Terrain Classification for Autonomous Robot Mobility: from Safety, Security Rescue Robotics to Planetary Exploration

Andreas Birk, Todor Stoyanov, Yashodhan Nevatia, Rares Ambrus, Jann Poppinga, and Kaustubh Pathak

Abstract— **Mobile robots are increasingly used in unstructured domains without permanent supervision by a human operator. One example is Safety, Security and Rescue Robotics (SSRR) where human operators are a scarce resource. There are additional motivations in this domain to increase robot autonomy, e.g., the desire to decrease the cognitive load on the operator or to allow robot operations when communication to a operator's station fails. Planetary exploration has in this respect much in common with SSRR. Namely, it takes place in unstructured environments and it requires high amounts of autonomy due to the significant delay in communication. Here we present efforts to carry over results from research within SSRR, especially work on terrain classification for autonomous mobility, to planetary exploration. The simple yet efficient approach to terrain classification is based on the Hough transform of planes. The idea is to design a parameter space such that drivable surfaces lead to a strong single response, whereas non-drivable ones lead to data-points spread over the parameter space. The distinction between negotiable and non-negotiable as well as other terrain type is then done by a decision tree. The algorithm is applied in the SSRR domain to 3D data obtained from two different sensors, namely, a near infra-red time of flight camera and a stereo camera. Experimental results are presented for typical indoor as well as outdoor terrains, demonstrating robust realtime detection of drivable ground. The work is then carried over to the planetary exploration domain by using data from the Mars Exploration Rover Mission (MER).**

I. INTRODUCTION

Autonomous behaviors are important for robots for planetary exploration even if a strong human-in-the-loop component is involved [1]. An accordingly important topic in the space robotics community is terrain classification to detect drivable ground [2], [3], [4], [5], [6]. Here we present an extension of work described in detail in [7], which deals with a very fast but nevertheless quite robust detection of drivable ground. The approach is based on range data from a 3D sensor like a time-of-flight Swissranger, respectively a stereo camera. The main idea is to process the range data by a Hough transform with a three dimensional parameter space for representing planes. The discretized parameter space is chosen such that its bins correspond to planes that can be negotiated by the robot. A clear maximum in parameter space hence indicates safe driving. Data points that are spread in parameter space correspond to non-drivable ground. In addition to this basic distinction, a more fine grain classification of terrain types is in principle possible with the approach. An autonomous robot can use this information for example to annotate its map with way points or to compute a risk assessment of a possible path.

The authors are with the Dept. of Electrical Engineering and Computer Science, Jacobs University Bremen, 28751 Bremen, Germany. a.birk@jacobs-university.de

Extensive experiments with different prototypical indoor and outdoor ground types have been carried out. Several datasets were gathered indoor and outdoor under very varying conditions and about 6,800 snapshots of range data were processed in total. It is shown that drivability can be robustly detected with success rates ranging between 83% and 100% for the Swissranger and between 98% and 100% for the stereo camera. The complete processing time for classifying one range snapshot is in the order of 5 to 50 msec. The detection of safe ground can hence be done in realtime on the moving robot, allowing using the approach for reactive motion control as well as mapping in unstructured environments. In addition to the extensive experiments done in various indoor and outdoor settings [7], we show here that the approach is very suited to deal with environments, which are cluttered with rocks in different sizes and densities much like on Mars or Moon.

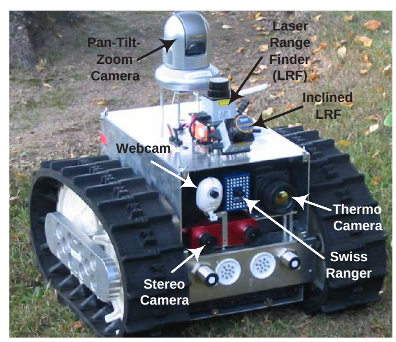


Fig. 1. The autonomous version of a *Rugbot* with some important onboard sensors pointed out. The Swissranger SR-3000 and the stereo camera deliver the 3D data for the terrain classification.

Fig. 2. Two Rugbots at the Space Demo at RoboCup 2007 in Atlanta.

