Künstl Intell (2015) 29:193–201
DOI 10.1007/s13218-015-0352-5

RESEARCH PROJECT

TRADR Project: Long-Term Human-Robot Teaming for Robot Assisted Disaster Response

Ivana Kruijff-Korbayová · Francis Colas · Mario Gianni · Fiora Pirri · Joachim de Greeff · Koen Hindriks · Mark Neerincx · Petter Ögren · Tomáš Svoboda · Rainer Worst

Abstract This paper describes the project *TRADR: Long-Term Human-Robot Teaming for Robot Assisted Disaster Response*. Experience shows that any incident serious enough to require robot involvement will most likely involve a sequence of sorties over several hours, days and even months. TRADR focuses on the challenges that thus arise for the persistence of environment models, multi-robot action models, and human-robot teaming, in order to allow incremental capability improvement over the duration of a mission. TRADR applies a user centric design approach to disaster response robotics, with use cases involving the response to a medium to large scale industrial accident by teams consisting of human rescuers and several robots (both ground and airborne). This paper describes the fundamentals of the project: the motivation, objectives and approach in contrast to related work.

Keywords Disaster response robotics · Persistent environment models · Persistent multi-robot action models · Persistent multi-robot collaboration models · Persistent human-robot teaming · User-centric design

1 Introduction

A real disaster response takes longer than a single sortie into the area. As witnessed recently for example in Japan (Fukushima) and in Northern Italy (Emilia Romagna) deployments can last days, weeks, months, if not years.

TRADR builds on the research and experience of the NIFTi project [21]. In July 2012 NIFTi assisted in structure damage assessment in Emilia Romagna, after it was hit by over 250 seismic events in May–June 2012, causing widespread damage to an area rich in cultural heritage (Fig. 1). Together with the Vigili del Fuoco, the Italian national rescue organisation responsible for disaster response, NIFTi fielded a human-robot team with a mobile

---

TRADR is an EU-funded Integrated Project in the FP7 ICT Programme, grant no. 609763, Nov. 2013–Dec. 2017. URL: www.tradr-project.eu

I. Kruijff-Korbayová (✉)
Language Technology Lab, Deutsches Forschungszentrum für Künstliche Intelligenz (DFKI), Stuhlsatzenhausweg 3, 66123 Saarbrücken, Germany
e-mail: ivana.kruijff@dfki.de

F. Colas
Eidgenössische Technische Hochschule Zürich (ETH), Zürich, Switzerland

M. Gianni · F. Pirri
Università degli Studi di Roma "La Sapienza" (ROMA), Rome, Italy

J. de Greeff · K. Hindriks
Technische Universiteit Delft (TUD), Delft, The Netherlands

M. Neerincx
Nederlandse Organisatie voor Toegepast Natuurwetenschappelijk Onderzoek (TNO), Soesterberg, The Netherlands

P. Ögren
Kungliga Tekniska Hoegskolan (KTH), Stockholm, Sweden

T. Svoboda
Czech Technical University in Prague (CTU), Prague, Czech Republic

R. Worst
Fraunhofer Institute for Intelligent Analysis and Information Systems, Sankt Augustin, Germany

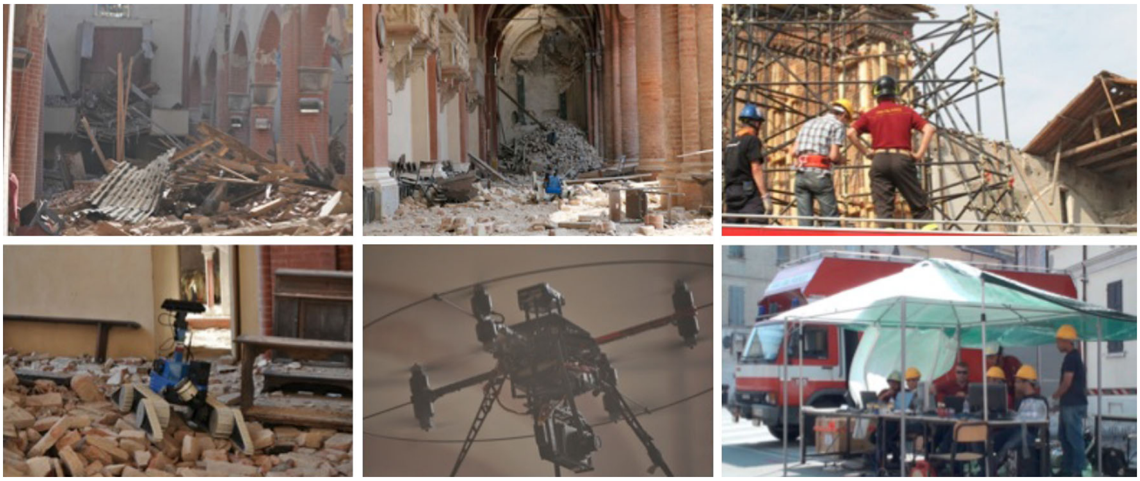


Fig. 1 NIFTi deployment in Emilia Romagna. Top: Structural damage on Duomo in Mirandola. *Bottom* (*left*-to-*right*): UGV, UAV and mobile command post

command post, two unmanned ground vehicles (UGVs), and two quadcopter unmanned aerial vehicles (UAVs). The crucial insight from this deployment was the need for *integrated persistent situation awareness* [22]. Multiple robots need to be sent into the area, together (*synchronous operation*) or one after another (*asynchronous operations*). Different kinds of robots play complementary roles in this process. They need to build integrated persistent situation awareness gradually over multiple sorties, to allow the team to coordinate its efforts (*team-level*), and learn to best execute its tasks (*task-level*).

