

# RoboCupRescue - Robot League Team

## RescueRobots Freiburg (Germany)

Alexander Kleiner<sup>1</sup>, Christian Dornhege<sup>1</sup>, Rainer Kümmerle<sup>1</sup>, Michael Ruhnke<sup>1</sup>,  
Bastian Steder<sup>1</sup>, Bernhard Nebel<sup>1</sup>, Patrick Doherty<sup>2</sup>, Mariusz Wzorek<sup>2</sup>, Piotr  
Rudol<sup>2</sup>, Gianpaolo Conte<sup>2</sup>, Simone Durante<sup>2</sup>, and David Lundström<sup>2</sup>

Institut für Informatik<sup>1</sup>,  
Foundations of AI  
Universität Freiburg,  
79110 Freiburg, Germany

Dep. of Computer and Inf. Science<sup>2</sup>  
AI and Int. Computer Systems Division  
Linköping University  
S-581 83 Linköping, Sweden

<http://www.informatik.uni-freiburg.de/rescue/~robots>

**Abstract.** This paper describes the approach of the *RescueRobots Freiburg* team, which is a team of students from the University of Freiburg that originates from the former CS Freiburg team (RoboCupSoccer) and the ResQ Freiburg team (RoboCupRescue Simulation). Furthermore we introduce *linkMAV*, a micro aerial vehicle platform.

Our approach covers RFID-based SLAM and exploration, autonomous detection of relevant 3D structures, visual odometry, and autonomous victim identification. Furthermore, we introduce a custom made 3D Laser Range Finder (LRF) and a novel mechanism for the active distribution of RFID tags.

## 1 Introduction

RescueRobots Freiburg is a team of students from the University of Freiburg. The team originates from the former CS Freiburg team [12], which won the RoboCup world championship in the RoboCupSoccer F2000 league three times, and the ResQ Freiburg team [5], which won the RoboCup world championship in the RoboCupRescue Simulation league in 2004. The team's approach proposed in this paper is based on experiences gathered at RoboCup during the last six years. Our research focuses on the implementation of a cheap and fully autonomous team of robots that quickly explores a large terrain while mapping its environment.

In this paper we introduce our approach to Rescue Robotics, which we have been developing for the last two years. Our main focus concerns RFID-based SLAM and exploration, autonomous detection of relevant 3D structures, visual odometry, and autonomous victim identification. Furthermore, we introduce a custom made 3D Laser Range Finder (LRF) and a novel mechanism for the active distribution of RFID tags. The Autonomous Unmanned Aerial Vehicle Technologies Lab (AUTTECH) at the Department of Computer and Information Sciences, Linköping University, Sweden, developed the micro aerial vehicle platform *linkMAV* which will also be introduced in this paper.

The motivation behind RFID-based SLAM and exploration is the simplification of the 2D mapping problem by RFID tags, which our robots distribute with a tag-deploy-device. RFID tags provide a world-wide unique number that can be read from distances

up to one meter. The detection of these tags and thus the unique identification of locations is significantly computationally cheaper and less erroneous than identifying locations with camera images and range data <sup>1</sup>.

RFID-based SLAM and exploration has advantages for Urban Search and Rescue (USAR): We believe that the distribution of RFID tags in the environment can also be very valuable to human task forces equipped with a RFID reader. From recognized RFID tags the system is able to generate a topological map which can be passed to a human operator. The map can be augmented with structural and victim-specific information. Travel paths to victims can directly be passed to human task forces as complete plans that consist of RFID tag locations and walking directions. In fact, tags can be considered as signposts since the topological map provides for each tag the appropriate direction. Given a plan of tags, task forces can find victim locations directly by following the tags, rather than locating themselves on a 2D or 3D metric map beforehand. 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. Our autonomous RFID-based marking of locations is a straight forward extension of this concept.

RoboCupRescue confronts the robots with a real 3D problem. In order to find victims, robots have to overcome difficult terrain including ramps, stairs and stepfields. The managing of these tasks autonomously without human control is one goal of our research. Therefore, we started to investigate approaches for visual odometry and 3D structure recognition, which we will present in this paper.

## 2 Team Members and Contributions

- Team Leader: Alexander Kleiner
- Selflocalization: Christian Dornhege
- Mapping: Rainer Kümmerle
- Controller Design and Behaviors: Bastian Steder
- Victim Identification: Michael Ruhnke
- Advisor: Bernhard Nebel

## 3 Operator Station Set-up and Break-Down (10 minutes)

Our robots are controlled by a lightweight laptop via a *Logitech Rumblepad*, which all can be transported together in a backpack. It is possible for the operator to select between different robots as well as between different views/cameras from a single robot on the fly.

