between utility and cost, respectively.

The basic idea of RFID-based exploration is to leave behind information via RFID tags, which helps other robots to reduce the overlap of exploration targets. Therefore, we store on RFID tags the relative locations of frontier cells  $F_{tag} = (\Delta f_1, \Delta f_2, \dots, \Delta f_n)$  and the relative locations of *visited* cells  $V_{tag} = (\Delta v_1, \Delta v_2, \dots, \Delta v_m)$ . Tags are intended to provide information for a local area of the exploration space, thus their influence radius, i.e. maximal distance of relative locations, is limited by the distance  $\tau$ . Robots passing a tag subsequently synchronize the data of the tag with their

frontier cells and visited locations within range  $\tau$ , and vice versa. We assume that the robots IMU is based on a compass and thus the local coordinate frames of the robots are equally aligned to magnetic north.

Each robot maintains a collection  $V_r$  containing time-stamped locations  $l_t = (x, y)$ . During each cycle  $t$ , the robot adds its current pose  $l_t$  and all future poses  $(l_{t+1}, l_{t+2}, \dots, l_{t+n})$  from its planned trajectory to  $V_r$ . Note that the ratio behind considering cells on the planned trajectory as already visited, is to prevent other robots from crossing the robots trajectory. If the robot passes a RFID tag,  $V_r$  and  $V_{tag}$  are synchronized after Algorithm 1.

---

### Algorithm 1 Synchronization of $V_r$ and $V_{tag}$

---

```

for all  $\Delta v_i \in V_{tag}$  do
  add absolute location  $(\Delta v_i + l_0)$  to  $V_r$ 
end for
for all  $v_j \in V_r$  do
  if  $\|v_j - l_0\| < \tau$  then
    add relative location  $(v_j - l_0)$  to  $V_{tag}$ 
  end if
end for

```

---

Furthermore, each robot maintains a collection  $F_r$  containing frontier cells  $f = (x, y)$  with absolute locations  $x, y$ . Let  $isFrontierCell(f)$  determine whether  $f$  is a frontier cell, i.e. whether it has been explored and neighbors an unexplored cell. Then, if passing a tag, the robot synchronizes  $F_r$  and  $F_{tag}$  after Algorithm 2. As shown by Algorithm 2,

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### Algorithm 2 Synchronization of $F_r$ and $F_{tag}$

---

```

for all  $\Delta f_i \in F_{tag}$  do
  if  $isFrontierCell(l_r + \Delta f_i)$  then
    add absolute frontier cell  $(l_r + \Delta f_i)$  to  $F_a$ 
  else
    remove  $(l_r + f_i)$  from  $F_{tag}$ 
  end if
end for
for all  $f_j \in F_r$  do
  if  $\|l_r - f_j\| < \tau$  then
    add relative frontier cell  $(l_r - f_j)$  to  $F_{tag}$ 
  end if
end for

```

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frontier cells are removed from  $F_{tag}$  if they already have



been explored by the robot. Hence, the number of frontier cells stored on a tag decreases continuously as robots explore the surrounding of the tag.

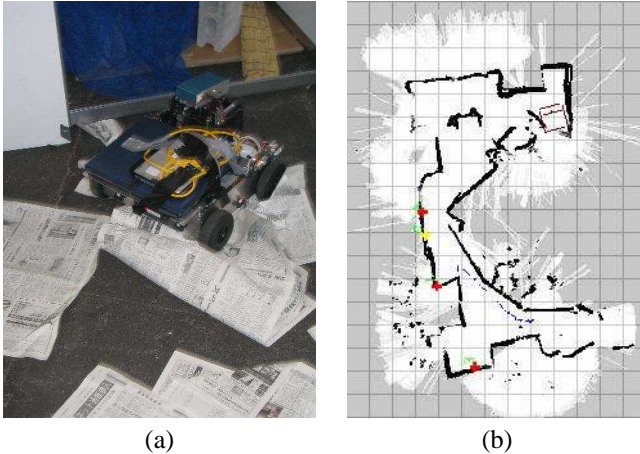
With respect to  $V_r$  and  $F_r$ , the utility function from Equation 6 is calculated as follows:

