Development of a Search and Rescue field Robotic Assistant

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Abstract— **The work introduced in this paper was performed as part of the FP7 INTRO (Marie-Curie ITN) project. We describe the activities undertaken towards the development of a field robotic assistant for a Search and Rescue application. We specifically target a rubble clearing task, where the robot will ferry small pieces of rubble between two waypoints assigned to it by the human. The aim is to complement a human worker with a robotic assistant for this task, while maintaining a comparable level of speed and efficiency in the task execution. Towards this end we develop/integrate software capabilities in mobile navigation, arm manipulation and high level tasks sequences learning. Early outdoor experiments carried out in a quarry are furthermore introduced.**

I. Introduction

As (Urban) Search and Rescue ((U)SAR) is an arduous and dangerous task, in this work we aim to develop software capabilities for a field robotic assistant for SAR scenarios. Specifically we target the task of clearing rubble in the aftermath of an event such as an earthquake. A task such as this would ordinarily be carried out by a team of human USAR workers. The motivation of this work is to replace one of these humans with a semi-autonomous robotic assistant, while maintaining comparable performance in task execution. Such a robot would require autonomous capabilities in arm manipulation, navigation and behaviour learning. The INTRO project tackled several complementary research challenges (as part of PhD thesis works by 8 PhD students of the consortium), and have the outcomes integrated as part of relevant application scenarios – including the SAR scenario presented here.

Figure 1 shows the robotic platform used in the development. Development and software integration work was done using the ROS (Robot Operating System) [2] robotic software framework. This was chosen for language interoperability and software reuse features.

II. HRI In Urban Search and Rescue

Urban Search And Rescue (USAR) robotics covers a wide range of mobile robotics activities: the baseline situation is a disruptive event, originating either from natural phenomenon (e.g. earthquake, floods…) or human activities (e.g. building site fire, chemical plant disaster, terrorism…). In such contexts, robot platforms can be sent to acquire information or to intervene with manipulation capabilities at locations where human interventions would otherwise be risky or hazardous. For instance in the case of hazardous material dispersion, information about the type of substance is of paramount importance regarding the decision to send or not rescue teams. Besides, USAR robotics applications also deal with simultaneous on site human and robots interventions. In such setups, either the robotic platforms can be used independently from rescue teams for specific purposes (e.g. victim detection, hazards evolution monitoring…), or can be in a certain extent integrated to operating squads, providing contextual support and / or collaborating with human rescuers.

The former, e.g. loose joint operation, has already been demonstrated in real USAR events, noticeably during the World Trade Center disaster of 2001 (HRI related issues have been reported in [3]). Although studied in the HRI community, the latter has barely been demonstrated in real USAR setups: indeed the process of getting robotic platforms included and accepted within intervention teams' tools is not straightforward, and requires both high maturity of technologies (readiness level) and having the robotic technologies accepted by users. To our knowledge, the only areas where robotic platforms are commonly accepted as integrated tools in USAR like type of activities are (i) bomb disposal, and (ii) aerial surveillance (with Unmanned Aerial Vehicles).

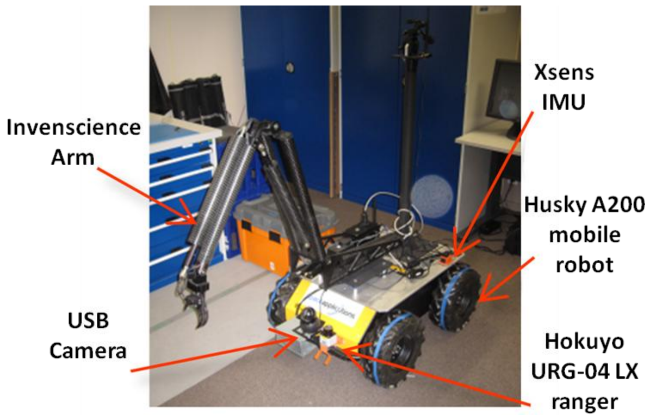

Figure 1. Outdoor mobile manipulator platform

Mobile robots teleoperation has been used or considered in various areas for decades. A number of teleoperation interface designs exist in the literature, either explicitly considering USAR type of applications [4][7] or addressing teleoperation interface design in more general terms [5][6]. Remote robots monitoring and control is a convincing way to bring robotic platforms to the contact of human workers and eventually get robots accepted as efficient tools and / or co-workers. Though teleoperation is also used in complement of the work presented in this paper, the focus here is rather on

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proximate human robot interaction (as defined by Yanco in [8]).