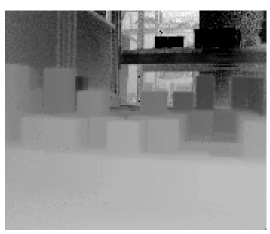
Our first interest in the problem was motivated by work on intelligent behaviors up to full autonomy on a line of Safety, Security, and Rescue robots developed in the Robotics

Laboratory of Jacobs University Bremen since 2001 [8], [9], [10], [11], [12], [13], [14], [15], [16]. The latest type of robots from Jacobs University are the so-called Rugbots, short for "rugged robot" [17]. A picture of this type of robot with important sensor highlighted is shown in figure 1. These robots have been tested on various occasions including a field test demo dealing with a hazardous material road accident, the European Land Robotics Trials (ELROB) and several RoboCup Rescue competitions (figure 3). The safety, security, and rescue robotics (SSRR) domain has many aspects in common with planetary exploration, especially the challenge to enable intelligent up to fully autonomous behaviors of mobile robots in highly unstructured environments. We hence started to participate in space robotics evaluations including the first RoboCup@Space demo in Atlanta 2007 (figure 2).

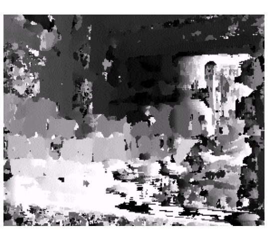
II. The Approach

The terrain classification is based on the following idea. Range images, here from simple 3D sensors in the form of an optical time-of-flight camera and a stereo camera, are processed with a Hough transform. Concretely, a discretized parameter space for planes is used. The parameter space is designed such that each drivable surface leads to a single maximum, whereas non-drivable terrain leads to data-points spread over the space. The actual classification is done by a decision tree on the binned data (see algorithm 1). In addition to binary distinctions with respect to driveability, more fine grain classifications of the distributions are possible allowing to recognize different categories like plain floor, ramp, rubble, obstacle, and so on in SSRR domains, respectively flat ground, small rocks, large rocks, and so on in planetary exploration scenarios. This transform can be computed very efficiently and allows a robust classification in real-time.

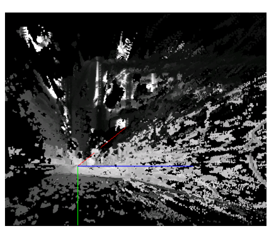
(a) Normal image



(b) Swissranger distance image



(c) Stereo disparity



(d) Stereo point cloud

Fig. 4. Examples of sensor data.

Classical obstacle and free space detection for mobile robots is based on two-dimensional range sensors like laser scanners. This is feasible as long as the robot operates in simple environments mainly consisting of flat floors and

TABLE I

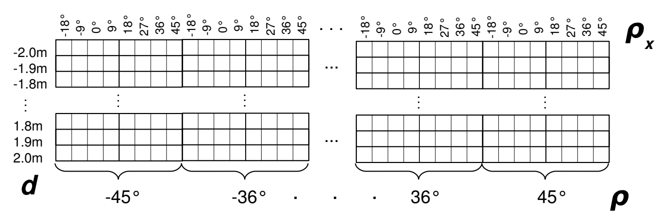
The seven datasets used for the experiments presented in [7] and the additional eighth one with planetary data from the Opportunity mission.

dataset	description	snap-shots	aver.# points
stereo			
set_1	inside, rescue arena	408	5058
set_2	outside, university campus	318	71744
set_3	outside, university campus	414	39762
TOF			
set_4	inside, rescue arena	449	23515
set_5	outside, university campus	470	16725
set_6	outside, university campus	203	25171
set_7	outside, university campus	5461	24790
MARS			
set_8	planetary, sand & rocks	500	7200

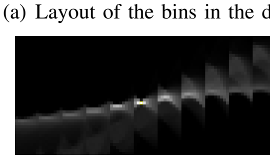
TABLE II

Success rates and computation times for drivability detection

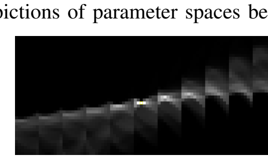
dataset	success rate	false negative	false positive	time (msec)
stereo				
set_1	1.00	0.00	0.00	4
set_2	0.99	0.00	0.01	53
set_3	0.98	0.02	0.01	29
TOF				
set_4	0.83	0.17	0.00	11
set_5	1.00	0.00	0.00	8
set_6	1.00	0.00	0.00	12
set_7	0.83	0.03	0.14	12
MARS				
set_8	0.992	0.006	0.002	5



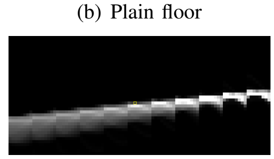
(a) Layout of the bins in the depictions of parameter spaces below



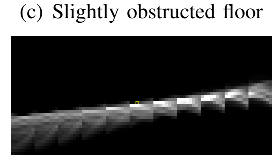
(b) Plain floor



(c) Slightly obstructed floor



(d) Ramp



(e) Random step field

Fig. 5. Two-dimensional depictions of the three dimensional parameter space for several example snapshots. Distances are on the y-axis, angles are on the x-axis, where ρ_y iterates just once and ρ_x iterates repeatedly. Hits in the bins are represented by grayscale, the darker the less hits.