$$U(f) = k(f) - \beta \sum_{l_t \in V_r} \frac{\|f - l_t\|}{age(l_t)}, \text{ with} \quad (7)$$

$$k(f) = \begin{cases} 1.0 & \text{if } f \in F_o; \\ 0.0 & \text{otherwise.} \end{cases} \quad (8)$$

whereas  $age(l_t)$  denotes the age of the location's time stamp,  $F_o$  is the set of frontier cells originating from other robots, and  $\beta$  regulates the trade-off between the influence of visited locations and the exploration targets from other robots, respectively. The ratio behind preferring exploration targets from other robots is that, within vicinity  $\tau$ , these targets are more likely to be unexplored than the robot's own targets, since the other robots already explored within this area.

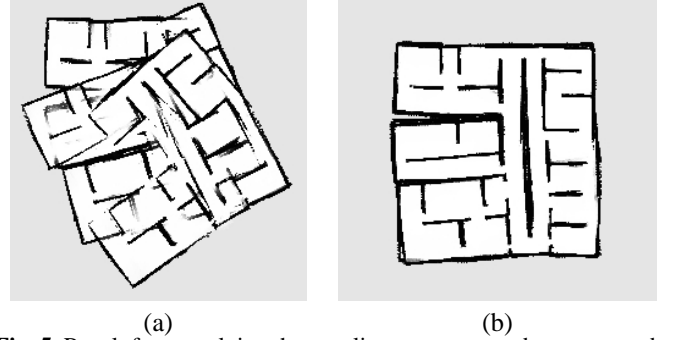
## VI. EXPERIMENTS



**Fig. 4.** Zerg robot during the final of the *Best in Class autonomy* competition at RoboCupRescue 2005 in Osaka: (a) slipping on newspapers and (b) the autonomously generated map. Red crosses mark locations of victims which have been found by the robot.

The system introduced in this paper is based on the *Zerg* robot that won the “Best in Class Autonomy” competition, held in the NIST arena for Urban Search and Rescue (USAR) [6] during RoboCup 2005. In that scenario robots had to explore autonomously within 20 minutes an unknown area, to detect all victims, and finally to deliver a map sufficient for human teams to locate and rescue the victims. Conditions for exploration and SLAM were intentionally made difficult. For example, the occurrence of wheel spin was likely due to newspapers and cardboards covering the ground, which was partially made of steel and concrete. Stone bricks outside the robot's FOV caused the robot to get stuck, and walls made of glass caused the laser range finder to return far readings. As shown in Figure 4, the system was able to cope with these difficulties and also to reliably build a map, augmented with victim locations detected by the robot.

The proposed method for RFID-based SLAM has extensively been tested with data generated by a simulator [7] and also on a real robot. The simulated robot explored three different building maps, a *small* map, *normal* map, and *large* map of the size  $263m^2$ ,  $589m^2$ ,  $1240m^2$ , respectively, while automatically distributing RFID tags in the environment. Figures 3 (a) and (b) show the averaged results from 100 executions of our method with linear correction to trajectories generated from the robot's odometry at five different levels of noise. We measured a computation time of 0.42 seconds on



**Fig. 5.** Result from applying the non-linear mapper to data generated in the simulation. (a) The small map with odometry noise and (b) the correction of the map.

the small map, 2.19 seconds for the normal map, and 13.87 seconds for the large map, with a *Pentium4 2.4GHz*. The result of the non-linear correction of the small map is shown in Figure 5. For this result, the robot distributed approximately 50 RFID tags.

In another experiment we collected data from a real robot autonomously exploring for 20 minutes in a cellar while detecting RFID tags on the ground. The robot continuously tracked its pose as described in Section IV. As depicted by Figure 6, the non-linear method successfully corrected the angular error. The correction was based on approximately 20 RFID tags.

