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On the Integration of Adaptive and Interactive Robotic Smart Spaces

Abstract: Enabling robots to seamlessly operate as part of smart spaces is an important and extended challenge for robotics R&D and a key enabler for a range of advanced robotic applications, such as Ambient Assisted Living (AAL) and home automation. The integration of these technologies is currently being pursued from two largely distinct view-points: On the one hand, people-centred initiatives focus on improving the user's acceptance by tackling human-robot interaction (HRI) issues, often adopting a social robotic approach, and by giving to the designer and - in a limited degree – to the final user(s), control on personalization and product customisation features. On the other hand, technologically-driven initiatives are building impersonal but intelligent systems that are able to pro-actively and autonomously adapt their operations to fit changing requirements and evolving users' needs, but which largely ignore and do not leverage human-robot interaction and may thus lead to poor user experience and user acceptance. In order to inform the development of a new generation of smart robotic spaces, this paper analyses and compares different research strands with a view to proposing possible integrated solutions with both advanced HRI and online adaptation capabilities.

Keywords: Human Robot Interaction; Smart Homes; Ambient Assisted Living; Robotic Ecology

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1 Introduction

Smart home technology utilizes sensors and microprocessors throughout the home to collect data and information in order to provide useful services, such as monitoring the daily activity, safety, health and security of the house occupants. Notwithstanding its benefits to the user's life style, such as allowing elderly persons to live independently in their own homes and postponing or perhaps even avoiding a potential move to a residential care facility, the technology is still largely confined to research laboratories and is far from reaching widespread adoption by consumers. The biggest barriers to the widespread adoption of such technologies are still their prohibitive costs (which, when they are employed for AAL applications, often include installation, customization charges and monthly monitoring fees), and low levels of user acceptance. Much of the elderly population is simply not comfortable with what they perceive as obtrusive and impersonal technology. Current systems are also unreliable, which is one of the main reasons why such a large proportion of them are confined to research laboratories and why commercial products are mostly limited to basic monitoring services.

Notably, users are rarely actively involved in current systems. They are passive recipients of smart services, their actions are constantly monitored by using sensors pervasively embedded in their homes, and their context and needs are guessed by the system using models of their past behaviour and/or by using knowledge that was imbued into the system at design time. Consequently, the perceived value and trust in the technology can be seriously undermined and curbed by the constant monitoring and ill-advised or poorly-timed interventions, as well as the user's lack of control and understanding of the capabilities and limitations of the technology.

To tackle some of these issues, autonomous and interactive robots have been or are being integrated with smart spaces and AAL systems in a number of research projects [1–7, 9, 93]. On one hand, the smart environment can act as a service provider for the robot, e.g. feeding it with information about the user's whereabouts and state, by using sensors pervasively embedded in the environ-

ment and/or worn by the user. The robot can then provide useful services thanks to its physical presence and mobility capabilities. For example, when the doorbell rings the robot could find the person in the house and visually attract his attention to the doorbell. Note that this is not possible with passive devices such as phones, which may easily be misplaced or not heard. On the other hand, the robot provides the user with a user interface that acts as a representative of the services that the intelligent environment offers. This increases the user's acceptance of the technology and offers added value with services such as cognitive stimulation, therapy management, social inclusion/connectedness, coaching, fall handling, and memory aid.

Studies on people's attitude to these robots have shown how their acceptance not only depends on the practical benefits they can provide, but also on complex relationships between the cognitive, affective and emotional components of peoples' image of the robot [10]. Furthermore, Human Robot interaction (HRI) studies for domestic or personal robot companions have raised personalization and social interaction as important considerations for guiding the design of this type of robot application [12, 13]. For these reasons, the same systems have been increasingly equipped with easy-to-use and adaptable HRI capabilities, such as speech and touch screens in order to understand simple orders, and also to account for users' vision or hearing impairments. Studies have been performed examining situational and platform-specific influences on human preferences, concerning design factors such as robots' proxemic behaviour and appearance, and also focused on the role of individual differences in terms of personality and other demographic factors. However, these studies usually adopt a design-centred approach; they require a prototype at the outset of the investigation, long user trials and usability analysis. Consequently, the results of this kind of acceptance research are typically limited to one particular system. The insights gained cannot readily be generalized across different systems and services. They can inform the development of customised solutions but those solutions have limited abilities to respond to the users' in-situ response or adapt to changing contexts and evolving users' needs, habits and preferences.

A particularly interesting case is the recent emergence of the robotic ecology paradigm in which many robotic devices, pervasively embedded in everyday environments, cooperate in the performance of possibly complex tasks. Instances of this paradigm include network robot systems [14], sensor-actuator networks [15], ubiquitous robotics [16], and PEIS (Physically Embeded Intelligent Systems) Ecologies [38]. Common to these systems is

the fact that the term 'robotic device' is taken in a broad sense, including mobile robots, static sensors or actuators, and automated home appliances. In particular, cognitive robotic ecologies with information processing algorithms such as perception, learning, and planning are increasingly capable of adapting autonomously to evolving situations and achieving useful services that are not restricted to only those situations and methods that are envisioned by their designer [39]. This can greatly simplify design and customization, and support online adaptation to evolving environments and changing user needs. However, to date, these research efforts have mostly focused on the development of the enabling technologies: sensing, acting, coordination and learning infrastructures, and have largely ignored user - system interaction. We argue that huge opportunities are missed by the lack of a deeper interaction and cooperation between robotic ecologies and their users and much more work is needed to transform them into user-focused systems, by improving the ways they operate and interact in a human populated environment. Reconciling social and personalized human-robot interaction with the ubiquity and the novel opportunities afforded by cognitive robotic ecologies (sensing, acting and interacting through distributed sensors and actuators), still remains a largely unexplored area of research.