Fig. 3. Left: A Jacobs robot at the Rescue Robot Fieldtest 2006 in Bremen, Germany. The robot supports a firebrigade in the situation assessment in a hazmat rescue drill. Center: A Jacobs land robot cooperating with an arial robot at the European Land Robotics Trials (ELROB) 2007 in Monte Ceneri, Switzerland. The aerial robot has to search for hazard areas like seats of fire in a forest, which the land robot then has to reach. Right: Two Jacobs robots support first responders at ELROB in the situation assessment after a simulated terrorist attack with NBC substances. The two robots are supervised by only a single operator. The robots can operate fully autonomously and they coordinate their joined exploration of the area.

TABLE III
SPECIFICATION OF THE TWO 3D SENSORS

	Swissranger	**Stereo Camera**
Manufacturer	CSEM	Videre Design
Model	SR-3000	Stereo-on-Chip (STOC)
Principle	Time of Flight (TOF)	Stereo images' disparity
Range	$600 - 7500$ mm	$686 - \infty$ mm
Horiz. Field of View	47^o	65.5^o
Vert. Field of View	39^o	51.5^o
Resolution	176×144	640×480

plain walls. The generation of complete 3D environment models is the other extreme, which requires significant processing power as well as high quality sensors. Furthermore, 3D mapping is still in its infancy and it is non-trivial to use the data for path planning. The approach presented here lies in the middle of the two extremes. A single 3D range snapshot is processed to classify the terrain, especially with respect to drivability. This information can be used in various standard ways like reactive obstacle avoidance as well as 2D map building. The approach is very fast and it is an excellent candidate for replacing standard 2D approaches to sensor processing for obstacle avoidance and occupancy grid mapping in non-trivial environments. More details about the implementation of the approach in general can be found in [7].

III. EXPERIMENTS AND RESULTS

A Swissranger SR-3000 time-of-flight range camera [18][19] and a Videre STOC stereo camera [20][21] are used for 3D ground classification. Their locations on the robot are indicated in figure 1. Both sensors allow update rates of around 30 Hz. The most important feature of this fast data acquisition is that robot motion does not influence it. It does not matter for the classification whether the robot is driving or not.

The technical details of the sensors are summarized in Table III. Figure 4 shows typical outputs. Their relative accuracy is compared in figure 6. As mentioned before, the advantage of fast update rates is bought at the cost of rather high noise rates. Nevertheless, robust classification is possible as shown later on.

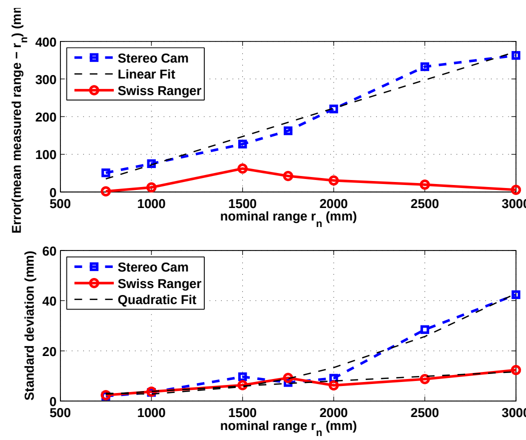


Fig. 6. Comparing the mean error and the standard deviation of the Swissranger versus the stereo camera. The standard deviation increases as the square of the range [21] for both sensors. The stereo camera is in general less accurate and also has a systematic error in the mean error which is linear with respect to the range.

In figure 5, there are 2D histograms depicting the bins of the parameter space for three more or less typical snapshots. The origin of the histogram is in the top left corner, the down-pointing axis contains the distances, the right-pointing axis contains both ρ_x and ρ_y. This is accomplished by first fixing ρ_y and iterating ρ_x, then increasing ρ_y and iterating ρ_x again and so on. This is depicted graphically in sub-figure 5(a). The bin which corresponds to the floor is indicated by a little frame. The magnitude of the bins is represented by shade, where white corresponds to all magnitudes above the threshold $t_m = 2/3$, which is used in the decision tree classification. All the other shades are scaled uniformly and thus the different histograms are better comparable in contrast to a scheme where just the top bin is white.