Our *Zerg* and *Lurker* robots can either be transported by a moveable case with wheels or backpacked. The whole setup and breakdown procedure can be accomplished within less than 10 minutes, including booting the computers, checking the network connection, and checking whether all sensors work properly.

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<sup>1</sup> Note that even for humans the unique identification of a location is hard, when for example exploring a large office building.

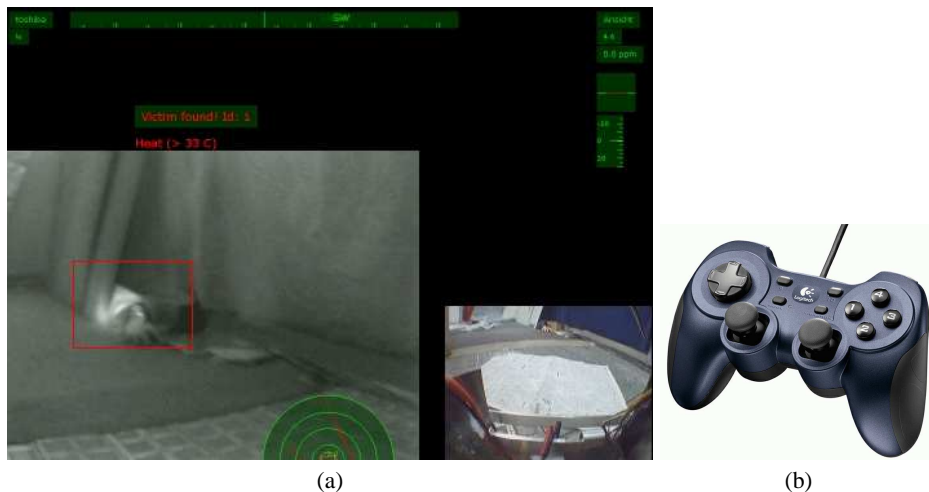
## 4 Communications

Autonomous as well as teleoperated vehicles are communicating via wireless LAN. We use a D-Link DI-774 access point, which is capable of operating in the  $5GHz$  as well as in the  $2.4GHz$  band. All communication is based on the Inter Process Communication (IPC) framework, which has been developed by Reid Simmons [8]. The simultaneous transmission of multiple digital video streams is carried out by an error-tolerant protocol which we developed based on the IPC framework.

## 5 Control Method and Human-Robot Interface

### 5.1 Teleoperation

We have developed a Graphical User Interface (GUI), which can be used to control multiple robots at the same time (see Figure 1(a)). The GUI is realized by a similar approach



**Fig. 1.** (a) A graphical user interface for controlling and monitoring robots. (b) Joypad for operator control.

as proposed by the RoBrno team at RoboCup 2003[13]. Images from video cameras are shown in full size on the screen, and additional sensor information is overlaid via a Head Up Display (HUD). The operator might change the kind of information and the transparency (alpha value) of the displayed information via the joypad. Our system is capable of generating a 2D map of the environment autonomously during the teleoperation of the operator. Within this map, victim locations and other points of interest can be marked.

Operator control is carried out with a joypad, which is connected to a portable Laptop (see figure 1(b)). Besides images from the thermo camera and video camera mounted on the robot, the operator receives readings from other sensors, such as range readings from the LRF, compass measurements, and the battery state of the robot. Data from the LRF is used to simplify the operator's task of avoiding obstacles.

## 5.2 Autonomous Control

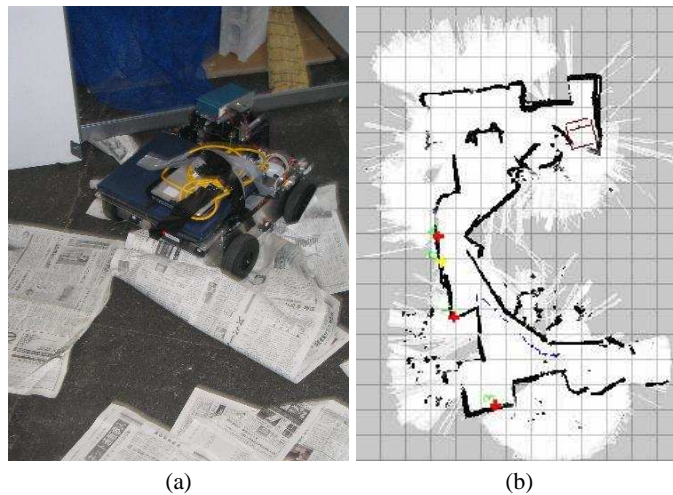
During RoboCup 2005, our robots were capable of reliable autonomous control, even within the harsh conditions of the finals (we are actually thankful for them). However, this control was limited to operation within “yellow arena like” structure. Complex obstacles such as stairs, ramps, and stepfields were not explicitly recognized and also not overcome by the robots.