In order to inform the development of this new generation of smart robotic spaces, this paper provides an overview of different research strands with the view of proposing possible integrated solutions that would support our vision by offering their combined advantages while overcoming their current limitations.

Specifically, the remainder of this paper is organized in the following manner: Section 2 considers past and current projects combining service robots in smart spaces. Our overview focuses on the analysis of how those projects have addressed HRI and users' acceptance issues in order to draw a set of requirements for their adaptation, customisation and personalization needs, and before discussing in more detail a specific case study exemplifying best practices addressing these concerns. Section 3 provides an overview of past and current projects that have embraced a cognitive robotic ecology (CRE) approach, focusing on how they tackle issues such as coordination and context-awareness, before focusing on a specific case study of a system that is purposefully designed for supporting adaptation to changing requirements. Finally, Section 4 offers a number of concrete proposals to inform the development of smart and robotic spaces with both advanced HRI and online adaptation (CRE) capabilities, by building on existing systems and by defining a common roadmap for com-

plementary, but until today largely independent research strands.

2 HRI in Smart Spaces

In this section we consider how researchers have approached the issues of HRI in smart spaces, such as sensorised homes, and highlight important issues in HRI relevant to this area (for a general introduction to HRI see Goodrich and Schultz [72]). There are already a number of approaches using robots in smart homes with HRI capabilities. For instance, robots in CompanionAble [1], KSERA [2], HOBBIT [5], Florence [3], Robo-Care [93] and ACCOMPANY [7]. Note that the projects on this list are mentioned as they have specific HRI aims, compared to works that focus on the development of multi-purpose assistive robotic solutions, such as [8]. However this is not an exhaustive review of all projects in this research field, for a more extensive survey of robots in health and social care see Dahl and Boulos [73].

CompanionAble's unique feature is in attempting to provide dementia patients with cognitive stimulation. To this end, CompanionAble provides a synergy of robotics and ambient intelligence technology and their semantic integration to support a caregiver's assistive environment, mediated by a robotic companion (mobile facilitation) working collaboratively with a smart home environment (stationary facilitation). CompanionAble is specifically aimed at persons with mild cognitive impairment. CompanionAble stores context based rules and makes inferences from an OWL/RDF based ontology supporting the smart home environment. Interaction is via touch screens and simple voice commands. An anthropomorphic robot provides support via the integration of personal therapy management from health professionals using home TV, together with video-conferencing, to prevent isolation and support social engagement of the care-recipient with his/her carers and the wider social setting. Activity management including medication reminders is via diary management functions.

The KSERA project uses a NAO robot from Aldebaran Robotics [19] to provide support for the elderly. One of the unique features of KSERA is in its social support for patients with Chronic Obstructive Pulmonary Disease (COPD). One of the main goals of this project is to ensure that HRI issues are addressed by applying research from (cognitive) psychology and human motor control with the aim of providing natural human-robot interaction. This is achieved via visual attention using gaze direction and

attempting to build trust through repeated interaction episodes. Functions provided include external monitoring for weather reports, diarised medical reminders and monitoring of health parameters as well as video communication with external carers or family.

Florence aims to improve the acceptance of AAL (Ambient Assisted Living) robotic services by providing both assistance and fun oriented lifestyle functions, and by positioning them as autonomous lifestyle products. Florence's unique feature is attempting to put the robot as the connecting element between AAL services and the elderly person. It includes diaries for medical appointments etc., answers to simple questions and also an interface to the smart home itself. Aspects of HRI include proxemics, robot voice characteristics, facial expressions of the touch screen avatar, and the altering of the personality of the robot in different circumstances.

The HOBBIT project uniquely focuses on a new user-centred concept called 'Mutual Care' aimed at building a mutually assistive bond between users and socially assistive robots. Such an approach is motivated by sociological and psychological insights, which suggest that it might be easier to expect and accept assistance from a robot if the user can also assist the machine in certain situations.

Robocare built a prototypical intelligent home, in which sensors, robots, and AI-based techniques are exploited to provide support in the daily activities of an elderly person, thus setting the scene for many of the systems surveyed in Section 3. The system focuses on ensuring, through daily activity monitoring, the adherence of the assisted person's behaviors to "good living" behavioral patterns. These patterns are represented in the form of flexible schedules, predefined by a caregiver as an initialization phase of the system and are reasoned upon by means of state-of-the-art scheduling technology. Notable, however, is also Robocare's emphasis in the development of mixed initiative HRI functionalities and in evaluating the acceptability of the overall system. User-initiative interaction is triggered by a speech input from the assisted person, for instance, asking questions such as "Have I taken my pills?" or "Can I make an appointment for tomorrow at 5 pm?". System-driven interaction is triggered whenever the system detects potentially dangerous or anomalous/inconsistent situations. In those cases, the system notifies a carer or triggers a proactive dialogue with the assisted person.

ACCOMPANY envisages an autonomous robot, integrated into a smart home infrastructure, that provides re-enablement and empathic interaction to elderly users. In order to move away from static models of users' and system's behaviours, and to enable their adaptation and per-

sonalisation, the project focuses on a co-learning relationship between a user and a robot. The details of this approach and its HRI aspects are discussed in the case study in section 2.2 below.