TRADR addresses the ensuing challenge of making the experience of a human-robot disaster response team persistent over multiple sorties during a prolonged mission. We employ proven-in-practice user-centric design methodology (Fig. 2, left), involving tight cooperation with end users and tight integration of technology. The TRADR use cases involve response to a medium to large scale industrial accident by teams consisting of human rescuers and several ground and airborne robots (Fig. 2, right). The team collaborates to explore the environment and gather measurements and physical samples. TRADR's goal is to enable the team to gradually develop its understanding of the disaster area over multiple synchronous and asynchronous sorties (persistent environment models), to improve team members' understanding of how to work in the area (persistent single- and multi-robot action models), and to improve team-work (persistent human-robot teaming). TRADR missions will ultimately stretch over several days in increasingly dynamic environments.

Project Partners The TRADR consortium consists of 12 partners,[1] including 3 research institutes: DFKI (coordinator), Fraunhofer, TNO; 5 universities: ETH, KTH, CTU, ROMA and TUD; one industry partner: Ascending Technologies; and 3 end-user organizations, representatives of the fire-brigades from Germany (Stadt Dortmund Institut für Feuerwehr und Rettungstechnologie), Italy (Vigili del Fuoco directed by the Ministero Dell'interno) and the Netherlands (Gezamenlijke Brandweer). 8 of the partners have already collaborated very successfully in the NIFTi project.

2 The TRADR Concept

In this section we present the research challenges addressed in TRADR in more detail and contrast the TRADR approach with related work.

2.1 Persistent Environment Models

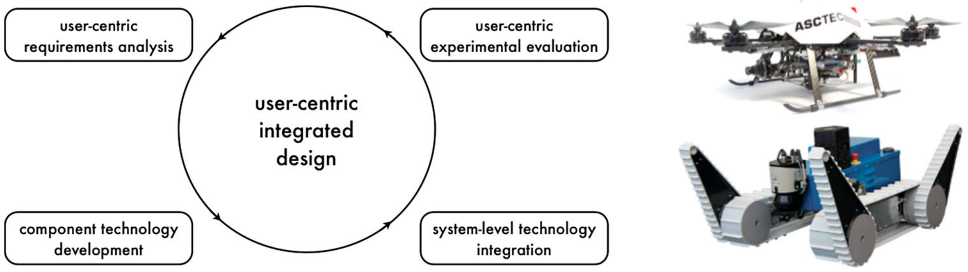
Low-level situation awareness of the TRADR system requires sensory data from all involved robots registered in space and time, to keep creating and updating robot centric representations, and ground them into the world coordinate frame. The obtained representations are furnished to other parts of the TRADR system, which maintain higher level situation awareness. Persistent multi-robot environment models are grounded in two different aspects: *environment representation* and *adaptive action*.

Regarding environment representation, 3D mapping has so far essentially been studied for a single robot starting from an empty map. In TRADR we need to develop new data structures similar to octrees [42] and multi-resolution surfel maps [37] but with the added capabilities to integrate different sensor modalities from different robots, to scale to arbitrary environment sizes, and to cope with dynamic

---

[1] Cf. the authors' list for full names of the institutes listed here only by an abbreviation. For more information on the partners, please visit the project website: www.tradr-project.eu

Fig. 2 *Left*: TRADR one-year-round development cycle. *Right*: TRADR UGV and UAV