Our current work focuses on the development of autonomous 3D control. We are confident that our current research on methods for detecting 3D structures, visual odometry, and behavior learning will help us to get closer towards this goal.

## 6 Map generation/printing

### 6.1 Simultaneous Localization And Mapping (SLAM)

Our team performed SLAM successfully during the final of the *Best in Class autonomy* competition at RoboCup 2005 in Osaka. The map shown in figure 2 (b) was autonomously generated by the system, i.e. directly printed out after the mission without any manual adjustment of the operator. Our overall system for SLAM is based on



**Fig. 2.** 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.

three levels, which are: *Slippage-sensitive odometry*, *Scanmatching*, and *RFID-based localization*.

When the robot operates on varying ground, for example, concrete or steel, sporadically covered with newspapers and cardboard (see Figure 2 (a)), or when 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. It turned out that a significant difference between two wheels on the same side (either left or right) indicates slippage of the wheels. We utilize this information for improving the robot’s localization.

Additionally, the robot’s pose is estimated by an incremental scan matching technique [4]. The technique determines from a sequence of 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 by estimating the new pose  $k_t$  of the robot by maximizing the likelihood of the scan alignment of the scan  $o_t$  at pose  $k_t$ . We fuse this estimate with the odometry estimate by a Kalman filter.

We tackle the “Closing The Loop” problem by actively distributing unique RFID tags in the environment, i.e. placing them automatically on the ground, and by utilizing the tag correspondences found on the robot’s trajectory for calculating globally consistent maps after the method introduced by Lu and Milios [6]. Suppose that the robot distributed  $n$  RFID tags at unknown locations  $l_0, l_1, \dots, l_n$ , with  $l_i = (x, y)$  and keeps track of all measured distances  $\hat{d}_{ij} = (\Delta x_{ij}, \Delta y_{ij})$  with corresponding covariance matrix  $\Sigma_{ij}$ , where  $d_{ij} = l_i - l_j$ , in database  $R$ . Our goal is now to estimate locations  $l_i$  of the tags that best explain the measured distances  $d_{ij}$  and covariances  $\Sigma_{ij}$ . This can be achieved after the maximum likelihood concept by minimizing the following Mahalanobis-distance:

$$W = \sum_{ij \in R} \left( l_i - l_j - \hat{d}_{ij} \right)^T \Sigma_{ij}^{-1} \left( l_i - l_j - \hat{d}_{ij} \right) \quad (1)$$