2.1 Important Aspects of HRI

2.1.1 Human-robot Interaction and Personalisation

Drawing on the related field of Human-Computer Interaction (HCI) [20] HRI researchers, in particular for domestic or personal robot companions, have raised personalization as an important issue. A robot companion that will interact with its user(s) across a variety of situations within a human-centred environment will necessarily have to adapt to the individual, and the specific requirements or preferences of its users. This recognised need has led to research on how these idiosyncratic effects impact different aspects of human-robot interactions. One important distinction between HCI and the work done in HRI has been the reliance of anthropomorphic, human-human interaction models for understanding the scope of personalisation features.

2.1.2 Proxemics

Proxemics, originating in studies on human-human interaction [21], has been a primary focus for HRI due to the unique ability of robots to move autonomously within the shared physical space of the user [22–25]. The ability to successfully negotiate spatial behaviour has been considered highly important in terms of the possible success or failure of a robotic companion in a domestic environment, in terms of user motivation, task efficiency and also in terms of eliciting emotional responses, and is dependent on individual differences and perceptions of relative social roles, so the scope for personalisation is large. Due to this, studies have been performed examining not only situational and platform-specific influences on human preferences with regards to these behaviours but have also focused on the role of individual differences in terms of personality and other demographic factors. These studies all show that there are clear, systematic differences between participants due to their measured individual differences, however these differences may interact both with each other as well as with how they impact evaluations of other robot behaviours. This suggests the importance of the ability for a system to respond to a user's in-situ responses to proxemic behaviour.

2.1.3 Appearance

Finally, appearance is also an aspect of human-robot interaction wherein personalisation is highly relevant. Evidence suggests that individual differences impact the preferences potential users will have regarding the appearance of a robot [26–28]. While the appearance of many robots are tightly constrained by their intended task or operating environment, studies suggest that users of robots will still try to customise them in terms of appearance, e.g. for socially and/or related motivations. With more zoomorphic robots, such as the Pleo [29] or AIBO [30], this customisation is also used to validate the personhood/animality of the robot, for instance by gendering the robot. These findings highlight the need for users to assert their ownership of robots in their environment through the customisation of appearance. This is regardless of the original appearance of the robot, as this phenomenon is reported from the box-on-wheel Roomba [31] to the highly realised zoomorphic AIBO and Pleo. These findings also suggest that this personalisation is associated with a more positive, accepting view of having the robot in one's domestic environment.

2.2 Case Study - ACCOMPANY

The main idea behind the ACCOMPANY project is to develop a companion robot, as part of an intelligent home environment, which assists elderly people to maintain their independence in their own homes. A key element of the approach is that of the 'robot companion' [32] whereby the robot satisfies two main criteria: 1) it must be able to perform a range of useful tasks or functions and, 2) it must share an environment with users in a manner that users are comfortable with and which they find socially acceptable. Whereas the former criteria is a technological challenge where the robotic and smart home systems are integrated to generate useful behaviours, the latter adds an important constraint on such developments: the technology has to be acceptable, comfortable and effective for a particular target user group in a target application domain. Thus, taking the concept of a companion robot seriously requires a user-centred perspective where users need to be involved in the design of the system from the initial stages as well as during various cycles of iterative testing, refinement and evaluation of the newly developed technology.

The target users are elderly people who the ACCOMPANY system may help to live in their own homes independently for longer. The target application domain is a robot as a home companion as part of an intelligent home in or-

der to support the independence of its users. The robot delivers physical and cognitive assistance, and provides motivation and advice for re-enabling users with skills that they have been losing. It should do this in a socially interactive acceptable and empathic manner, encouraging physical, cognitive and social activities in the user. The approach is one of co-learning where, rather than treating the robot solely as a support mechanism for an elderly person, and possibly disenfranchising the person from the problem being solved, both the robot and the person find solutions together. The elderly person remains at the heart of the problem solving exercise.

2.3 Key HRI Issues in ACCOMPANY

ACCOMPANY places major emphasis on social and empathic design of human robot interactions together with user based facilities for robot teaching, learning and adaptation [33, 34]. On the social and empathic design aspects the robot presents itself both physically and via handheld devices as an empathic being. For example, if the robot (a Care-O-bot3®robot [35] developed by Fraunhofer IPA) notices via sensors in the house that the person has not had a drink for some time, it will approach the person in a 'context aware' manner based on proxemics studies and user preferences, display an empathic mask [36, 37] on the user's tablet computer and suggest that they go to the kitchen and get a drink together (see Figure 1). If the user does not respond the empathic mask will change to look 'sadder' and the icon making the suggestion becomes larger. The robots physical presence also changes to 'lean forward' a little, suggesting concern. In this way both proxemics and appearance are combined to form a empathic partner.

In terms of teaching, learning and adaptability, ACCOMPANY assumes that the situation in the person's home will be fluid. A system designer cannot effectively predict the requirements of a person in the future, therefore robot behaviours can be created by end-users, family and carers themselves. This requires a disciplined approach to the underlying design of the robot and smart home ontologies such that the environment can be considered as a 'holistic' whole. This can be achieved by considering sensory information on a higher semantic level, where context analysis creates new sensors. For example, given that kitchen cupboards and the refrigerator are being opened and that the cooker or microwave is being used, a sensor 'user making meal' can be set to true. These types of higher level sensors can then be used to create more complex semantics. Given such an environment the user themselves can use a teach-

ing facility to create what they want, when they want it, based on the more semantically rich 'sensors'. Technical wrapping concerning the robot and house actuation can be automatically generated thus freeing the user from the concerns of the technical detail involved. The system can be personalised as the person's needs change, for example by the elderly person themselves or by other stakeholders such as healthcare professionals and informal caregivers. Informal carers might set up reminders (e.g. for the person to contact them), formal carers could set up safety indicators, for example sending SMS messages e.g. when there is an issue in the house (e.g. bathroom taps running for too long). At each stage in the teaching process the robot displays what it is currently capable of achieving (from previous behavioural setups), and so the users and robot effectively work together to achieve the user's goals.