Figure 3 (c) depicts the averaged performance of RFID-based exploration compared to *full* communication, i.e. robots share all of their sensor data, and *no* communication. During each of the 100 experiments, up to 5 robots started in sequence to explore from a random position on one of the three maps. The data exchange of full communication has been simulated by providing each robot the map that has been generated by its predecessor. It can be seen, that RFID-based exploration decreases the overlap of exploration targets and nearly reaches the performance of the full communication method that requires an exhaustive data exchange. We conducted the same experiment with a real robot navigating in a corridor. If the robot passed a door that was marked with a RFID tag from another robot, the robot continued its journey towards the next door in the corridor.

## VII. CONCLUSION

We showed that the introduced method allows the fast generation of maps and the coordinated exploration without explicit need for communication. This has the advantage that, particularly in the context of disaster response, the method

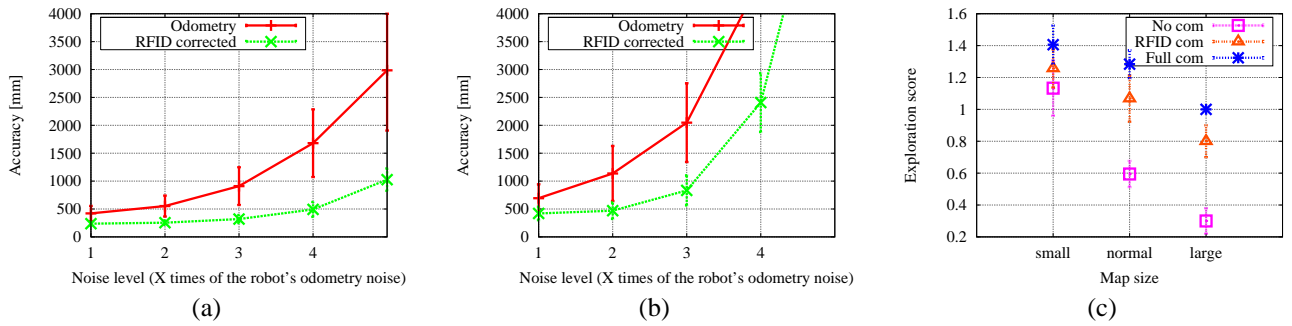


Fig. 3. The averaged results from applying the linear mapper to noisy odometry data from (a) the small map, and (b) the large map. (c) The averaged exploration score, i.e. area divided by summed distance, of 100 exploration runs from five robots on the small, normal and large map, respectively.

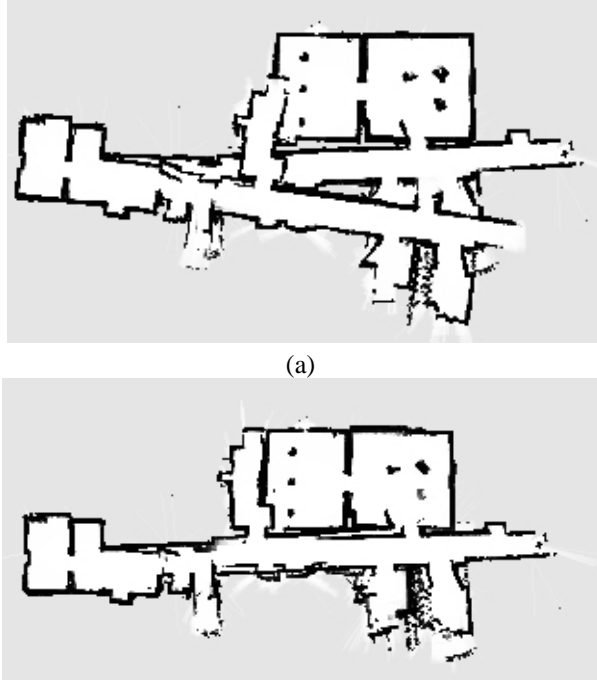


Fig. 6. RFID-based SLAM of a robot driving in a cellar: (a) The noisy map and (b) the corrected map.

can also be applied within harsh environments, i.e. where communication is disturbed by building debris or radiation. Due to the limited memory of current RFID chips, one has to decide a trade-off between the number of locations, location resolution, and maximal distance that can be managed via a tag. However, we are confident that this limitation will be revised within the next two years.