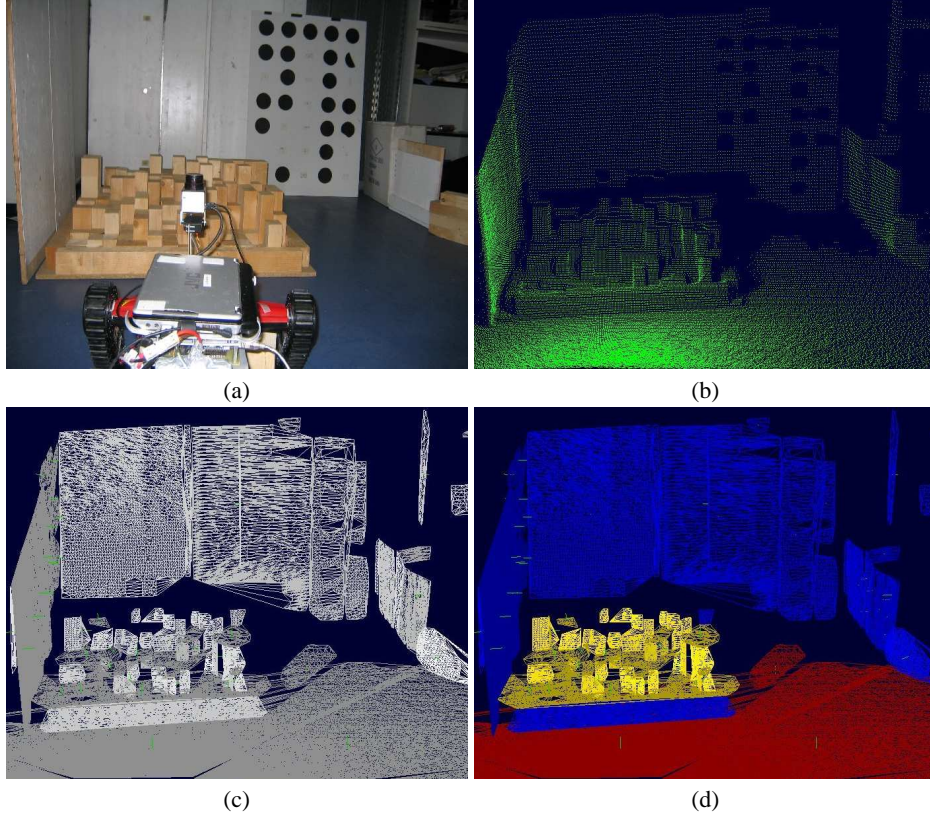
Note that since we assume the robot’s orientation to be measured by the IMU (whose error does not accumulate), we do not consider the robot’s orientation in Equation 1, hence the optimization problem can be solved linearly. It can easily be shown that the optimization problem in Equation 1 can be solved as long as the covariances  $\Sigma_{ij}$  are invertible [6]. For distributing the tags in the environment, we constructed a special aperture which is further described in Section 10.

The motivation for the introduced method is not restricted to the RoboCupRescue competition. We believe that the distribution of RFID tags in the environment can also be very valuable to human task forces equipped with a RFID reader. From recognized RFID tags, the system is able to generate a metric or topological map, which can be passed to a human operator. The topological map consists of RFID tags as vertices and navigation directions and lengths as edges. The map can be augmented with structural and victim specific information. Human task forces that are also equipped with a RFID tag reader might find the locations of victims more efficient than directly from a 2D/3D map, since RFID tags can be used as signposts.

## 6.2 Detection of 3D Structure

To extract information about objects from our 3D scans, we use an approach which is based on Markov Random Fields (MRFs). In the context of RoboCup Rescue, these objects may be stepfields, stairs, and ramps. Information about the objects surrounding

the robot is important for autonomous operation and might also be useful for teleoperation, e.g. adding this information to a map to simplify the teleoperation of a rescue robot. To achieve this, we extract various features out of the raw point cloud, e.g. planes and their normals. Our framework uses a pairwise MRF over discrete variables



**Fig. 3.** Detection of relevant 3D structures. (a) Robot takes 3D scan in front of a stepfield. (b) The generated 3D point cloud. (c) Planes extracted from the scan. (d) Automatic classification into walls (blue), floor (red), and stepfield (yellow).

$Y = \{Y_1, \dots, Y_N\}$ , where  $Y_i \in \{1, \dots, K\}$  represents the class label of a 3D scan element.  $y$  denotes an assignment of the values to  $Y$ . The underlying structure to represent the joint distribution is an undirected graph  $(\mathcal{V}, \mathcal{E})$  in which each node stands for one variable and has an associated potential  $\phi_i(Y_i)$ . Furthermore, each edge is associated with the potential  $\phi_{ij}(Y_i, Y_j)$ ,  $ij \in \mathcal{E}$ . The potentials specify a non-negative number for each possible value of the variable  $Y_i$  and for each possible pair of values of  $Y_i, Y_j$  respectively.

The random field specifies the following joint distribution

$$P_\phi(y) = \frac{1}{Z} \prod_{i=1}^N \phi_i(y_i) \prod_{ij \in \mathcal{E}} \phi_{ij}(y_i, y_j) \quad (2)$$



where  $Z$  is given by  $Z = \sum_{y'} \prod_{i=1}^N \phi_i(y'_i) \prod_{ij \in \mathcal{E}} \phi_{ij}(y'_i, y'_j)$ .