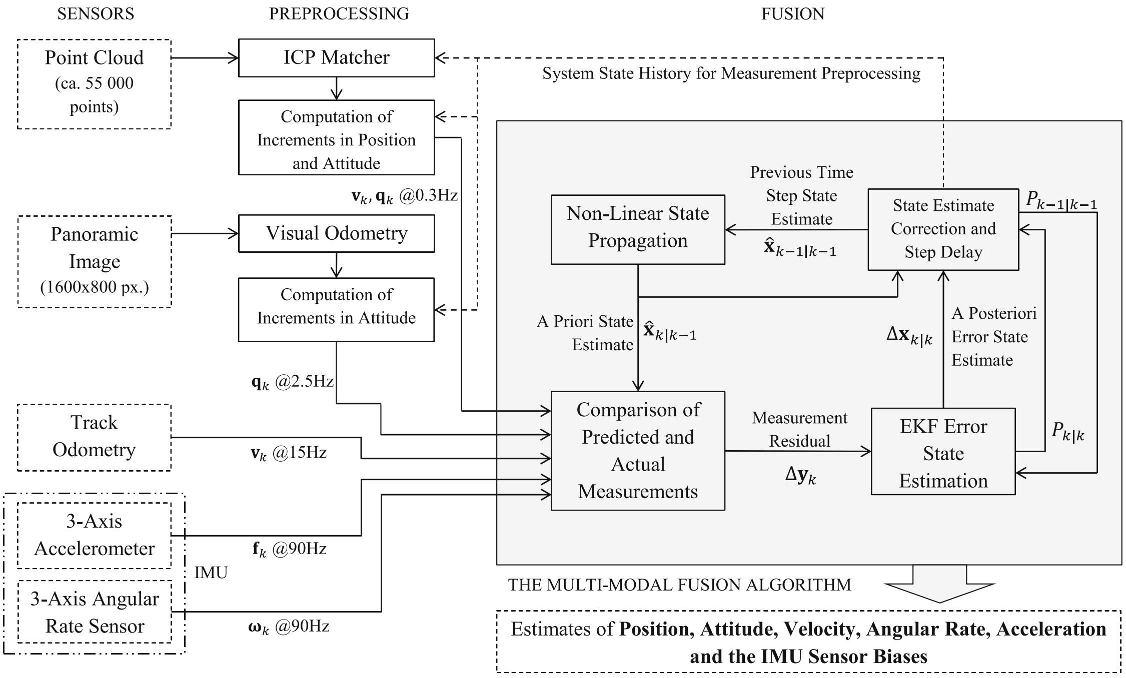


Fig. 3 Data fusion for grounding robot and maps. Figure from [23]

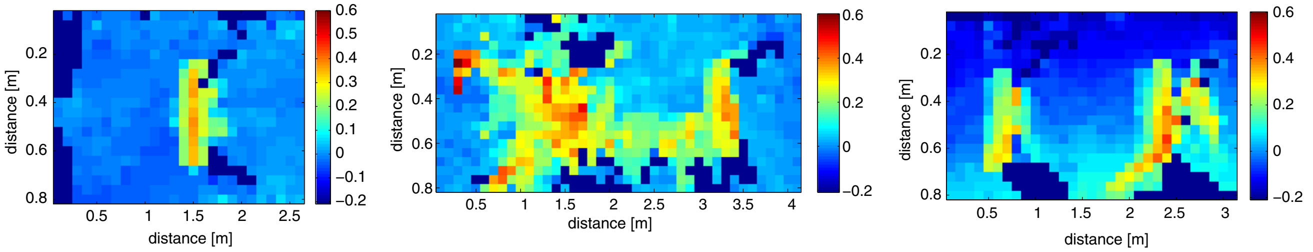
obstacles [34]. In order to achieve robust grounding we fuse all available modalities (Fig. 3).

Regarding adaptive action, impressive demonstrations of aggressive manoeuvres have shown the capabilities of UAVs but always in a closed environment with high-precision external tracking systems [25, 27]. To replicate these results in field experiments, it is necessary to improve the performance of current state estimation techniques relying on vision or laser sensors to complement IMU measurements [1, 41]. While for UAVs the difficulty lies often more in control since they are unstable systems, UGVs research is more focused on path planning. A plethora of algorithms allow robots on flat ground to find optimal paths using robot constraints [20, 35] but few approaches investigate moving in a rough terrain by using flippers [8, 31] and these are not yet ready for large-scale or dynamic environments. To this end, we develop algorithms to recognize different terrains in front of the robot and changing the morphology by adjusting the flippers (Fig. 5) for smooth traversal (Fig. 4).

2.2 Persistent Models for Acting

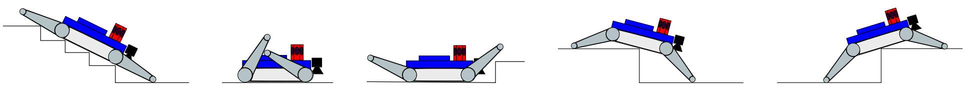
Building persistent models for action in TRADR basically corresponds to the human-robot team *learning on the job*. The models for acting will obviously rely heavily on the world models described above, but also learn from experiences generated in human-robot interaction on *different autonomy levels*.

Consider the following example. A UGV is sent to explore a given part of a building and retrieve some samples. It starts off in fully autonomous mode and successfully passes some difficult terrain and obstacles. Then it comes to an even more difficult area that is judged to be beyond its current capabilities. It stops and requests human support on a lower autonomy level. The human then guides



(1) simple obstacle (2) soft-terrain-sideroll obstacle (3) double obstacle

Fig. 4 Perception of obstacles, functional recognition. Overview of the Digital Elevation Maps (DEM) for given type of obstacles. Figure from [44]



I-shape V-shape L shape U-shape soft U-shape hard

Fig. 5 **Robot modes** Robot morphology, Figure from [44]

the UGV across the terrain in an intelligent teleoperation mode. The choices made by the human during the traversal are stored and made accessible to the system. The path chosen by the human will be a preferred option in the next autonomous traversal attempt. Similarly, when a door needs to be opened or a sample of a possibly toxic liquid needs to be collected, the autonomous mode can request help by a human and then learn from that experience.

