

System Design for Coordinated Multi-Robot Assistance Deployment in Smart Spaces

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Abstract—In this work, we set the bases of the integration of ambient intelligence (AmI) with mobile robot teams (MRT), aiming to enhance ambient assisted living services addressing a variety of tasks. We argue that people with reduced mobility can benefit from a synergy between AmI and MRT in various aspects. Towards this direction, we identify principal functionalities such an integrated system should provide in connection to relevant previous works and the way by which synergy could be accomplished, from low-level behavioural to higher-level task planning of a multi-layered system architecture.

I. INTRODUCTION

Endowing housing and health-care infrastructures with intelligent monitoring capabilities and device control for people with reduced mobility, constitutes a promising direction in complementing professional human intervention. The need for progressing home automation and ambient assisted living (AAL) technology is particularly highlighted by prospects on population evolution in terms of increased life expectancy with respect to birth rate, especially in western societies [6], [34]. Survey data [2] further suggest that public opinion is mostly positively preconditioned towards the use of companion robots in daily living or at work, which, in turn, fosters a keen scientific interest in AAL [5].

The motivations for this work are threefold. Firstly, to cope with tasks that need a collaboration of robot teams and smart spaces (e.g., provision of real-time information about space congestion in robot route planning). Secondly, to increase performance in multiple task assignment and execution (e.g., meal delivery to multiple patients in hospitals in given time frames). And thirdly, to benefit from emerging global hybrid intelligence including human and artificial intelligence that could better deal with the complexity of certain tasks.

We may distinguish two main paradigms for developing AAL technologies. On the one hand, AmI couples data collection at different time and space scales together with analysis, to play a mostly proactive rather than reactive role in alleviating the person's dependence to external human physical intervention. This is made feasible by monitoring human activities [31], profiling users, detecting deviations from normative behaviour, and sending alerts [25], [35]. By design, AmI is a system of predominantly, statically distributed components used for computation, communication and isolated actuation.

The second paradigm concerns the use of mobile robots whose enhanced physical interaction capabilities [14], notably, navigating in previously unknown and evolving spaces, manipulating objects and natural human-robot interaction via dialogue [33] or gesture [24], can foster application perspectives that are not feasible in the first paradigm. At the same time, there are examples in which integrating multiple diverse skills into a single robot proves overly complicated (e.g. the ROMEO2 robot <https://projetromeo.com/> which could not be commercialized as it was not possible to integrate all required skills) while using multiple cooperating robots with complementary skills appears more practical (cf. project RoboEarth <http://roboearth.ethz.ch/index.html>). Such considerations synthesize our incentive in distributing a number of system functionalities through an integration between the paradigms of smart spaces endowed with AmI and MRT. A comprehensive list of services that could benefit from such an integration are: (i) room tidying, (ii) human activity monitoring and tracking, (iii) item delivery such as meal or medicine and (iv) cleaning. At increasing scales, such services become more and more parallelizable and decentralized yet pose challenges in terms of communication, conjecture handling or data fusion/analysis that are better processed centrally.

In this article, we set the bases upon which such an integrated schema could be realized from an operational point of view. Relatedly, we review a number of earlier works in the domains of AmI and MRT, focusing on the different forms that human implication can take, from end-user requirements and system training to collaboration/teaming with agents and system evaluation (see Section II). We then converge on how these two paradigms could assemble a layered hierarchy of increased utility in AAL scenarios (see Section III) whose components are subsequently instantiated (see Section IV) on the basis of solid, earlier performed works. We conclude the article in Section V with a discussion on the open challenges and promising directions for subsequent work.