Figure 1: A HRI Scenario from the ACCOMPANY project. The robot had previously suggested, in an empathic manner, that it would be beneficial if the user had a drink having recognised that the user had not had a drink for some time. The cup also has a liquid level sensor and the robot can encourage the user, using an empathic mask, its proxemic distance and various gestures, to take a drink from the cup.

3 Cognitive Robotic Ecologies

PEIS [38], Robot-ERA [9], and RUBICON [39] are three of the most recent examples of projects pursuing a robotic ecology approach. Rather than primarily focusing on human-robot interaction and companion robotics issues, these projects integrate robots into smart environments so that they can accomplish useful services in a cost-effective way,

by exploiting distributed (and specific-purpose) sensors and actuators.

Note that the projects on this list are mentioned as they focus on intelligent decision making, compared to works that focus on (semantic) interoperability and communication issues, such as [14–16].

The overarching goal of these projects is to provide services that are useful, efficient and dependable. In PEIS, this requires that arbitrary combinations of a subset of the devices in the ecology should be able to be deployed in unstructured environments, such as those exemplified in a typical household, and then efficiently cooperate to achieve complex tasks. The central components in PEIS are (i) a robotic ecology middleware that enables heterogeneous devices to discover each other and to exchange information to support their collaboration [18], and (ii) a system planner serving as a central coordinator of the ecology [40]. The planner can autonomously decide what services should be used to assist the user and how the different devices in the ecology can collaborate to achieve them. On the example set in Robocare [93], the planner uses 'crisp' rules stating temporal relations (expressed in Allen's temporal algebra [41]) that a human domain expert has identified between sensor readings (such as 'the pressure sensor under the sofa is active while the TV is on'), inferred context (e.g., human activities, such as 'the user is relaxing in front of the TV') and actuation and device capabilities (i.e. plans that provide contextualized assistance to the user, such as 'fetch a drink for the user when she relaxes in front of the TV', and rules stating the capabilities of each device, such as 'robot1 is able to fetch a drink').

Robot-ERA [9] focuses on robotic issues to build reliable robotic services to improve independent living, quality of life and the efficiency of care for elderly people. The project adopts user-centered design methods and works toward demonstrating and assessing the general feasibility, scientific/technical effectiveness and social/legal plausibility and acceptability by end-users of a plurality of complete advanced robotic services integrated into intelligent environments. To this end, Robot-ERA employs cooperative service robots acting in both indoor and outdoor environments, and within an AmI infrastructure. The latter is fully integrated into domestic and urban contexts, and it is used to facilitate the operations and supervision of these robots. Using already available and commercial robotic systems, and by further extending the efficacy of plan-based control solutions [49], Robot-ERA is currently building and evaluating a number of advanced services: mediating voice and video calls; escorting around the house during the night; reminding of appointments or medications; delivering food from the building entrance to the apartment; and carrying laundry to the common laundry room and back.

Projects such as PEIS and Robot-ERA provide fundamental scientific principles, associated software solutions (middleware) and robotic services to support the operations of robotic ecologies of different scales and for different applications. However - as in the control systems employed in many of the service and companion robots reviewed in the previous section - they rely on pre-defined, static and brittle models of their users and of possible contexts. This means that the resulting systems lack the ability to autonomously, pro-actively and smoothly adapt to evolving settings, changing users' needs and preferences that were unforeseen at design time.

These issues have been the main focus of the RUBICON project [39], which provided robotic ecologies with cognitive capabilities to improve their ability to recognize and autonomously adapt to changing and evolving contexts. The issues related to such an approach, their relation to current solutions in smart environments, and the details of how they are addressed in RUBICON are discussed in the following sections.

3.1 Important Aspects for Cognitive Robotic Ecologies

Cognitive Robotic Ecologies (CRE) are not dissimilar to other smart environments, in their requirements for understanding their users and deciding how to best assist them. However, equipping them with cognitive capabilities, such as perception, planning and learning, poses key issues: from the computational constraints of the devices involved, to the range of different tasks where learning is necessary, to the difficulty of identifying suitable and reliable teaching information to drive the adaptation of automated services.

3.1.1 Learning for Sensor Fusion and Activity Recognition

Numerous related works in the AAL and smart environment areas have harnessed machine learning techniques to merge and interpret the information gathered by multiple noisy sensors [53, 57]. The ultimate goal is to determine the state of the users and possibly predict their behaviour, so that this information can then be used to deliver context-aware assistance. However, the majority of these solutions rely exclusively on supervised information, which demands time consuming annotation of users'

activities to build up labelled training examples. Besides the cost and the technical problems associated with data annotation, such an approach assumes the existence of pre-existing models of activities and associated events. This makes it impractical to account for novel users' activities, changes or just slight variations in users' habits. Furthermore, current learning solutions tend to be centralised and of limited scope [52, 60, 61], targeting very specific tasks.