To achieve the above, we build upon state of the art approaches such as the intelligent teleoperation described in [30], the Click and Grab functionality of [2], the augmented virtual reality interface of [3], and the flipper position control of [31]. But the ambition of learning action models on the job on a team level goes beyond those approaches. Also the ambition of developing these persistent models will influence the design of the algorithms, leading to new results across all autonomy levels.

2.3 Persistent Models for Multi-Robot Collaboration

Multi-robot collaboration presupposes intention to collaborate, awareness of roles, partial knowledge, distinct beliefs, desires, capabilities and goals [4, 5, 11, 15, 29, 39]. Although significant research results have been achieved in the last thirty years, the concept of persistent collaboration is new in TRADR, as it requires persistence to be verified through sorties where an enormous amount of data is collected by the robot team. The challenge is to model how the information content of the data collected is preserved, and it is lifted to knowledge, while changing the team, changing the ways of communication and changing the experience gathered. Persistence asks for strong communication structures at different layers for role assignment, for distributed task inference and for sharing the team members current state. Persistence also demands consistent continuous information sharing which is especially hard in damaged environments and has never been experienced before.

We aim to develop a statistical-logical model for flexible collaborative planning. This model exploits the powerful language of the Flexible Temporal Situation Calculus (FTSC) [13], extended with constraints specifying dependencies between robot’ abilities and their spatial distribution, also accommodating statistical inference [33]. The model includes a knowledge and memory structure which is used, through sorties, to manage information sharing, common plan generation and dynamic role allocation. Both role and task allocation is based on a cost assigned to resources, robot groups capabilities, tasks and contexts [16, 24]. A learning schema, based on a Bayesian approach to tensor factorization is proposed to build a relation between group composition and costs [43]. Group reconfiguration exploits the stimulus-response framework, proposed in [17], modeling the human inspired mechanism of task switching in robot cognitive control. Finally, an extension of the ACL communication language is proposed for modeling the information flow between robots, in order to support collaboration [14]. This language is also used for knowledge retrieval and updating, via OWL [40].

2.4 Persistent Models for Human-Robot Teaming

As robots become more sophisticated a tendency has arisen within HRI to perceive them as teammates rather than tools [19, 32]; also in the context of disaster response robotics the importance of robots capable of operating as a (social) team-member has been acknowledged and addressed [12, 28]. Even though in NIFTi multiple robots were employed, they did not necessarily partake on the team-level; each robot was controlled by an individual operator taking orders from the human commander. This is similar in a number of other projects, where teams of heterogeneous robots are employed in a collaborative fashion, but it is human operators who provide the linkage between the robots and the human rescue workers, e.g., [7, 9]. A stronger notion of human-robot collaboration is developed in the alpine rescue project SHERPA [26], employing a metaphor of the human as "busy genius" who collaborates with a group of robots with different capabilities (the "SHERPA animals") towards a common goal. TRADR will also go beyond an approach in which robots are mere tools, instead aiming at robots with an adaptive level of autonomy (e.g. semi-autonomous navigation, data gathering etc.) as members of flexible teams improving their collaboration over time. To realize this, TRADR is developing a framework for coordination of human-robot teaming, which is built on agent-based technology [18]. This framework manages the different roles, objectives, responsibilities and expectation for members of the team (which consists of both robots and humans and which may change over different sorties) and allows for conflict resolution and dynamical task-allocation depending on capabilities, task-load and chances of success.

2.5 Persistent Models for Distributed Joint Situation Awareness

Situation Awareness (SA) is paramount for a team to work effectively in disaster response missions [36]. To achieve robust SA on a team-level in TRADR, we are designing a *Tactical Display System* (TDS) that builds on the experiences gathered with the system developed to support distributed joint SA in NIFTi (Fig. 6, left) and existing end-users systems (e.g. the system employed by the GB fire-brigade, Fig. 6, right). The TDS will provide trustworthy and relevant tactical information about the physical environment and give access to a hierarchical representation of experiences to support tactical decision making (e.g., task allocation, (re)planning and coordination). It will be designed to support guided (a)synchronous information exchange between distributed or co-located actors through multi-modal interaction (graphical UI and spoken dialogue). This guidance needs to be personalized and context-tailored. A survey [38] found that in many cases adaptivity towards the user is realized through a customizable interface that does not significantly affect the behavior or interaction patterns of the systems. Following in NIFTi footsteps, TRADR aims to push adaptivity beyond simple widget placement, concretely adapting the system's behavior to different use contexts.