II. BACKGROUND

We are here especially concerned with exploiting complementarity among heterogeneous entities, including humans. Human teaming with robots has been considered in applica-

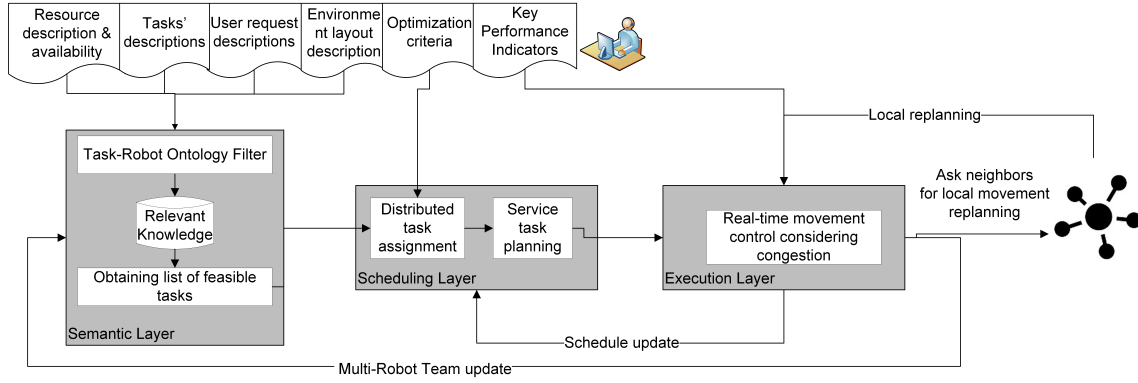


Fig. 1. Example of AmI and MRT integration using the RAMI architecture implemented in each robot.

tions ranging from Urban Search and Rescue (USAR) [13], co-production [10], more recently in scenarios related to AAL for people with reduced mobility [30], [8] and finally in general purpose scenarios [22]. AAL scenarios add another level of complexity because the end-users are not professional experts trained to use the underlying technology while there can be additional humans of different roles being involved aside the end-users (such as doctors, service personnel, etc). As a result, exploitation of multiple heterogeneous agents that need to collaborate, exchange information and maximally exploit human feedback is required.

The CASAS (Center for Advanced Studies in Adaptive Systems) project including the CASA-U (the CASAS User interface) [29] introduces an adaptive smart home system that applies machine learning techniques to discover patterns in resident's daily activities and to dynamically adapt to the user's explicit or implicit needs in daily routine activities. While the COBOT chat system [9] concentrates on adaptive behaviour in multi-user environments, learning from non-expert users implies considering different attitudes in giving feedback (some people tend to reward with positive actions and others penalize with negative actions).

The ongoing RADIO project (<http://www.radio-project.eu/>) (Unobtrusive, efficient, reliable and modular solutions for independent ageing) aspires to advance AAL technology via an ecosystem that interfaces AmI with a single robot, yet user implication is focused on an all-purpose system design rather than user-based system adaptation and compliant-based behaviour of its components.

In contrast, the vision of the GrowMeUp project (www.growmeup.eu) is to provide a robust, adaptable robot platform that constantly learns and adapts its behaviour according to the user in the short, middle and long-term. Supposedly, life-long robot learning [32] is accelerated by interconnecting dislocated robots and sharing learned models in the cloud.

In the context of COMRADES (COordinated Multi-Robot Assistance Deployment in Smart Spaces) project which is the focus of this work, we seek to mitigate the aforementioned challenges via an architecture that puts emphasis on the coordination and communication of multiple heterogeneous

components. Specifically, we account for the explicit and implicit impact of human actions in the integration of the system's components.

III. TOWARDS A LAYERED INTEGRATION OF AMI AND MR

The goal of integrating AmI with MRT is to provide a new set of services of increased utility to the human, rather than merely grouping the services provided individually by each (cf. the IFR's (International Federation of Robotics) definition <http://bit.ly/2zTBveP> of a service robot). To do so, we consider a system made of a team of multiple robots, human users and a network of AmI sensors controlling the physical space of interest. This is represented as a multi-agent system made of mobile robot, user and AmI agents. Our starting point for modelling such a system is the Robot Assisted Ambient Intelligence (RAmI) architecture [20], [21] for the distributed coordination of robots in task assignment and routing for item delivery (see Fig. 1). This architecture is presented in [21] and discussed in [20] together with its application and communication requirements to facilitate efficient usage of limited AmI and MRT resources.

In RAmI, user agents are installed via apps of a smart device of each user, while AmI agents are distributed throughout the infrastructure where each one monitors a certain area within its scope. Sensor agents can be cameras and iBeacons, wherein the later case the emitted signals are read by user agents and serve for localizing the users and recognize their activities (complemented by accelerometers of their smart devices).