3.1.2 Activity Discovery and Adaptation

Unsupervised learning of a user's most common behaviours and preferences is an important step towards allowing an environment to provide automated, proactive and customized services. The combined abilities to discover a users' behavioural patterns and to automate appliances, such as lights, heating, and blinds, is already showcased in a number of initiatives developing adaptive smart environments, although not involving service robots [54, 57, 64, 65]. Often these systems employ Q-learning [62] or other adaptation policies based on utility maximization. In addition, in some cases they exploit users' feedback to drive the customization of the smart environment. For instance, in [54], the user can take advantage of interfaces to manually activate or rate their automation preferences and the one automatically selected by the system. Activity discovery methods can be used to discover frequent patterns associated with different actions carried out by the user [51, 58, 59]. The same systems can be used to detect anomalies in users' behavior, such as deviation from daily routines which may be symptoms of problems worthy of notification to carers or to the users directly. However, the majority of these methods are not integrated with activity recognition solutions but take information collected by sensors as a starting point. Besides the missed opportunity for building integrated, efficient and modular solutions, it is difficult for these systems to account for the richness of heterogeneous sensor sources to which activity recognition solutions are now accustomed. Consequently, it is common for these systems to be limited to the offline analysis of only binary sensor data (e.g. [58]).

3.1.3 Learning for Adaptive Planning

One of the key advantages of using planning techniques with robotic ecologies is the possibility of using alternative means to accomplish application goals when multiple courses of action are available to increase the robustness of the overall system. For instance, a robot may be able to localise itself through the use of its on-board laser sensor, but also by detecting RFID tags placed under the floor, if the more precise laser-based localization fails for some reason. A similar approach could be used to personalize a robotic ecology to its user(s). For instance, the user may dislike the presence of a robot equipped with a camera in the bedroom. Consequently, an alarm-clock service in a robotic ecology with multiple robots should choose to send a robot without a camera to wake up the user in the morning. While planners in general can easily support these scenarios, all these options, dependencies and preferences must be explicitly modelled and pre-programmed in the planning domain. The last generation of configuration planners for robotic ecologies, e.g. those used in Robot-ERA and RUBICON, go even further by combining several reasoners to account for causal, temporal, resource and information dependencies in multi-robot systems [49]. However, there is a strong rationale for limiting the amount of specification that must be considered by these systems. Besides adding a significant burden to the design effort, the inability of modelling other (unforeseen at design time) information in the domain is what ultimately impacts on the effort required to configure the system for different physical environments and to adapt it to modification to the environment and/or changing users' preferences and evolving requirements.

3.2 Case Study - RUBICON

RUBICON builds on existing software middleware, planning and monitoring systems for robotic ecologies, and harnesses them in a modular and distributed manner to tackle the issues outlined in the previous section. Contrary to existing smart environment solutions, data analysis and decision making functionalities are distributed amongst all the components of a RUBICON ecology, including tiny embedded sensors, actuators and robots. The RUBICON integrated system for AAL is tested in a fully functional apartment (shown in Figure 2). This is equipped with embedded sensors, actuators and mobile robots able to provide simple services to the user, such as vacuum cleaning and fetching medical equipment. The ecology is used to identify and react to user needs, activities, and preferences. For instance, this may include the delivery of notifications in response to dangerous or anomalous situations, learning to clean the floor after the users have had their meal, or fetch their medicines when they are indisposed.

Figure 2: Photo from the TECNALIA HomeLab AAL test-bed used to test some of the AAL services developed exploiting RUBICON solutions (taken from [84], with permission).
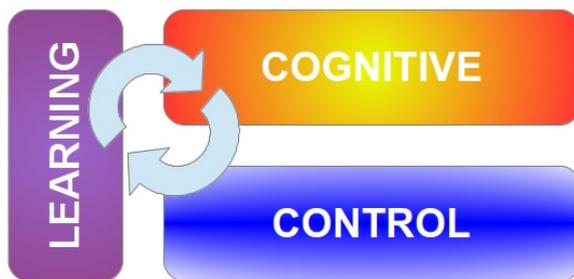
Figure 3: Schematic representation of the RUBICON integrated layered architecture.

3.3 Key Issues in RUBICON

Communication and Control : The starting points of the RUBICON architecture (illustrated in Figure 3) are a Communication Layer [71] used to integrate the various parts of the system, and to communicate between robots and heterogeneous wireless sensor and actuator networks, and a Control Layer [63]. The latter is a multiagent system that models each device in the ecology as an autonomous agent with sensing and acting capabilities, and which uses a central planner [49] to find ways for these agents to cooperate to achieve a number of useful services.

The key approach to enable adaptive, proactive and computationally efficient behaviour in the RUBICON ecology is (i) to improve the ecology's ability to extract meaning from noisy and imprecise sensed data, to (ii) learn what services to pursue, and (iii) how to pursue them, from experience, rather than by relying on predefined goal and plan selection strategies.

RUBICON Learning Layer : The first and the last of these challenges are met by using the RUBICON Learning Layer [42], a distributed and adaptable learning infrastruc-

ture that can be used to support a variety of learning requirements for a robotic ecology. The Learning Layer employs learning modules based on recurrent neural network models (echo state networks [43]) tailored to the very low-computational capacity of the sensor motes used in current wireless sensor network solutions. The Learning Layer can recognize relevant situations out of streams of raw sensor data, and it can process both binary and non-binary sensors to provide short-term predictions based on temporal history of the input signals. For instance, the Learning Layer can be trained to forecast the exact location of the user by examining the history of the radio signal strength index (RSSi) received from a wearable device worn by the user [44], or to provide timely and predictive information on the activities being performed by the user, such as recognizing that the user is eating by analysing the signal and temporal pattern received from sensors installed in the kitchen [50].