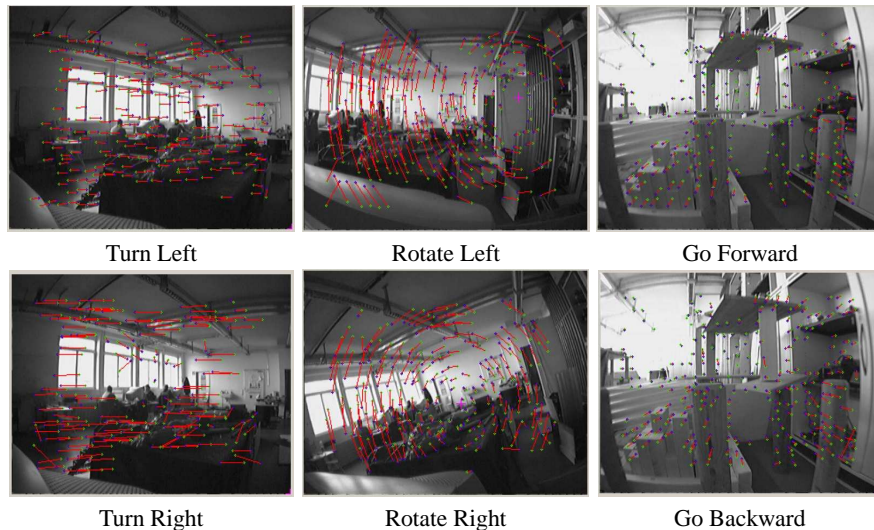
Classifying the objects in the 3D scan is done by solving the maximum a-posteriori (MAP) inference problem in a MRF, which is to find  $\arg \max_y P_\phi(y)$ . A preliminary result of the successful segmentation of a 3D scan is shown in Figure 3.

## 7 Sensors for Navigation and Localization

### 7.1 Visual Odometry for Mapping with Autonomous Tracked Vehicles

A robot that traverses three-dimensional terrain has to cope with the difficulty of gaining a meaningful odometric measurement for self-localization. Classical approaches such as using wheel (or track) encoders can be misleading because it is very likely that the robot will get in a situation, e.g. stairs or a steep ramp, where the tracks are moving forward but the robot is not moving at all. Thus we chose to use visual odometry to get a movement estimation that relates to the robot's movement relative to the environment. The system works in two steps: First, features between two images are selected and tracked; as a second step, these trackings are classified as a certain type of movement.

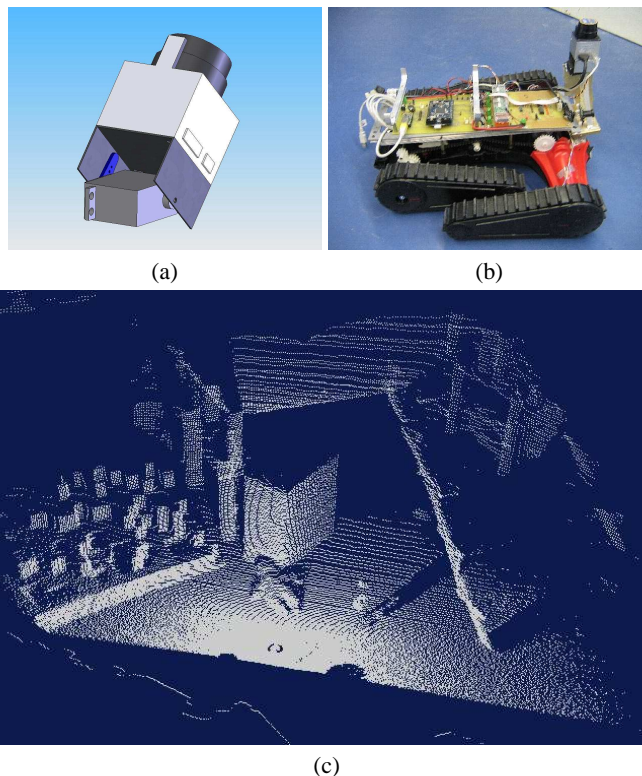
For tracking we use a KLT tracker [7,9], which has been implemented by Stan Birchfeld [2]. Tracked features between two images are represented as a vector  $(x, y, l, a)^T$  where  $x, y$  describe the position in the image and  $l, a$  describe the length and angle of the tracked feature. Based on these features, the probability  $P(class|feature)$  is learned by labeled data. As a representation for the learning, we use Tile Coding with the weights representing the probabilities, using the update formula  $w_{i+1} = w_i + \frac{1}{m}(p_{i+1} - w_i)$  where  $w_i$  is the weight after the  $i$ th update step,  $p_{i+1}$  is the probability that the feature was labeled with in step  $i + 1$ , and  $m$  is the number of updates that already occurred on this feature.