The RAmI architecture contains a *semantic*, *scheduling* and an *execution* layer. Contrary to similar ORCAS architecture [18], in RAmI, robot configuration is assumed to be fixed and each robot's delivery capacity is limited by maximum item's weight and dimensions. Moreover, all resources and each item delivery are semantically described by a human operator: e.g., meal/medicine, time of delivery, weight, dimensions, and type of a meal/medicine. The resource description and availability description contains the information of available items and their locations.

In the semantic layer, a set of compatible robots for each end-user demand is found by using a SPARQL-DL query

engine. The scheduling layer contains the task assignment and route planning module. Based on the semantically described delivery demand, each robot agent coordinates with other robot agents for the task assignment through the bi-level task assignment algorithm in [17]. While MRT is responsible of the MRT task assignment, the AmI network is responsible of updating the travel times under congestion in the network and distributively optimizing robots' routes by using the route finding algorithm in [19]. Robots receive updated routes and travel times information from the closest AmI agent. In the execution layer, the individual performance is monitored in real time and in case of unpredicted events, a robot tries to coordinate locally with its neighbours to lower their impact. If local coordination is inefficient, the scheduling layer recomputes the robots' routes. In the case of larger contingencies or the addition of robots that can improve the MRT's performance, the RAml architecture recomputes the routes starting from the semantic layer.

In addition to route guidance, RAml user assistance tasks may include, among others, encouraging physical activity, medical supervision, offering entertainment, maintaining social ties, item delivery (e.g., meal or medicine) and assisting a user in the case of urgency. Such activities can be coordinated based on priorities provided in the semantic layer of RAml.

A. Supervised task modelling and composition

In AAL scenarios, the way by which a task is accomplished may be automatically obtained by the system on the basis of pre-set optimization measures, by the system's designers (e.g. caregivers or doctors) or by the human user herself. In the RAml example that was just presented agents coordinate autonomously in order to accomplish a task, but there are cases where tasks are defined in a supervised manner, for example when the user is asked to perform a rehabilitation task instructed by a professional. In addition to automated task assignment and execution, we find equally important the capacity to manually specify a certain sequence by which a task is to be accomplished.

In this respect, we had developed a prototype in [1] allowing to define various elementary sub-tasks (grains) (see schema in Fig. 2) and the way by which alternative sequences could be composed. It is an authoring tool allowing integration and reuse of sub-tasks for the creation of different, customized, composite task-oriented scenarios. Applied recursively, the decomposition procedure may affect each sub-task enriching the sub-task base with instances of arbitrary granularity.

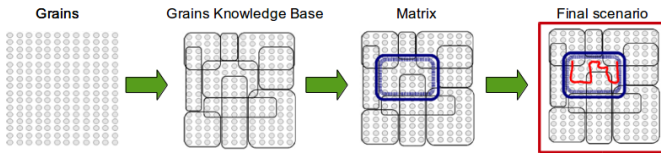


Fig. 2. Custom-defined task modeling and composition process [1]

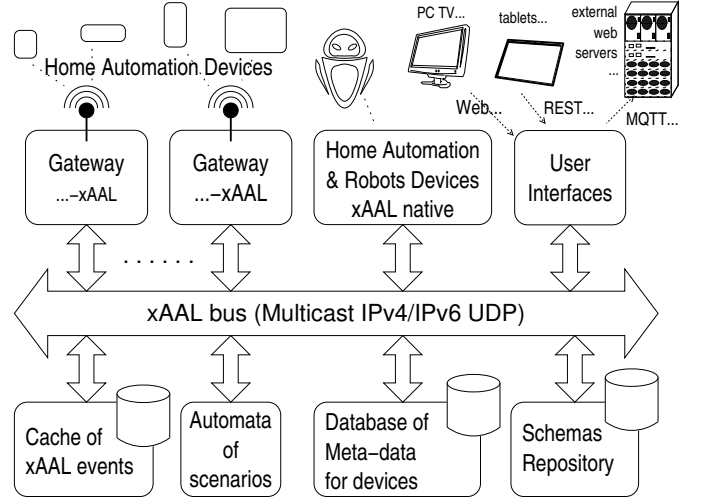


Fig. 3. xAAL interoperability schema.