RUBICON Cognitive Layer : The second challenge, i.e. deciding what service goal the ecology should enact in any given situation, is the responsibility of the RUBICON Cognitive Layer [46] – a reasoning module built over Self Organising Fuzzy Neural Networks (SOFNNs) [47]. The Cognitive Layer does not analyse sensor data directly, but it reasons over the events already classified by the Learning Layer to learn to predict the need to activate appliances and robotic services. These cognitive abilities are used to instruct the Control Layer with the goals it should achieve under different environmental scenarios, and to learn which goal is most suitable to which situation.

3.3.1 Support for Continuous Adaptation

The system described in the previous section can be equipped with some initial knowledge and supervised information, and trained to provide some basic services. Noticeably, since a cognitive robotic ecology needs to provide a safe, reliable, robust, and goal-oriented service environment, it is not in the best interests of the user to demand that the system has to learn everything from scratch, possibly producing unsafe or annoying behaviour. Learning robotic ecologies requires both functional primitives (perception and robotic skills) and initial strategies to reduce the need for online learning. However, this is only the starting point for a RUBICON ecology: It makes sure that the system will not behave too erratically during its initial period after it is installed in a new environment, while it collects data to adapt to its environment and to its user(s).

The system can self-adapt in a number of ways: Firstly, the Cognitive Layer can drive the exploration phase of the

ecology by trying out new goals in different situations, while the Control Layer can gather feedback and/or instructions from the user. For instance, by observing past instances in which the user has summoned her cleaner robot to the kitchen after eating her meal, the system learns to send the robot without waiting for the user's request. Secondly, the Control Layer can monitor the performances and the outcomes of its own plans, and feed them (as teaching signals) to the Learning Layer in order to learn previously un-modelled users' preferences. For instance, [11] shows how a robot can use the information it receives from the sensors in the environment to learn what are the best situations in which cleaning a certain room will be less likely to annoy the user.

4 Proposals and Future Roadmap

In the sections above we have outlined both person-centred initiatives via HRI facilities and technologically driven initiatives which focus on autonomously evolving to meet users' needs. However, it is clear that both of these approaches will need to be applied if we are to successfully use robotics technologies in smart home environments.

The two strands of research typically differ technologically in their approach to cognitive awareness. In the first, typical 'HRI' approach, robot behaviours are often derived from previous experimental studies (for example in proxemics), and held in knowledge databases for retrieval in appropriate circumstances. This approach has the advantage of meeting initial user requirements, but has the disadvantage of being difficult to adapt to changing circumstances in the house. For example, consider a robot that has been taught behaviours (derived from HRI studies) that a user has breakfast between 8am and 8.30am and it must be available to collect dishes and cutlery from the kitchen to transport to the dining table. It knows this because it has rules which typically say 'If time is between 8am and 8.30am and the user is in the kitchen and the fridge has been opened etc. then proceed to the kitchen'. If the user starts arriving early for breakfast then this behaviour will not execute. Adaptation of the behaviour would have to be explicit. Having a system which automatically adapts to changing circumstances would be advantageous here. Similarly consider a behaviour which infers the user is having lunch because 'The user is sitting at the dining table'. If for any reason the user left the dining table temporarily, the 'having lunch' inference would no longer apply. This rigidity of behaviour expression could be modified with less strict conditions; however a better approach

might be to accept that human activities inherently have some 'noise'.

The second approach, using Cognitive Robotic Ecologies (CRE), typically learns the rhythms of the house and the user over time and creates behaviours automatically. Thus the robot, rather than using pre-specified behaviours, will gradually learn over time what actions to take. In the example above, the robot would learn that it had to be present in the kitchen to help with breakfast. A major advantage with this approach is flexibility and adaptation. If the user started having breakfast early, the system would automatically adapt. However, this approach also has disadvantages; typically that learning in this way takes time, and often takes many iterations, before the final behaviour is derived. Also, how can we be sure that the derived behaviour is appropriate without continually asking the user to confirm this? In terms of adaptability to noise, the CRE approaches are typically more resilient in this regard, and thus the example above of having lunch would not necessarily be affected by the user temporarily vacating the dining table.

Therefore an approach which combines both the HRI approach and the CRE approach would be desirable in order to have the appropriate behaviours in place at the start, and then adapting them automatically as needs change (as schematically illustrated in Figure 4). Such an approach would combine smart homes with smart robots in a seamless manner. As the person's requirements change there would be no need to explicitly repersonalise the system. The benefits of this combined approach would allow the HRI/CRE system to effectively 'grow' with the person and flexibly adapt as needs change.

It would also seem that a combination of both approaches in differing circumstances might be appropriate. For example, the CRE approach might learn that the user likes to watch TV at certain times. The HRI approach may have a rule to motivate the user to be more active if they sit on the sofa for too long. A derived rule from the CRE system to the HRI system might be to disable the motivation rule when the TV is on.

An additional aspect that might further help the integrative approach outlined above concerns the relationship between the user and the smart-environment. Note, the debate of whether users should be helped by intelligent, autonomous systems or whether those systems should be under the direct control of the user is a reoccurring discussion that was hotly debated in the late 1990's. Advocates of the autonomous software agents such as Pattie Maes argued with human-computer interaction experts such as Ben Shneiderman on issues of user control and system predictability [48]. This computer-interface debate of indirect

management versus direct manipulation, in the context of autonomous robots in smart home environments can be bridged – arriving at a synthesis of both approaches facilitated through interaction, context and setting an appropriate, intuitive and easy to understand relationship and interaction model between user and robot [12].