The approach was tested with extensive test runs in complex indoor and outdoor settings as described in [7]. The results of the test-runs include about 6,800 snapshots of range data. As shown in table II, the approach can robustly detect drivable ground in a very fast manner. The success rates

Algorithm 1 The classification algorithm: it uses three simple criteria organized in a decision tree like manner. $\#S$ is the cardinality of S, bin^{max} is the bin with most hits. The algorithm returns after the first assignment to class.

if $\#\text{bin}_{\text{floor}} > t_h \cdot \#\text{PC}$ **then**
  class $\longleftarrow$ floor
else
  if $(\#\{\text{bin} \mid \#\text{bin} > t_m \cdot \#\text{bin}^{\text{max}}\} < t_n)$ **and** $(\#\text{bin}^{\text{max}} > t_p \cdot \#PC)$ **then**
    class $\longleftarrow$ type($\text{bin}_{\text{max}}) \in \{\text{floor}, \text{plateau}, \text{canyon}, \text{ramp}\}$
  else
    class $\longleftarrow$ obstacle
  end if
end if

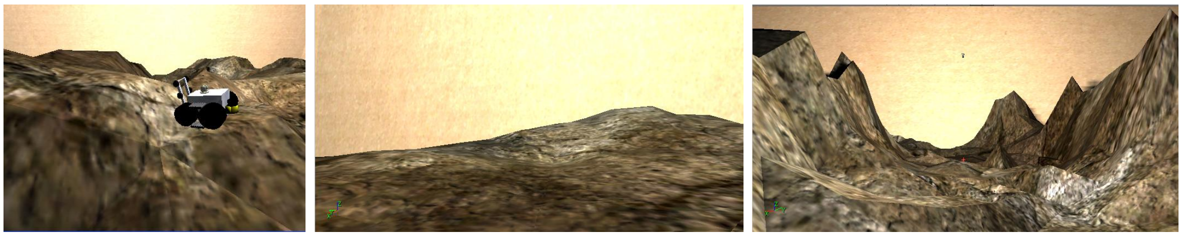


Fig. 8. A Jacobs Rugbot in the RoboCup Virtual Simulator (left), exploring its environment on different planetary surface types (center and right).

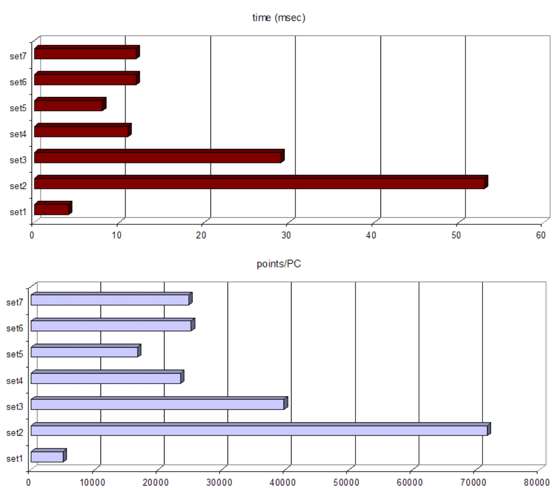


Fig. 7. The average time per classification directly depends on the average number of 3D points per snapshot in each dataset.

Fig. 9. A Rugbot on Mars in the vicinity of the Endurance crater; the environment is modeled based on original data from the opportunity mission.

range between 83% and 100%. The stereo camera has the drawback that it does not deliver data in featureless environments, but it allows an almost perfect classification ranging between 98% and 100%. The Swissranger behaves poorly in strongly sunlit situations. In these cases, the snapshot is significantly distorted but not automatically recognizable as such. According situations occurred during the recording of the outdoor data of set_4 and set_7 causing the lower success rates for the Swissranger in these two cases. The two sensors can hence supplement each other very well. The processing can be done very fast, namely in the order of 5 to 50 msec.