2.6 User-Centric Design and Development

TRADR adopts a scenario-based roadmap to guide iterative development of the persistent models described in the previous subsections, to drive continuous integration of the development results into a technical system, and to allow evaluation of the integrated system with end-users in yearly cycles (Fig. 2).

The roadmap defines a large-scale industrial disaster scenario. This is a kind of disaster where persistence is key to a successful mission. We need multiple robots to investigate the disaster from different angles (literally), and we need to use them over a number of sorties to gradually build up and maintain situation assessment, e.g., through observation and sample gathering. Within the industrial accident scenario, the roadmap then defines yearly use cases which deal with situation assessment under increasingly more complex circumstances, as described in Tab. 1. In Fig. 7 various use case setups at the TRADR end user training facilities are illustrated.

End users are closely involved in TRADR: each year of the development cycle in Fig. 2 starts by a deep domain analysis with end-users, followed by the development and

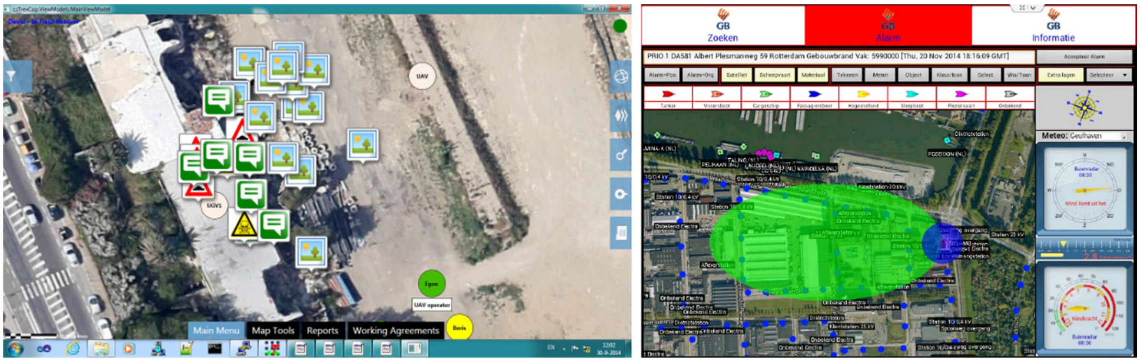


Fig. 6 *Left*: screen capture from the NIFTi TREX system showing a base map of the disaster area and various icons depicting location of rescue workers, robots, warnings, notes etc. *Right*: screen capture from the GB fire-brigade system showing various tactical information

Table 1 TRADR roadmap: year-by-year use cases within the industrial disaster scenario

Year 1	A fixed human-robot team with 1 UGV and 1 UAV gradually builds up situation awareness of a *static* disaster site over multiple *asynchronous* sorties.
Year 2	A fixed human-robot team with 1 UGV and 1 UAV gradually builds up situation awareness of a *dynamic* disaster site over multiple *synchronous or asynchronous* sorties.
Year 3	A human-robot team with multiple UGVs/UAVs carries out multiple sorties. Focus is on how environment models get fused, and may be used. Task adaptation moves from a strictly individual focus, to a multi-robot setting: How could a robot learn from its use of information provided by others, to adapt its own tasks as well as anticipate requests for such collaboration in (future) plans?
Year 4	A human-robot team with multiple UGVs/UAVs collaborates in various ways, synchronously and asynchronously. Persistence in modeling the environment covers ever-increasing complexity in local and global dynamic events, appearing on an ever-larger spatiotemporal scale. Team competence gradually improves based on experience.

Fig. 7 TRADR use cases set up at training sites in Germany, Italy, and the Netherlands

integration of the components. The development cycle is rounded off by evaluating the developed components on system-level and performing end-user evaluations of the integrated system.

Integration takes place in a continuous process. An (as far as possible) automated procedure combines periodically the latest component versions, performs a static analysis of the code, and executes run-time tests. Reports of successes and failures are reported to the responsible developers, who can take the necessary actions. The components are mainly based on the ROS framework; however, since in TRADR more than one mobile robot is involved in the mission, we must set up a multi-master mechanism, which is necessary for the cooperation of multiple ROS-based systems.

2.7 Related European Projects

Several other European projects address the deployment of (teams of) UGVs and UAVs in various disaster response scenarios. ICARUS [9] and DARIUS [7] target the development of robotic tools that can assist during disaster response operations, focusing on autonomy. SHERPA [26] is focused on the development of ground and aerial robots to support human-robot team response in an alpine scenario. None of these projects addresses the persistence issues. In TIRAMISU [6], a toolbox is developed for removal of anti-personnel mines, submunitions, and Unexploded Ordnance (UXO). It includes a component called TIRAMISU Repository Service, which provides a centralized data-sharing platform that contains the locations of detected landmines and UXOs. The TRADR concept of persistent situation awareness goes beyond this in various respects as we described above. On the other hand, the EU project STRANDS [10], aims at modeling the spatio-temporal dynamics in human indoor 3D environments in order for a single robot to adapt to and exploit long-term experience in months-long autonomous operation. In contrast, TRADR deals with multiple sorties into an unstructured outdoor environment carried out by a human-robot team.