Human-system relationships can develop too, during long-term interactions. But making such relationships explicit will allow users, especially in the initial interactions where crucial 'first impressions' are being formed in the user's mind about acceptability and usability of the system, to gain an initial understanding of the system and its role in relation to the user. Going back to the example above, the initial relationship of the smart home with the user could be framed as an 'automated assistant' - which only carries out pre-defined tasks. The user will know about the systems' limitations, and via co-learning (see section 2.3) the user will improve the system. Later this role can develop into a 'smart assistant' - whereby the system learns on its own, shows different behaviours, becomes more independent of the user, 'grows up' ([12], footnote 2).

Making such relationships and associated changes explicit might help the user to ultimately get accustomed to a smart home environment that is constantly learning and adapting.

Noticeably, our analysis has revealed how CRE approaches can support this vision, with systems that can be driven by using easily identifiable (albeit rough) rules, while delegating, over time, symbolic reasoning to data-driven inference for the purpose of increasing flexibility, robustness, adaptation, and personalization.

4.1 Roadmap

The previous section has highlighted how the combination of HRI and CRE approaches can set a path for users and smart robotic environments to grow together leading to both increased levels of efficiency and users' acceptance.

Users must be engaged and stimulated by the technology for it to be successful, and total automation should not be a goal of smart home technologies. Besides the obvious negative effects to the user's healthy lifestyle, if a system is entirely automatic and autonomous and does not engage the user, the user will lose interest and studies suggest they may also fear that they have lost control of their environment [92]. However, a system that interacts and collaborates with users provides the necessary support and assistance, while also stimulating the user and affording them a sense of involvement and control.
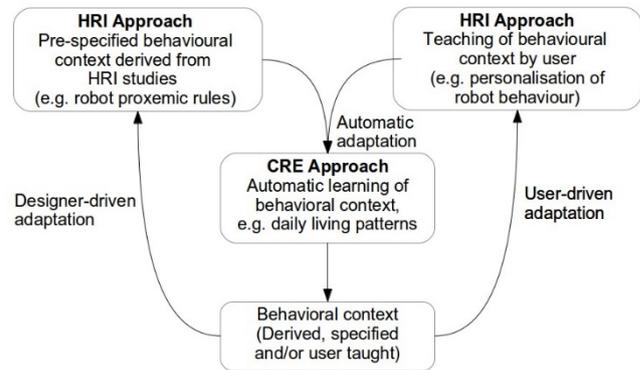
Figure 4: Union of HRI and Cognitive Robotic Ecological Approaches. Shown is a pictorial representation of the two approaches. The strengths of each approach are retained but now complement each other. HRI approaches are characterised by contexts derived from user studies or personalisation carried out by the end user or designer of the system. CRE approaches can be initialized with basic domain and service knowledge and account for user's feedback while they derive context through observation of daily life activities and adapt as such activities change. Thus the CRE approach combined with the HRI approach allows the system as a whole to grow with the user as their needs and requirements change, whilst still retaining the ability to directly personalise and modify contexts if required.

Over the longer term, we envision a new generation of smart robotic environments. Compared to existing examples, these new systems should use their capabilities to give more control to their end-users. HCI in general has embraced control through feedback as one of the most accepted guidelines in the design of interaction [74], to create intuitive systems and promote user-driven patterns to shape the adoption of the technology [75, 76]. There are many lessons to be learnt in the way interaction design research has sought to create a balance between being able to provide support for people based on collecting and using information from sensor data and using them to decide, select and tailor system functionality. These systems seek to communicate the information they gather to their users, and leverage the unique comprehension that their users have of their own needs and situations to provide an enabling environment to facilitate human activities. In addition to what was discussed in Section 2, HRI research has also produced some examples of collaborative and mixed-initiative interaction strategies [77] aimed at resolving the perception ambiguities of single robots while seeking a compromise between their need for human supervision and the cognitive load imposed on their human supervisors.

Similar principles may find applications in smart robotic environments to complement and improve the so-

lutions discussed in this paper, for example, by engaging with human users in a mixed-initiative and co-operative manner. On one hand, the users may ask the smart robotic environment for new services, or to tailor existing ones to their own requirements. On the other hand, the robotic ecology may suggest the automation of some services given its observation of the user's past behaviour, or propose alternative actions. Finally, the smart robotic environment may need to inform the user of its capabilities and intentions, or get their approval before performing certain actions. Furthermore, the system may also ask for help and/or point out its own limitations, both in its action, and in its knowledge and perception capabilities; for example, when it is not obvious for the system how it can recognize contexts, objects and places relevant to the service it has been requested to perform and to the settings where it is required to operate.

Shown below is a suggested roadmap to address the issues outlined in this paper.

1. Describe practical scenarios where CRE/HRI approaches can be used (a) Do such approaches add-value to AAL applications?
2. Derive Commonalities (a) What are the basic technologies used to support CRE and HRI AAL applications? (b) Are there technological equivalences that can be merged? E.g. sensor/actuation control mechanisms etc.
3. Merge Commonalities (a) Find AAL ontology equivalent
4. From Pre-specified to CRE (a) Investigate how pre-specified behaviours can be converted to CRE behaviours (b) Research the control issues that result.
5. Personalisation of CRE (a) Investigate how CRE behaviours can be personalised by users (b) Research the control issues that result.
6. Integrate and Implement (a) What are the costs of merging these approaches vs. benefits derived from step 1?
7. Evaluate in Scenarios (a) Evaluate the merged approach in scenarios derived from step 1

The roadmap above outlines a systematic framework with which to start merging the results of the two research trends discussed in this paper. The execution of this framework will give us insights on the way pre-specified behaviours could be converted to automated behaviours (e.g. to be built over CRE learning and planning solutions), and how the personalization of the latter may be supported and complemented with co-learning features.