The practical advantage of the proposed method is that human rescue teams can easily be integrated into the search. They can receive data from the RFIDs with a PDA and thus localize themselves within the map and also leave information, related to the search or to victims, behind. Furthermore, they can easily reach victims which have been found by the robots, by following plans consisting of RFID tags and directions. The idea of labeling locations with information that is important to the rescue task has already been applied in practice. During the disaster relief in New Orleans in 2005, rescue task forces marked buildings with information concerning, for example, hazardous materials or

victims inside the buildings. A description of these kinds of markings can be found in a document published by the U.S. Dep. of Homeland Security [11]. Our autonomous RFID-based marking of locations is a straight forward extension of this concept.

## VIII. ACKNOWLEDGEMENTS

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## REFERENCES

- [1] Alien technology. <http://www.alientechnology.com/>, 2003.
- [2] T. Balch and R. C. Arkin. Communication in reactive multiagent robotic systems. *Autonomous Robots*, 1(1):27–52, 1994.
- [3] W. Burgard, M. Moors, C. Stachniss, and F. Schneider. Coordinated multi-robot exploration. *IEEE Transactions on Robotics*, 21(3):376–378, 2005.
- [4] D. Hähnel. *Mapping with Mobile Robots*. Dissertation, Universität Freiburg, Freiburg, Deutschland, 2005.
- [5] D. Hähnel, W. Burgard, D. Fox, K. Fishkin, and M. Philipose. Mapping and localization with rfid technology. In *In Proc. of the IEEE International Conference on Robotics and Automation (ICRA)*, 2004.
- [6] A. Jacoff, E. Messina, and J. Evans. Experiences in deploying test arenas for autonomous mobile robots. In *Proceedings of the 2001 Performance Metrics for Intelligent Systems (PerMIS) Workshop*, 2001.
- [7] A. Kleiner and T. Buchheim. A plugin-based architecture for simulation in the F2000 league. In *Proc. Int. RoboCup Symposium '03*. Padova, Italy, 2003.
- [8] F. Lu and E. Milios. Globally consistent range scan alignment for environment mapping. *Auton. Robots*, 4:333–349, 1997.
- [9] P. S. Maybeck. *Stochastic models, estimation, and control*, volume 141 of *Mathematics in Science and Engineering*. 1979.
- [10] H.P. Moravec. Sensor fusion in certainty grids for mobile robots. *AI Magazine*, 9(2):61–74, 1988.
- [11] U.S. Department of Homeland Security. *National Urban Search and Rescue (USR) Response System - Field Operations Guide*, September 2003.
- [12] Mu Chip Data Sheet. *HITACHI*, 2003. [http://www.hitachi-eu.com/mu/products/mu\\_chip\\_data\\_sheet.pdf](http://www.hitachi-eu.com/mu/products/mu_chip_data_sheet.pdf).
- [13] R. Simmons, D. Apfelbaum, W. Burgard, D. Fox, S. Moors, M. and Thrun, and Younes H. Coordination for multi-robot exploration and mapping. In *Proc. of the National Conference on Artificial Intelligence (AAAI)*, 2000.
- [14] J. Svennebrink and S. Koenig. Building terrain-covering ant robots: A feasibility study. *Auton. Robots*, 16(3):313–332, 2004.
- [15] B. Yamauchi. A frontier-based approach for autonomous exploration. In *IEEE International Symposium on Computational Intelligence in Robotics and Automation (CIRA '97)*, 1997.
- [16] R. Zlot, A. Stentz, M. Dias, and S. Thayer. Multi-robot exploration controlled by a market economy. In *Proceedings of the IEEE International Conference on Robotics and Automation*, 2002.