3 Conclusions

We presented an overview of the TRADR aims and approach. TRADR advances the use of the user-centric methodology established in the NIFTi project, and builds on the experience and insights obtained through the deployment of the NIFTi system, that there is a need for persistent, integrated situation awareness gathered over multiple sorties during a mission, and that different kinds of robots each play complementary roles in this process. To this end TRADR develops the capacity for persistent environment models, persistent multi-robot action models and persistent human-robot teaming.

References

1. Achtelik M, Bachrach A, He R, Prentice S, Roy N (2009) Stereo vision and laser odometry for autonomous helicopters in GPS-denied indoor environments. In: SPIE Defense, Security, and Sensing, vol 7332. International society for optics and Photonics, p 733219
2. Anderson D, Howard T, Apfelbaum D, Herman H, Kelly A (2009) Coordinated control and range imaging for mobile manipulation. In: Experimental robotics. Springer, pp 547–556

3. Atherton J, Goodrich M (2009) Supporting remote manipulation with an ecological augmented virtuality interface. In: Artificial intelligence and simulation of behaviour (AISB) on New Frontiers in Human-Robot Interaction, Edinburgh, UK
4. Brenner M, Nebel B (2009) Continual planning and acting in dynamic multiagent environments. Auton Agent Multi-Agent Syst 19(3):297–331
5. Burgard W, Moors M, Stachniss C, Schneider FE (2005) Coordinated multi-robot exploration. IEEE Trans Robot 21(3):376–386
6. Cantelli L, Mangiameli M, Melita CD, Muscato G (2013) UAV/UGV cooperation for surveying operations in humanitarian demining. In: Safety, Security, and Rescue Robotics (SSRR), 2013 IEEE International symposium on 21–26 Oct 2013, Linköping. IEEE, pp 1–6
7. Chrobocinski P, Zotos N, Makri E, Stergiopoulos C, Bogdos G (2012) DARIUS project: Deployable SAR integrated chain with unmanned systems. In: Telecommunications and Multimedia (TEMU), 2012 International conference on 30 Jul–1 Aug 2012, Chania. IEEE, pp 220–226
8. Colas F, Mahesh S, Pomerleau F, Liu M, Siegwart R (2013) 3D path planning and execution for search and rescue ground robots. In: Intelligent robots and systems (IROS), 2013 IEEE/RSJ international conference on 3–7 Nov 2013, Tokyo. IEEE, pp 722–727
9. De Cubber G, Doroftei D, Serrano D, Chintamani K, Sabino R, Ourevitch S (2013) The EU-ICARUS project: developing assistive robotic tools for search and rescue operations. In: Safety, Security, and Rescue Robotics (SSRR), 2013 IEEE international symposium on 21–26 Oct 2013, Linköping. IEEE, pp 1–4
10. Duckett T, Hanheide M, Krajnik T, Fentanes JP, Dondrup C (2014) Spatio-temporal representations for cognitive control in long-term scenarios. In: AAAI spring symposium on qualitative representations for robots, 27–28 March 2014, Stirling, Scotland, UK
11. Duncan B, Ulam P, Arkin R (2009) Lek behavior as a model for multi-robot systems. In: Robotics and biomimetics (ROBIO), 2009 IEEE International Conference on 19–23 Dec 2009, Guilin. IEEE, pp 25–32
12. Fincannon T, Barnes LE, Murphy RR, Riddle DL (2004) Evidence of the need for social intelligence in rescue robots. In: IEEE/RSJ International conference on intelligent robots and systems (IROS), vol 2. IEEE, pp 1089–1095
13. Finzi A., Pirri F (2005) Representing flexible temporal behaviors in the situation calculus. In: Proceedings of the 19th international joint conference on Artificial intelligence, pp 436–441
14. FIPA: FIPA ACL message structure specification (2002). url: http://www.fipa.org/specs/fipa00061
15. Gerkey BP, Mataric MJ (2000) Murdoch: Publish/subscribe task allocation for heterogeneous agents. In: AAAI/IAAI, p 1070
16. Gerkey BP, Mataric MJ (2003) Multi-robot task allocation: analyzing the complexity and optimality of key architectures. In: IEEE International Conference on Robotics and Automation (ICRA), IEEE, pp 3862–3868
17. Gianni M, Kruijff GJM, Pirri F (2014) A stimulus-response framework for robot control. ACM Trans Interact Intell Syst 4(4)