IV. FUNCTIONAL COMPONENTS

We continue our description by reviewing a number of functional components that we deem as paramount in the integration of the paradigms of AmI and MRT.

A. Interoperability and AmI-MRT Communication

It is nowadays feasible to provide AAL services to dependent people and more widely to the general public, largely thanks to the large offer of home automation devices and connected objects. Conversely, the diversity of available devices raises the issue of the interoperability of heterogeneous devices. Simply speaking, each vendor proposes its own proprietary solution with the aim of catching customers on a captive market. Proprietary solutions differ on the characteristics of the physical layer and of the transmission channel in use (frequency, throughput, bandwidth, data coding, etc). Furthermore, sensors and actuators are dependent on application domains (home-automation, heater control, energy, comfort, health and well-being, etc.). Once the consumer has chosen a vendor for its smart house, he/she is then unlikely to purchase devices from another vendor to equip his/her housing.

To overcome these limitations, new market actors emerge proposing so-called “multi-protocol gateways”: a box (a small computer) is equipped with two or more modules, each module *talking* in a given home-automation protocol; then, a software component over those modules makes it possible to forward messages between protocol A and protocol B. Moreover, those boxes embed additional functions to make all of these usable: HMI (via Web and/or smartphones), configuration facilities, connectors to extra services in the cloud, etc. In previous work, Lohr et al. [15] presented a review of existing solutions that prove highly centralized and partial from the interoperability point of view, as each box manages a limited number of low-level protocols and boxes are hardly able to talk to each other.

The xAAL Interoperability Protocol: To alleviate the aforementioned limitations, we have proposed the xAAL system

[15] (see Fig. 3) whose foundation is to reorganize and formalize the architectures of those boxes, which are in fact all composed of the same functionalities. xAAL relies on a distributed architecture of functional entities, communicating to each other via a secure message bus over IP [16].

In xAAL, the set of functions commonly implemented by home-automation boxes is arranged into well-defined separated functional components: elementary gateways for technology-specific devices, native-xAAL devices, caches, configuration database, user interfaces, scenarios automata, etc. Each component may have multiple instances, may be shared by several boxes and be physically located on any box.

In turn, a device has a type described by a schema that provides its semantics and describes its capabilities: a list of possible methods on this device, a list of notifications that it sends spontaneously and a list of attributes. Those schemas are inspired by the UPnP approach [7]. Messages are transported by an IP multicast bus. As proposed by UPnP, a bus allows the discovery: when a new component appears in the installation, it announces itself. All other entities can then take it into account. Likewise, when a new component enters, it can query the bus to discover the other components already present.

The above design greatly facilitates the configuration and allows great flexibility which makes it a good candidate for integrating AmI-MRT. On this base, we recently developed a prototype implementation of an AAL scenario where xAAL is used to integrate a robot and a smart-home system [23] demonstrating the following use-case:

- 1) Detecting a person's fall. In this demonstration, we used an RGB-D camera and compared the heights of the hip and head to hypothesize a fall.
- 2) Performing a confirmation of the fall, to alleviate the reliability problem of the fall detection system. This confirmation relies on speech interaction with a social robot. We used the humanoid robot Nao (by SoftBank Robotics).
- 3) Securing the house owing to actuators in the house. (e.g. switching off the oven)
- 4) Facilitating communication with the family or rescue services, through both telephones and robot-embedded cameras that are made reachable by Internet.
- 5) Allowing access to the house for rescue, owing to automated door unlocking.

The described use-case showcases a seamless integration of IoT and robots for smart home automation interoperability. We argue that facing the numerous home automation devices and the numerous robots developed, but also due to the variability of each home and the variability of the users' use, we need a plug-and-play system that can integrate any robot and any smart home device.