**Fig. 4.** Visual Odometry: Features detected in images indicate the movement of the robot.

## 7.2 Small and Light-Weight 3D Sensor

In Rescue Robotics, the environment that is relevant to the task is three-dimensional and thus requires highly developed sensors for navigation. Hence our team developed a light-weight 3D Laser Range Finder (LRF) device for structure detection and mapping in the rescue arena. A picture of the sensor can be seen in Figure 5. The LRF sensor is rotated by a strong servo that allows fast and accurate vertical positioning of the device. As can be seen from Figure 5, the device can be rotated by more than 180 degrees, which suffices to generate 3D scans from objects, such as stairs, ramps, and stepfields. Our design differs from the design of other 3D scanners in that it can be implemented by a simple “U-shaped” piece of metal and a servo, which altogether can be produced for approximately 100 USD.



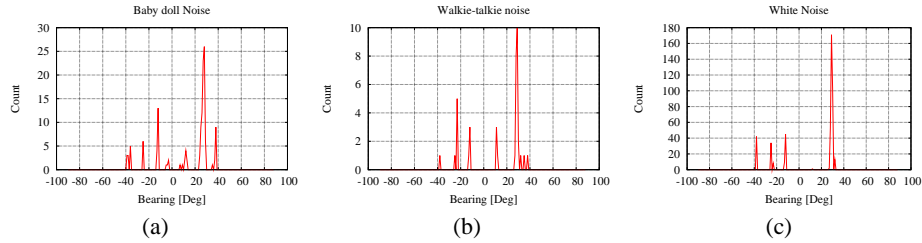
**Fig. 5.** A hand-crafted light-weight 3D Laser Range Finder (LRF) device. (a) A model of the 3D LRF. (b) Mounted on the robot. (c) 3D scan taken in front of stepfield and baby doll.

## 8 Sensors for Victim Identification

### 8.1 Victim Detection from Audio

We perform audio-based victim detection by positioning two microphones with known distance. Given an audio source left, right or between both microphones, we are measuring the time difference, i.e. phase shift, between both signals. This is carried out by





**Fig. 6.** Sound source detection by the Crosspower Spectrum Phase (CSP) approach of different sound sources, which all are located at bearing +30 degree. (a) Sporadic noise from a baby doll, e.g. scream or saying “Mama”. (b) Sporadic noise from a walkie-talkie, e.g. alert noise. (c) Continuous white noise.

the Crosspower Spectrum Phase (CSP) approach, which allows to calculate the phase shift of both signals based on the Fourier transformation [3]. As shown in Figure 6, the bearing of the sound source can be successfully determined, even for different kinds of noise.