This work was now supplemented with an additional dataset, which included a typical planetary scenario, namely the terrain of the Eagle crater on Mars (dataset #8). The underlying environment model (figure 8) is based on ground truth data from the Mars Exploration Rover (MER) mission data archives [22]. Like in the SSRR experiments, the range snapshots derived from the MER data where first classified by hand as a comparison basis. The overall data of the Eagle crater consists of an elevation map with 2700 by 2700 data points with 0.01 m resolution. The 500 range snapshots extracted from the data are 90x80 pixels each. Also in this case, the approach performed very fast and robust (table II).

This work on terrain classification for planetary exploration by autonomous robots can be carried out in USARsim, a high fidelity mobile robot simulator first developed for SSRR [**?**], [**?**], by importing the ground truth MARS data from the MER missions. The simulator provides validated robot and sensor models, hence it allows realistic experiments. An other significant advantage over real world experiments is that it allows a systematic generation of environment types (figure 8). This allows for example to generate different terrains with sandy ground and rocks of different sizes distributed in different densities in a controlled manner. Therefore, it allows experiments without the tedious hand labeling of real world data as a comparison basis for assessing the robustness of the algorithm.

IV. Conclusion

A simple but fast and robust approach to classify terrain for mobility is presented. It uses range data from a 3D sensor like a time-of-flight Swissranger, respectively a stereo camera. The range data is processed by a Hough transform with a three dimensional parameter space for representing planes. The discretized parameter space is chosen such that its bins correspond to planes that can be negotiated by the robot. A clear maximum in parameter space hence indicates safe driving. Data points that are spread in parameter space correspond to non-drivable ground. The actual classification is done by a decision tree on the binned data. This also allows a more fine grain classification in addition to the basic distinction of negotiable and non-negotiable terrain. An autonomous robot can use this information for example to annotate its map with way points or to compute a risk assessment of a possible path. Extensive experiments with different prototypical indoor and outdoor ground from the Safety, Security and Rescue (SSRR) domain have been carried out previously [7]. Here we show that the work can extend to planetary exploration as application domain. For this purpose, experiments with ground truth data from the Mars Exploration Rover (MER) mission were carried out.

Acknowledgments

The authors gratefully acknowledge the financial support of *Deutsche Forschungsgemeinschaft* (DFG).

Please note the name-change of our institution. The Swiss Jacobs Foundation invests 200 Million Euro in **International University Bremen (IUB)** over a five-year period starting from 2007. To date this is the largest donation ever given in Europe by a private foundation to a science institution. In appreciation of the benefactors and to further promote the university's unique profile in higher education and research, the boards of IUB have decided to change the university's name to **Jacobs University Bremen**. Hence the two different names and abbreviations for the same institution may be found in this paper, especially in the references to previously published material.

References

[1] P. G. Backes, J. S. Norris, M. W. Powell, M. A. Vona, R. Steinke, and J. Wick, "The science activity planner for the mars exploration rover mission: Fido field test results," in *Proceedings of the IEEE Aerospace Conference*, Big Sky, MT, USA, 2003.

[2] K. Iagnemma, C. Brooks, and S. Dubowsky, "Visual, tactile, and vibration-based terrain analysis for planetary rovers," in *IEEE Aerospace Conference*, vol. 2, 2004, pp. 841–848 Vol.2.

[3] K. Iagnemma, H. Shibly, and S. Dubowsky, "On-line terrain parameter estimation for planetary rovers," in *IEEE International Conference on Robotics and Automation (ICRA)*, vol. 3, 2002, pp. 3142–3147.

[4] S. Lacroix, A. Mallet, D. Bonnafous, G. Bauzil, S. Fleury, M. Herrb, and R. Chatila, "Autonomous rover navigation on unknown terrains: Functions and integration," *International Journal of Robotics Research*, vol. 21, no. 10-11, pp. 917–942, 2002.

[5] ——, "Autonomous rover navigation on unknown terrains functions and integration," in *Experimental Robotics Vii*, ser. Lecture Notes in Control and Information Sciences, 2001, vol. 271, pp. 501–510.

[6] D. B. Gennery, "Traversability analysis and path planning for a planetary rover," *Autonomous Robots*, vol. 6, no. 2, pp. 131–146, 1999.

[7] J. Poppinga, A. Birk, and K. Pathak, "Hough based terrain classification for realtime detection of drivable ground," *Journal of Field Robotics*, 2007.

[8] A. Birk and S. Carpin, "Rescue robotics - a crucial milestone on the road to autonomous systems," *Advanced Robotics Journal*, vol. 20, no. 5, pp. 595–695, 2006.