Capabilities in the scope of search and rescue is still arguably un-mature, but obvious benefit can be expected with it. As part of the INTRO project, we are addressing a set of proximate collaboration capabilities, under the form of manipulation assistance. As a main scope, the collaboration consists in semi-autonomous object fetching from a rescuer's hand, and disposing objects at some distance.

We provide in the following sections insights regarding approach followed, and initial results obtained.

III. ROBOTIC PLATFORM

The mobile robot is a Husky A200 [1], with in-built odometry wheel encoders. We use an Xsens MTi IMU (Inertial Measurement Unit) for pose orientation correction. An EKF (Extended Kalman Filter) pose estimation node is used to fuse wheel odometry and IMU data, and this provides the pose estimation input into the SLAM/localization node. For the observation sensor we used the common Hokuyo URG-04 LX laser range finder [9], mounted on the front bumper (note that a Sick LMS 151 now replaces it for more effective outdoor applications).

For manipulation tasks we deployed a 5 DOF robotic manipulator manufactured by Invenscience [10], mounted on the robot's main plate. We used a fixed USB camera for marker extraction for manipulation tasks, also mounted on the front bumper. For onboard processing the robot contains a Mini-ITX PC in its internal compartment.

IV. PROJECT CONCEPT AND TECHNICAL APPROACH

Broadly there are 3 software components developed and integrated during this work:

- High level behavior learning, in order to learn the overall rubble-clearing behavior.
- Robotic arm manipulation, in order to be able to pick up, carry and deposit pieces of rubble.
- Autonomous mobile navigation, in order to navigate between the pickup and dropoff waypoints.

A. *High Level Sequence Learning*

The high level sequence learning software was developed by researchers at a partner institution [11][12][13], participating in this integration project. In order to learn a behavior it must first be defined as an ordered sequence of high-level actions. The idea is that this behavior is executed repeatedly once learned. We define the rubble clearing behavior with the following 3 actions:

- "Explore" – we optionally map the environment with SLAM; the immediate area in which the rubble clearing task takes place. A static map may alternatively be used; in either case an area map is necessary for the behavior to continue. The user then assigns a waypoint to the robot which is interpreted as the "pickup" waypoint, and the action concludes when the robot navigates to the waypoint.
- "Grasp" – upon arriving at the "pickup" waypoint, the robot takes the object (rubble) from the USAR Worker.
- "Move" – similarly to the first action, the user assigns another waypoint to the robot. This waypoint is interpreted as the "dropoff" waypoint. The robot navigates to the "dropoff" waypoint and deposits the object at a target location.

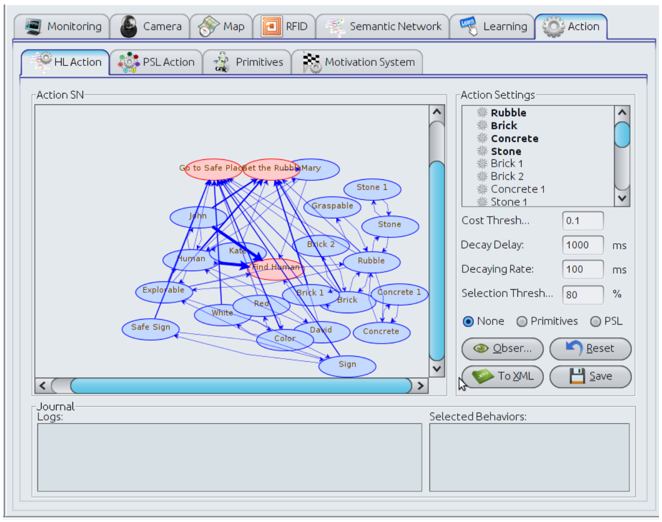

Figure 2. High Level Learning Interface – subsequent knowledge representation is based on a semantic network

Knowledge within this learning system is represented as a Semantic Network (SN) (see Figure 2.), where the actions are pink nodes and concepts (knowledge) are blue nodes. Currently activated nodes are coloured green.

During the learning phase, each action is first learned individually. The action node is created (e.g. Grasp) and then linked to related concept nodes in the network. For example, as we are grasping rubble, "Grasp" would be linked with "Rubble" and sub-types of rubble. In this manner all of the required actions are added to the network. Once this is done, we manually compose these actions into an ordered sequence, thus defining the behavior.