18. Hindriks KV (2009) Programming rational agents in GOAL. In: A.E. Seghrouchni, J. Dix, M. Dastani, R.H. Bordini (ed.) Multi-agent programming: languages, tools and applications. Springer, pp 119–157
19. Hoffman G, Breazeal C (2004) Collaboration in human-robot teams. In: Proceedings of the AIAA 1st intelligent systems technical conference, Chicago, IL, USA
20. Koenig S, Likhachev M (2005) Fast replanning for navigation in unknown terrain. IEEE Trans Robot 16(3):354–363
21. Kruijff G, Colas F, Svoboda T, van Diggelen J, Balmer P, Pirri F, Worst R (2012) Designing intelligent robots for human-robot teaming in urban search & rescue. In: Proceedings of the AAAI 2012 spring symposium on designing intelligent robots
22. Kruijff G, Tretyakov V, Linder T, Pirri F, Gianni M, Papadakis P, Pizzoli M, Sinha AEP, Corrao S, Priori F, Febrini S, Angeletti S (2012) Rescue robots at earthquake-hit Mirandola, Italy. In: Proceedings of the 10th IEEE international symposium on safety, security, and rescue robotics (SSRR-2012). IEEE Press, USA, p 5–8
23. Kubelka V, Oswald L, Pomerleau F, Colas F, Svoboda T, Reinstein M (2014) Robust data fusion of multi-modal sensory information for mobile robots. J Field Robot. doi: 10.1002/rob.21535
24. Lerman K, Jones C, Galstyan A, Mataric MJ (2006) Analysis of dynamic task allocation in multi-robot systems. Int J Robot Res 25(3):225–241
25. Lupashin S, Schoellig A., Sherback M, D'Andrea R (2010) A simple learning strategy for high-speed quadrocopter multi-flips. In: IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2010 IEEE international conference on 3–7 May 2010. IEEE, pp 1642–1648
26. Marconi L, Leutenegger S, Lynen S, Burri M, Naldi R, Melchiorri C (2013) Ground and aerial robots as an aid to alpine search and rescue: Initial sherpa outcomes. In: Safety, Security, and Rescue Robotics (SSRR), 2013 IEEE international symposium on 21–26 Oct 2013, Linköping. IEEE, pp 1–2
27. Michael N, Fink J, Kumar V (2010) Cooperative manipulation and transportation with aerial robots. Auton Rob 30(1):73–86
28. Murphy RR (2004) Human-robot interaction in rescue robotics. IEEE Trans Syst Man Cybern C Appl Rev 34(2):138–153
29. Nair R, Tambe M, Marsella S (2003) Role allocation and reallocation in multiagent teams: towards a practical analysis. In: Proceedings of the second international joint conference on Autonomous agents and multiagent systems, AAMAS '03ACM, New York, USA, pp 552–559
30. Ögren P, Svenmarck P, Lif P, Norberg M, Söderbäck, N (2014) Design and implementation of a new teleoperation control mode for differential drive UGVs. J Auton Robot 71–79
31. Okada Y, Nagatani K, Yoshida K, Tadokoro S, Yoshida T, Koyanagi E (2011) Shared autonomy system for tracked vehicles on rough terrain based on continuous three-dimensional terrain scanning. J Field Rob 26(6):875–893
32. Ososky S, Schuster D, Jentsch F, Fiore S, Shumaker R, Lebiere C, Kurup U, Oh J, Stentz A (2012) The importance of shared mental models and shared situation awareness for transforming robots from tools to teammates. In: Proceedings of SPIE 8387, Unmanned Systems Technology XIV, 838710–1
33. Pirri F (2011) The well-designed logical robot: learning and experience from observations to the situation calculus. Artif Intell 175(1):378–415
34. Pomerleau F, Krüsi P, Colas F, Furgale P, Siegwart R (2014) Long-term 3D map maintenance in dynamic environments. In: IEEE International Conference on Robotics and Automation (ICRA), IEEE, pp 3712–3719
35. Rufli M, Ferguson D, Siegwart R (2009) Smooth path planning in constrained environments. In: IEEE International conference on robotics and automation (ICRA). IEEE, pp 3780–3785
36. Salmon PM, Stanton NA, Walker GH, Jenkins PD (2009) Distributed situation awareness: theory, measurement, and application to teamwork. Ashgate, UK
37. Stückler J, Behnke S (2014) Multi-resolution surfel maps for efficient dense 3D modeling and tracking. J Vis Commun Image Represent 25(1):137–147
38. Van Velsen L, Van Der Geest T, Klaassen R, Steehouder M (2008) User-centered evaluation of adaptive and adaptable systems: a literature review. Knowl Eng Rev 23(03):261–281