[9] W. Chonnaparamutt and A. Birk, "A fuzzy controller for autonomous negotiation of stairs by a mobile robot with adjustable tracks," in *RoboCup 2007: Robot WorldCup XI*, ser. Lecture Notes in Artificial Intelligence (LNAI), U. Visser, F. Ribeiro, T. Ohashi, and F. Dellaert, Eds. Springer, 2008.

[10] M. N. Rooker and A. Birk, "Multi-robot exploration under the constraints of wireless networking," *Control Engineering Practice*, vol. 15, no. 4, pp. 435–445, 2007.

[11] K. Pathak, A. Birk, S. Schwertfeger, I. Delchev, and S. Markov, "Fully autonomous operations of a jacobs rugbot in the robocup rescue robot league 2006," in *International Workshop on Safety, Security, and Rescue Robotics (SSRR)*. IEEE Press, 2007.

[12] A. Birk and S. Carpin, "Merging occupancy grid maps from multiple robots," *IEEE Proceedings, special issue on Multi-Robot Systems*, vol. 94, no. 7, pp. 1384–1397, 2006.

[13] A. Birk, S. Carpin, W. Chonnaparamutt, V. Jucikas, H. Bastani, I. Delchev, I. Krivulev, S. Lee, S. Markov, and A. Pfeil, "The IUB 2005 rescue robot team," in *RoboCup 2005: Robot Soccer World Cup IX*, ser. Lecture Notes in Artificial Intelligence (LNAI), I. Noda, A. Jacoff, A. Bredenfeld, and Y. Takahashi, Eds. Springer, 2006.

[14] A. Birk, "The IUB 2004 rescue robot team," in *RoboCup 2004: Robot Soccer World Cup VIII*, ser. Lecture Notes in Artificial Intelligence (LNAI), D. Nardi, M. Riedmiller, and C. Sammut, Eds. Springer, 2005, vol. 3276.

[15] A. Birk, S. Carpin, and H. Kenn, "The IUB 2003 rescue robot team," in *RoboCup 2003: Robot Soccer World Cup VII*, ser. Lecture Notes in Artificial Intelligence (LNAI), D. Polani, B. Browning, A. Bonarini, and K. Yoshida, Eds. Springer, 2004, vol. 3020.

[16] A. Birk, H. Kenn, M. Rooker, A. Akhil, B. H. Vlad, B. Nina, B.-S. Christoph, D. Vinod, E. Dumitru, H. Ioan, J. Aakash, J. Premvir, L. Benjamin, and L. Ge, "The IUB 2002 rescue robot team," in *RoboCup-02: Robot Soccer World Cup VI*, ser. LNAI, G. Kaminka, P. U. Lima, and R. Rojas, Eds. Springer, 2002.

[17] A. Birk, K. Pathak, S. Schwertfeger, and W. Chonnaparamutt, "The iub rugbot: an intelligent, rugged mobile robot for search and rescue operations," in *IEEE International Workshop on Safety, Security, and Rescue Robotics (SSRR)*. IEEE Press, 2006.

[18] CSEM, *The SwissRanger, Manual V1.02*, CSEM SA, 8048 Zurich, Switzerland, 2006. [Online]. Available: http://www.swissranger.ch

[19] R. Lange and P. Seitz, "Solid-state time-of-flight range camera," *Quantum Electronics, IEEE Journal of*, vol. 37, no. 3, pp. 390–397, 2001.

[20] Videre-Design, *Stereo-on-a-chip (STOC) stereo head, user manual 1.1*, Videre Design, February 2006. [Online]. Available: http://www.videredesign.com/vision_systems.htm

[21] K. Konolige and D. Beymer, *SRI Small vision system, user's manual, software version 4.2*, SRI International, February 2006. [Online]. Available: http://www.ai.sri.com/~konolige

[22] MER-Science-Team, "Mars exploration rover (mer) mission data archives," http://anserver1.eprsl.wustl.edu/anteam/merb/merb_main2.htm, 2007.

[23] S. Carpin, A. Birk, M. Lewis, and A. Jacoff, "High fidelity tools for rescue robotics: results and perspectives," in *RoboCup 2005: Robot Soccer World Cup IX*, ser. Lecture Notes in Artificial Intelligence (LNAI), I. Noda, A. Jacoff, A. Bredenfeld, and Y. Takahashi, Eds. Springer, 2006.

[24] USARsim, "Urban search and rescue simulator," http://usarsim.sourceforge.net/, 2006.