When executing the behavior, each action is either triggered manually through the graphical interface or through some sensory observation. The important constraint is that the actions must execute in the correct order, as defined in the behavior. The behavior is repeatable and continues for as long needed to clear rubble. Of course, the mapping phase in the first action is only done once.

B. *Robotic Arm Manipulation*

The arm manipulation software was developed by researchers at partner institution [14][15], participating in this integration project.

The purpose of this software module is to learn the (previously unknown) inverse kinematic model of the robotic arm, and use it to carry out the grasping/depositing actions.

During the learning phase, we perform data collection with random-walk motor-babbling movements of the arm, while the target object is being held in the gripper (see Figure 3). The collected data consists of the 3D position of the target object, and the arm motor commands. Thus far target objects are marked with ARToolKit markers, whose position is extracted from a basic usb camera's images. Once this data set is collected, we use it to train an artificial neural network to learn the mapping from the target object position to the arm commands.

An interesting benefit of this approach, is the ability to perform on-field "re-calibration" of the inverse kinematics, should degradations or damages occur to the arm, impacting its performances. Should e.g. one of the joints fail (or misbehave), the arm may continue working in a degraded mode after going into a new round of motor babbling process, with empirical learning of the new inverse kinematics corresponding to the degraded configuration.

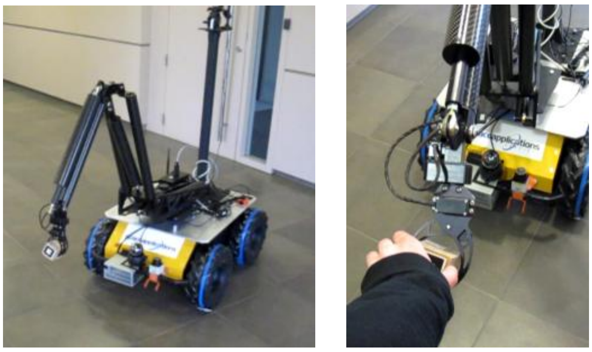

Figure 3. Motor babbling learning (left) and grasping action execution (right)

This learned model is subsequently used to perform grasping actions with the arm to take objects from the human, when the 3D position of the target object is extracted from the camera image (see Figure 3. - right). The same principle is applied when depositing objects; a similar marker is used to designate the deposit position.

C. *Mobile Navigation*

The ROS navigation stack [16] is a collection of mobile navigation software packages developed by the ROS community. It offers capabilities for map building, localisation, local obstacle avoidance and global path planning and execution. A significant limitation within the context of our scenario is that the navigation stack is designed for 2D environments, however at the time of writing no similar 3D navigation packages exist in ROS.

We apply Gmapping 2D SLAM (grid-mapping) [17] as a baseline for a map building phase in the "Explore" action. The Gmapping node also continues to provide localization throughout the execution of the behavior. Alternatively, a static map may be used with a pure localization node AMCL (Adaptive Monte Carlo Localisation). In both cases the environment representation is a regular grid map with customizable resolution.

Navigation to waypoints is accomplished using a local and a global planner. The local planner provides obstacle avoidance and the global planner computes the global path to the waypoint. Each planner also has its own cost-map. A cost map is a grid map as above, with the addition of a cost value for each cell, where the cost indicates how traversable the cell is. The local planner uses a small rolling-window cost map with the robot at the center, which is dynamically cleared and populated with obstacles based on the latest laser scans. The global cost map is created from the SLAM/static map as above. This scheme allows the robot to plan a path through the mapped environment while being able to dynamically adapt to unexpected obstacles with the local planner.