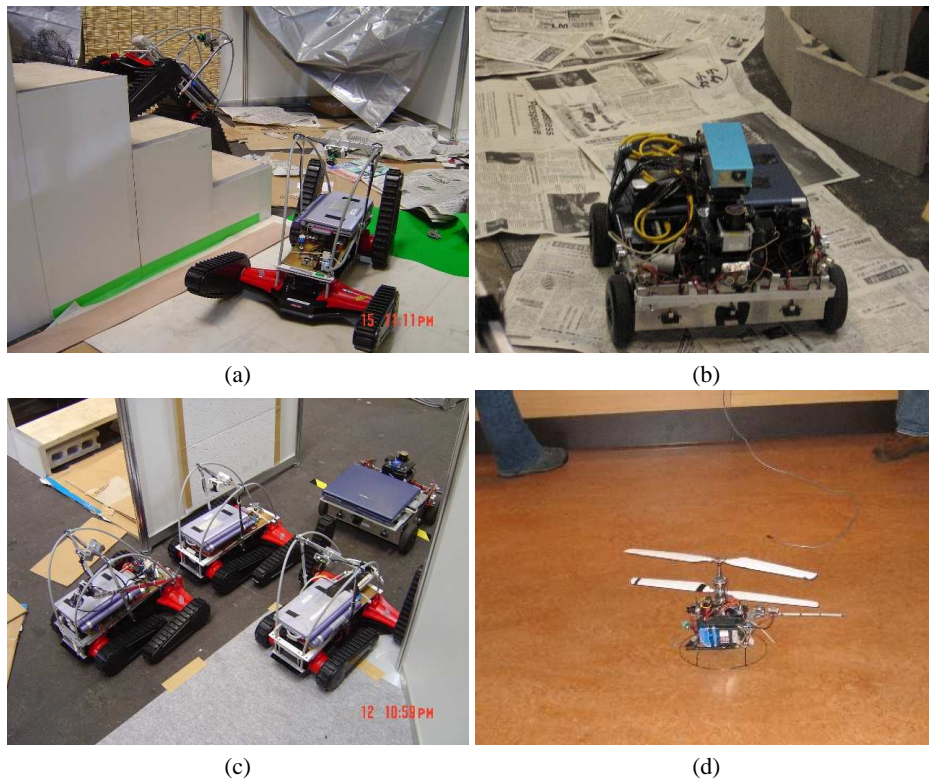
## 8.2 Victim Detection from Video

Besides color thresholding (or heat thresholding on thermo images), we implemented methods for motion and face detection, respectively. We utilized a fast approach for detecting motion within video streams which is based on the analysis of differences between subsequent images. After filtering out the difference information, a clustering that is used for estimating the probability of human motion is calculated. Furthermore, we utilize face detection by the approach introduced by Viola and colleagues [10].

## 9 Robot Locomotion

Locomotion is carried out based on two different ground-based robot platforms and one aerial vehicle. In figure 7 robots of our team are shown. Figure 7(a) shows the *Lurker* robot, which is based on the *Tarantula* R/C toy. Although based on a toy, this robot is capable of climbing obstacles, such as stairs, ramps, and stepfields. Figure 7(b) shows a fast and agile robot that is used for the autonomous team exploration of a large area, and Figure 7(c) shows the *linkMAV*, a micro aerial vehicle platform that has been developed by the Autonomous Unmanned Aerial Vehicle Technologies Lab (AUTTECH) at the Department of Computer and Information Sciences, Linköping University, Sweden.

The LinkMAV is a dual coaxial rotor platform. This configuration increases energy efficiency as compared to a traditional helicopter design. It is powered by two brushless electrical motors. The LinkMAV weighs 495 grams and has a maximum dimension of 49 cm (rotors diameter). The endurance ranges between 14 and 30 minutes, depending on the battery / payload configuration. As standard payload, it is equipped with a high-resolution micro board color CCD camera which is connected to an analog video transmitter. The LinkMAV can be operated in 3 modes: Back-up mode, Manual Ordinary (MO) mode and Autonomous mode. The operator can switch to and from any of the modes during flight. The Autonomous mode is used for following waypoints based on a GPS signal. Current activities include extending navigation capabilities for indoor



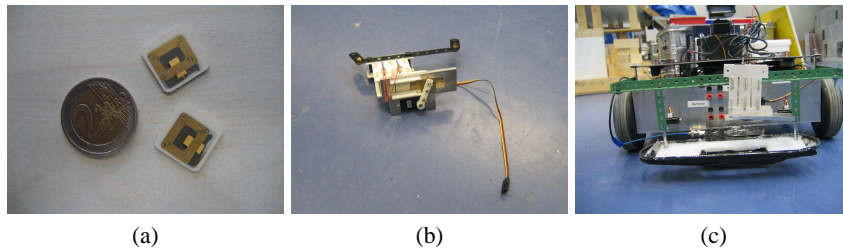
**Fig. 7.** Robots built by our team. (a) The *Lurker* robot and (b) the *Zerg* robot during the RoboCup competition in Osaka. (c) The team of robots waiting for the mission start and (d) the linkMAV, a micro aerial vehicle from AUTTECH. Pictures (a) and (c) were taken by Adam Jacoff.

environments using vision. The LinkMAV has been awarded with the *Best Rotary Wing MAV* prize at the 1st US- European MAV Competition, held in Garmisch Partenkirchen, Germany, Sept, 2005. Have a look to our homepage for a video that demonstrates the safe flight behavior of the robot [1].

## 10 Other Mechanisms

Figure 8(b) shows the prototype of a novel mechanism for the active distribution of RFID tags. The mechanism can easily be mounted on a robot or a R/C car and is automatically triggered when the robot navigates through narrow passages.