This convinces us that xAAL serves as a good candidate for AmI-MRT. As home-automation devices, each robot can be described by an xAAL schema in order to explicit its capabilities and available services (mobility, transport, planning, knowledge sharing, etc.). Robots can then discover each other, in addition to their connected environment (smart-home

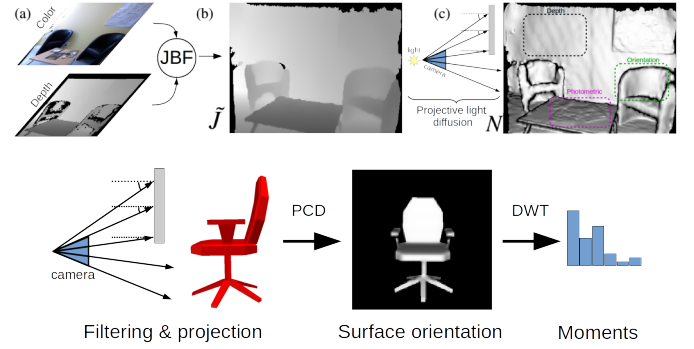


Fig. 4. PLDI on-line (first row) and off-line (second row) extraction pipelines.

devices, connected objects, sensors, actuators, etc.). They can send request messages to others, receive requests and decide to obey if it does not conflict to a globally directed task plan.

B. Environment Mapping via MRT

Smart space actuators have a predefined, non-evolving state space wherein a limited set of actions can be performed, e.g. switching on/off lights, opening/closing windows, etc. In contrast, the underlying state space of MRT is subject to evolution due to variable human activities.

Mapping an environment therefore amounts to autonomously building the state space within which mobile robots can operate for navigation and manipulation tasks. For AAL scenarios agents should be able to perform updates at regular time intervals to account for changes incurred by human activity. Going beyond conventional metric mapping for allowing advanced AAL, the semantic attributes of the environment should be extracted, namely, segmenting and classifying regions of interest. This amounts to a *semantic, object-based mapping* of the environment wherein landmarks on top of a metric map are annotated with pairs containing the hypothesized category and tasks that can be performed, e.g. (chair, {push, pull}), (telephone, {lift, call number}), etc.

We recently developed a prototype implementation of such a functionality in the context of the ROMEO2 project [14], by processing RGB-D (color and depth) sensory data to extract *Projective Light Diffusion Images* as object descriptors [26] (see Fig. 4). Although it concerned a single robot mapping its environment, the integration of AmI and MRT allows the synthesis of multiple egocentric maps into a globally consistent object-based map. The role of MRT is thus to serve as roving sensors while AmI centralizes the collected object-action pairs and dispatches robots according to tasks. Notably, the use of objects as mapping landmarks greatly facilitates data transmission within the network, as opposed to transmitting raw map occupancy data.

Object-based maps can be used to perform services such as object localization and transportation, room tidying, etc. but they are unsuited for performing navigation tasks. Metric-based maps are better suited as they provide accurate information for avoiding obstacles but at increasing space scales

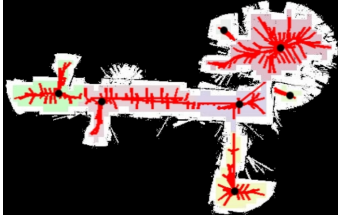


Fig. 5. Example topological map segmentation and corresponding collision free paths.

such as for hospitals they increase the complexity of finding optimal point-to-point, obstacle free-paths.

To reduce computational cost, an environment can be represented as a *topological graph* where nodes correspond to distinctive areas and edges mark the possible transitions among them. Point-to-point path planning is hence solved in a significantly reduced state space inside the graph while metric planning is constrained within the borders of adjacent node edges. Relatedly, in [27] we developed an efficient topological clustering algorithm that further provided as output collision-free robot paths within each node (see Fig. 5). A topological graph is a light-weight data structure that can be communicated in real-time by AmI to MRT, while agents themselves provide feedback on possible congestions that compromise the navigability of certain edges among nodes, allowing to globally update in real-time the topological map which would otherwise be impossible.

C. Human Activity Understanding and Compliant Operation

Understanding human activity and interactions among multiple participants is a prerequisite in making AAL-oriented technology socially embedded and adaptable to end-users. This is true both for AmI and MRT that can be considered ubiquitous, the former due to the numerous sensors and actuators that it interconnects and the latter because they can approach and physically interact with the users. Understanding human activity therefore implies that AAL services are timely performed while respecting privacy.