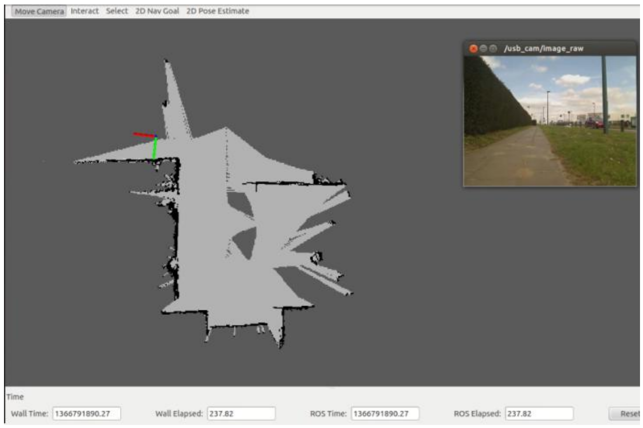

Figure 4. ROS navigation stack (GUI screenshot)

V. EXPERIMENTAL DATA COLLECTION

As a means to test in demanding conditions some of the outcomes (navigation related) capabilities worked out in INTRO, a series of outdoor trials in a relevant environment (the quarry of Haut-Le-Wastia, Belgium) was started in July 2013. Additionally, this series of outdoor trials has been further used as an opportunity to prepare and train aiming at attending the EURATHLON competition (that took place on September 2013 in Berchtesgaden, Germany [18] and for which authors ranked 3rd for the manipulation contest).

During the first trial, experimental data collection has been carried out, focusing on mobile navigation. The experiment has been performed at a large marble and granite rock quarry (see Figure 5). This environment is intended to reflect navigation in rugged terrain and possible search/rescue operations carried out in such terrain.

The purpose of the experiment was both (1) familiarization with the operational setup for the robotic platform deployment and exploitation, and (2) sensor data collection for subsequent offline 3D environmental model construction. This model could be used for autonomous navigation and visualization. Depending on the results, it may then be desired to move from offline to online processing. The focus was on mobile navigation sensors. Specifically, the following data was collected:

- Raw wheel odometry from the Husky mobile robot
- Xsens IMU 3D robot orientation data
- GPS coordinates using Septentrio AsteRx 2i HDC
- SICK LMS151 scanning laser range-finder (replacing the Hokuyo URG)
- Bumblebee XB3 stereo vision camera

Figure 5. Quarry environment where data collection was done

The SICK LMS151 scanner was on a fixed mount, and it will be investigated how conveniently and effectively these data can be used together with the IMU orientation data for 3D model construction. A planned advancement to this configuration is a motorized pan-tilt mount for the SICK scanner, which will enable 3D environment scans.

Figures 5 and 6 illustrate the environment where the data collection was performed. Salient features of the environment are:

- Reddish-brown granite rock faces and large to medium sized obstacle rocks
- Gray small-medium sized gravel rocks and gravel surfaces
- Light gray-brown fine dirt surfaces of varying inclination
- Sparse green bushes and shrubbery

This testing environment offers a wide range of visually detectable features, varying inclination of surfaces and obstacles of different shapes and sizes. It is well suited to a family of robotic experiments of a search and rescue nature, addressing both navigation and possibly arm manipulation. Preliminary examinations of the collected data show it to be promising.

Figure 6. Mobile navigation sensor data collection

VI. CONCLUSION

This paper presented capabilities developed towards a USAR mobile robot assistant in a rubble clearing task. Specifically this consists of arm manipulation, navigation and high level sequence learning.

We additionally performed a sensor data collection experiment in mobile navigation, for offline processing of the data. The purpose is to use the data to perform 3D environment modeling for autonomous navigation and visualization. This implies extending the application scope to work in this type of rugged outdoor environments. Following data analysis, the next step would be implementation of online environment modeling. Additionally, the mount of the SICK laser will be changed to a motorized pan-tilt device to enable 3D scanning. Additional experiments in the quarry environment may be planned to involve arm manipulation. The quarry would be well suitable to manipulation experiments due to an abundance of differently shaped and sized rocks for grasping.

Future improvements in existing capabilities are required, which implementation is in progress:

- Improvement of autonomous navigation capabilities from 2D to 3D models. It would include map building, obstacle avoidance and path planning. 3D laser scanning is required for this. It seems unlikely that existing 2D ROS navigation stack packages can be reused in their current form. Probably a promising way of achieving this is modifying the source code of the existing navigation packages to work with 3D environment models.

- Validation of the planned extensions to support operations in 3D environments on the basis of collected data as well as continued field trials at the Haut-le-Wastia quarry through autumn 2013.
- Migration from ARToolKit marker supported grasping of objects, to real rubble objects, whose localization in the 3D space would need to be vision based. Architecturally, the ARToolkit vision processing software module can be easily replaced with a different module that provides the position of the grasp object.
- Definition and implementation of safety protocols during the execution of the scenario, to ensure no dangerous interaction between the robot and USAR workers or the environment.

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