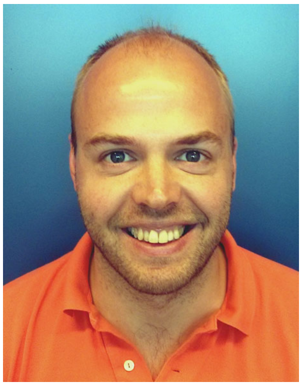
39. Vig L, Adams JA.(2005) A framework for multi-robot coalition formation. In: IICAI, pp 347–363
40. Wang X, Zhang D, Gu T, Pung H (2004) Ontology based context modeling and reasoning using owl. In: Pervasive computing and communications Workshops, 2004, Proceedings of the second IEEE annual conference on 14–17 Mar 2004. IEEE, pp 18–22
41. Weiss S, Achtelik MW, Lynen S, Chli M, Siegwart R (2012) Real-time onboard visual-inertial state estimation and self-calibration of MAVs in unknown environments. In: IEEE international conference on robotics and automation (ICRA), IEEE, pp 957–964
42. Hornung A, Wurm K, Bennewitz M, Stachniss C, Burgard W (2013) OctoMap: an efficient probabilistic 3D mapping framework based on octrees. Auton Robot 34(3):189–206
43. Xiong L, Chen X, Huang TK, Schneider JG, Carbonell JG (2010) Temporal collaborative filtering with bayesian probabilistic tensor factorization. In: SDM, pp 211–222
44. Zimmermann K, Zuzánek P, Reinstein M, Hlaváč V (2014) Adaptive traversability of unknown complex terrain with obstacles for mobile robots. In: IEEE International Conference on Robotics and Automation (ICRA), IEEE, Piscataway, USA, pp 5177–5182

Ivana Kruijff-Korbayová Graduation in informatics, 1992, Czech Technical University; Ph.D. in mathematical linguistics, 1998, Charles University, Prague; 1999–2000 British Academy and Royal Society/NATO Fellowships, University of Edinburgh; 2001–2010 Saarland University; since 2008 DFKI. Research in various areas of discourse and dialogue processing.

Francis Colas Ph.D. in Computer Science from the INPG in 2006. 2007–2008 postdoctoral fellow at Collège de France in Paris in the *Laboratoire de Physiologie de la Perception et de l'Action*. Since 2009 postdoctoral fellow at the Autonomous Systems Lab (ETH Zurich). Research interests include Bayesian modeling of perception and action applied from cognitive sciences to robotics.

Mario Gianni Ph.D in Computer Engineering from DIAG—Department of Computer, Control and Management Engineering A. Ruberti at Sapienza University of Rome. Currently, post-doctoral researcher at ALCOR Laboratory. Research interests include statistics and logic, applied to robotics, autonomous navigation and adaptation for self-reconfigurable robots in cluttered environments, low and high-level control in multi-robot collaboration.

Fiora Pirri is currently full professor and head of the ALCOR Laboratory at the DIAG, Department of Computer, Control, and Management Engineering, "A. Ruberti" at Sapienza, University of Rome. She founded ALCOR Lab in 1998 and since then the Lab has widely to the theory and practice of Cognitive Robotics applied to rescue environments. Her research area is Cognitive Robotics, and in particular Perception, Attention and theories of Actions.



Joachim de Greeff Ph.D. in concept learning and human-robot interaction from Plymouth University, United Kingdom in 2013. In 2013-2014 employed as research fellow on the EU FP7 ALIZ-E project which was about the development of a robotic companion for children with diabetes. Currently working at Delft University of Technology on the TRADR project as a postdoctoral researcher. Research interests include cognitive modelling, human-robot interaction and teamwork, evolutionary robotics and general AI.

Koen Hindriks MSc degree from the University of Groningen; PhD degree from Utrecht University; part of PhD candidature at the University of Toronto. Currently Assistant Professor at the Delft University of Technology, Department of Electrical Engineering, Mathematics and Computer Science. Research in multi-agent technology.

Mark Neerincx After M.Sc. worked at the TNO Institute of Preventive Health Care, the University of Leiden and the University of Amsterdam. After Ph.D. became research scientist at TNO Human Factors and, from 2000, headed the Usability Engineering group. Also (part-time) full professor in Human-Centred Computing at Delft University of Technology. Extensive experience in applied and fundamental research. Conducted empirical studies in diverse domains, such as process control, defence, aerospace, health, public safety and e-commerce.

Petter Ögren MSc and PhD degree from KTH—Royal Institute of Technology, Sweden; part of PhD candidature at Princeton University. Currently Associate Professor at KTH, Department of Computer Vision and Active Perception (CVAP), School of Computer Science and Communication. Research interests include multi-agent coordination, formations, obstacle avoidance, intelligent teleoperation and applying ideas from computer games to robot control problems.

Tomáš Svoboda Ph.D. in artificial intelligence and biocybernetics from the Czech Technical University in Prague in 2000. Post-doc with the Computer Vision Group at the ETH Zurich (Swiss Federal Institute of Technology) for 3 years. Currently assistant professor and deputy head of the department of Cybernetics at the Czech Technical University. Research interests include multicamera systems for scene understanding and telepresence, tracking and motion analysis.

Rainer Worst Senior researcher at Fraunhofer IAIS. Diploma in Computer Science (Univ. Bonn, 1981). IT-Expert at a consulting company in Wiesbaden. In 1984 joined the former GMD (National Research Center for Information Technology) in Sankt Augustin, which merged 1999 with Fraunhofer. Experience as a consultant, researcher and project leader in the areas Software Engineering, Quality Management, Virtual Environments, and Autonomous Systems.