When integrating AmI and MRT, we acknowledge the importance of human activity understanding at the dimensions:

a) Human-Machine Interaction: This dimension mostly concerns tasks performed by mobile robots and which are triggered upon recognition of certain classes of human activity. Examples include explicit assistance requests indicated through user gestures (e.g. object delivery, communication, etc) or implicit recognition of actions (e.g. fall detection, monitoring of user-habits, etc).

To this end, we had previously developed a framework for mapping the spatial interactions among groups of people by processing of human skeletal articulation data [28]. The derived map serves in quantifying complex social proxemics cues (see [4] for a recent survey) that robots can exploit to optimize their responses in initiating or avoiding an interaction (see Fig. 6). The added value in integrating AmI and MRT at this point is sought at the level of data fusion since human

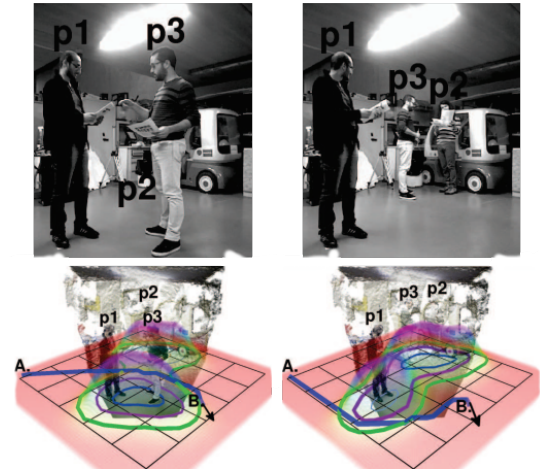


Fig. 6. An example of social mapping application to groups of interacting individuals and planned robot paths that maximally respect the deduced dynamic social proxemics.

interactions are susceptible to very high levels of occlusion and interference from the participating entities. Where a single sensor/viewpoint is highly unlikely to resolve such ambiguities, the synergy of AmI and MRT is highly advantageous.

b) Service personalization: In order to make the proposed services more acceptable, especially by elderly users, such services must be chosen and done while respecting the user's preferences and way of living. In previous work, semi-supervised learning and Markov-based models were used to generate adaptive and personalized decisions in multi-users environments [11], [12]. In this work, we consider that users through their reactions and feedback (implicit or explicit) are an important source of information on how to achieve tasks in an adaptive and personalized way (time to give medicine, path recommendation, etc.) and we must know their activities to adapt the decision accordingly to the current status [3].

On the other hand, the learning process should deal with the confusion caused by the lack or contradicted feedbacks. A lack of feedback in some scenarios might represent a satisfaction and in others it might represent an unsatisfying situation. Furthermore, in the RAMI architecture, data gathered from AmI agents (sensors) in addition to those gathered by the robots can help handling conflicts and ambiguities during learning. In addition, using human-robot verbal interaction or interfaces carried by the robots can allow requesting explicit feedback on some situations to speed up the learning process.

V. DISCUSSION

Integrating AmI with MRT is very promising towards advancing AAL technology and at the same time challenging in a number of aspects. Notably, there needs to be consensus among the various different actors involved (end-users, caregivers, engineers, researchers) in defining terms that may bear different meaning depending on each one's background and context. Notions such as a *task*, a *service* or *skill* may need to be clarified based on the context. Furthermore, there is a need

in developing quality standards for AAL technologies to lead to the evaluation of proposed solutions.

In proposing this work as basis for the integration of AmI and MRT, we acknowledge that some adaptations should be performed to allow the individual components to co-exist and to cooperate. The xAAL interoperability protocol is meant for this but its capacity is not yet tested at large scale with multiple interactive robots that need to exchange large volumes of data. Furthermore, xAAL allows artificial agents to be integrated in the system and communicate while for the humans we currently rely on appropriate interfaces. Finally, integrating AmI with MRT should rely on models of human behaviour allowing worst-case, expected-case and best-case analysis of human activity. This should increase the compliance of the integrated system made of RAmI architecture and xAAL interoperability protocol by reducing conflicts and improving coordination when possible.

We are currently in the phase of introducing various new robot platforms in the xAAL ecosystem, from humanoid robots to small service vehicles. We are planning to test the behaviour of the proposed integrated system in complex simulation scenarios and subsequently in a laboratory setting.

VI. ACKNOWLEDGEMENTS

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