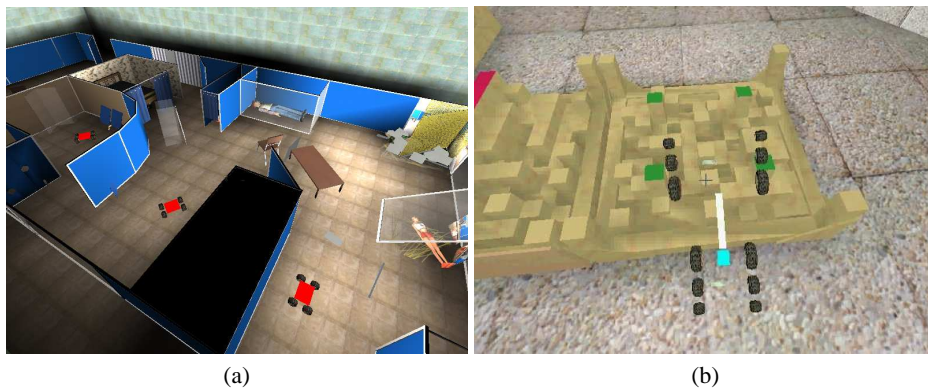
The mechanism consists of a magazine containing up to 80 RFID tags which can be released by a servo. Due to a special construction it is guaranteed that for each trigger signal, only one tag will be released. Furthermore, the robot detects if a tag has been released successfully by the antenna mounted around the mechanism. Since the tags are transported out of the range of the antenna, they are only detectable after being released. Figure 8 (c) shows the complete construction mounted on a robot, and Figure 8(a) shows the  $1.3\text{cm} \times 1.3\text{cm}$  small RFID chips, which we utilized for our application. Tags once deployed by robots can easily be collected with a vacuum cleaner.



**Fig. 8.** A novel mechanism for the active distribution of RFID tags. (a) The utilized RFID tags. (b) The mechanism with servo. (c) The mechanism, together with an antenna, mounted on a *Zerg* robot.

## 11 Team Training for Operation (Human Factors)

For the development of autonomous robots a sufficiently accurate physics simulation is absolutely necessary. Therefore, we utilized the USARSim simulation system [11], which is based on the *Unreal2004* game engine (see figure 9) for simulating and developing the autonomous behavior of our robots. The simulation of the robots is crucial in order to speed-up the development of multi-agent behavior as well as to provide data for learning approaches. Figure 9 shows the two models of our robots simulated in USARSim.



**Fig. 9.** Robot simulation with USARSim, based on the Unreal2003 game engine. (a) Simulating the *Zerg* unit. (b) Simulating the *Lurker* unit.

## 12 Possibilities for Practical Application to Real Disaster Site

Our team had no direct experience with any practical application in the context of real disaster response. However, we are confident that some of the techniques utilized by our team are very useful in the context of USAR.

Our approach of autonomous exploration with RFID tags might be very helpful in case the disaster site is large and partially blocked with rubble, such as the yellow arena. The idea of labeling locations with information that is important to the rescue task has

already be 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. Our autonomous RFID-based marking of locations is a straight forward extension of this concept.

Another advantage of our approach, i.e. an increase of the likelihood that it might be deployed, is that our robots are comparably cheap, due to a toy-based or homemade platform. We believe that Rescue Robotics can only win recognition if the equipment is cheap and can also be afforded by institutions with low budget.

### 13 System Cost

Generally, our philosophy is to provide solutions that are both good and cheap at the same time. Hence some of our robots are based on toys, i.e. R/C cars that can be bought for less than 100 USD. The following tables list the approximate costs of each robot type.

Name	Part	Price in USD	Number	Price Total in USD
Robot Base	Handmade	500	1	500
Micro Controller	MC9S12DG256	120	1	120
IR Sensor	GP2D12	12	9	108
Sonic Sensor	SRF08	53	3	159
Compass Sensor	CMPS03	50	1	50
Flex Sensor	FLEXS	18	2	36
Pyroelectric Sensor	R3-PYRO01	60	1	60
Odometry Sensor	R238-WW01-KIT	60	1	60
Acceleration Sensor	ADXL202	100	1	100
WLAN Adapter	ADL-AG650	70	1	70
USB Camera	Logitech Quickcam 4000	50	1	50
IMU	InertiaCube	1500	1	1500
RFID Reader	Medio S002	370	1	370
Laser Range Finder	Hokuyu URG-04LX	1600	1	1600
Thermo Camera	Thermal Eye	5000	1	5000
Laptop	JVC MP-XP731DE	1500	1	1500
Sum Total:				11283

Table 1. Costs for the *Zerg* robot.

Name	Part	Price in USD	Number	Price Total in USD
Robot Base	Tarantula	100	1	100
USB Camera	Logitech Quickcam 4k	50	2	100
Laptop	Sony Vaio PCG-C1VE	1000	1	1000
IMU	InertiaCube	1500	1	1500
Micro Controller	MC9S12DG256	120	1	120
WLAN Adapter	ADL-AG650	70	1	70
Laser Range Finder	Hokuyu URG-04LX	1600	1	1600
Sum Total:			3	4490

Table 2. Costs for the *Lurker* robot.

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