Future systems will need to leverage the advancements in the machine learning solutions used to detect and predict relevant events, for instance, from research initiatives targeting environments with multiple users, and from works combining sub-symbolic learning with symbolic/ontological reasoning [1, 53]. However, reconciling the HRI and adaptation aspects surveyed in this paper, and taking advantage of the novel opportunities arising from their combination will necessarily demand the extension of this type of research in a number of directions. We outline the most important ones in the remaining part of this section and discuss how they relate to current research efforts.

Framing HRI Studies in an Ecological Context: We observe how the HRI studies underpinning the solutions discussed in Section 2 are limited in scope to single robots while the remaining components of the smart environment are mostly considered as a source of data and context information. Extending these studies into an ecological context will be essential for a smart robotic environment that seeks to maximize its mutual understanding with the users while leaving as much control as possible to them to decide their favourite way of interacting with the system.

One promising research direction on this front is the study of the interaction between users and systems framed as a dynamic process which can change over time and with repeated exposure, specifically, by exploiting the idea of 'perceptual crossing' [91] between user and robot/house services (e.g. we perceive whilst being perceived). For example, an automatic door might better signal its intention to open by some indication of readiness i.e. a light getting brighter. This signal might be triggered as a user approaches. Thus the door perceives and reacts to the user, but the user also perceives the intentions of the door and reacts to it. Note, such cues may in the long-term be experienced as annoying or repetitive by users. However, in a system equipped with online learning functionalities, over time, the door learns when to open, and the user learns when it will open, and therefore the indicator light may become unnecessary. Such adaptations will change the user-system relationship as perceived by the users and reflected in the system's increased knowledge on how to support the user and adopt increasing responsibilities while user and system are 'growing together' over time.

Teaching Robot Behavioural Skills: The CRE solutions discussed in Section 3 have the ability to improve the way they reason about context and service rules, and even improve the way they achieve useful services by coordinating their existing capabilities. However, they cannot acquire new skills and behavioural primitives. Robot programming by demonstration (PbD) (also called robot

learning by demonstration or by example [66]) has made many advances during the past decade. In contrast to reinforcement or trial-and-error learning methods, PbD is much faster and user-friendly. While the state of the art in PbD systems is still far from being usable by inexperienced and untrained users, these characteristics make it an interesting proposition for service robots operating in human daily environments. For instance, [67] describes a household robot able to learn how to collaborate with humans in cooking tasks, while [68] and [70] show how a robot can decompose a demonstrated task into sequential manipulation primitives in order to learn how to manipulate everyday objects. Another interesting approach, that could be combined with the ones above to enable user-driven definition or personalization of services in a cognitive robotic ecology, is the one presented in [69], where a hand-held augmented reality device is used to instruct a sequential task to a household robot.

Human-Aware Planning: Supporting cooperative and personalised system-user interaction will require a substantial improvement in the capabilities of plan-based CRE solutions. Recent extensions of this paradigm manage to exploit implicit user feedback to adapt to the characteristics of a changing environment and/or to the personal preferences of the user [11]. However, these approaches do not make explicit provision for the preferences of users, nor do they leverage possibly beneficial interactions with the humans. The latter includes relying on the human to collect further information and/or request simple tasks such as opening a door or turning off a (non-automated) device. In the robotics field, the works that consider human-robot co-habitation often focus on issues such as safety or human-aware manipulation [78, 79]. Works addressing planning in human-robot collaborative systems [80, 81], and works integrating planning with recognition and forecasting of human plans [82, 83] will be relevant to the creation of smart environments treating humans as active participants.

Technological Readiness Level and Integration: Compared to the tele-operated robotic healthcare solutions (e.g. [85]), which are close to reaching the consumer market, but are not autonomous and require a remote carer to be operated, the feasibility and the user acceptance of domestic service robots in smart environments have mostly been evaluated in short experiments. Usually these experiments are carried out with real users and in realistic situations (e.g. in test-bed facilities) but under the supervision of researchers and developers and only for limited tests with proof-of-concepts services, and by taking advantage of Wizard of Oz solutions [1–3, 7].

More recent research initiatives, such as the MOnarCH project [94], intend to move forward in the development of robots that can carry on autonomously for long periods of time without the aid of their operators. In order to demonstrate and evaluate how such systems can benefit their users in assisted living applications, and their adaptability to evolving requirements, it will be necessary to setup and run long-term trials with fully autonomous systems helping real users in their own homes. To this end, whereas existing solutions are mostly based on research-oriented software, in the future they should be able to interact with mainstream domotic/AAL solutions and reach industry-strength levels of usability, robustness, and manageability. Besides interoperability and networking issues [86–88], this raises issues pertaining to conceptual modelling and system integration, for instance, to validate the general applicability of the modular integration approach already showcased in RUBICON [39].

Finally, future efforts should address the fragmentation we observe in current contributions, such as robot behaviours, learning modules, and user interfaces, for instance, by developing common component models in conjunction with standardization initiatives in robot software (e.g. ROS [90]) and AAL frameworks (e.g. [89]).

5 Summary

We have suggested that the technologies currently being used to support a range of adaptive robotic applications to AAL scenarios are being pursued from differing viewpoints - one using a social robotic approach to human-robot interaction issues, the other pursuing a technologically-driven approach, building impersonal but intelligent systems. We have highlighted the requirements and the lessons learnt from these two perspectives, and outlined how they can complement each other by examining the case studies of two such systems, which have been selected for their emphasis on adaptation. Finally, we have described a number of concrete proposals to inform the development of smart and robotic spaces with both advanced HRI and on-line adaptation capabilities, by building on the existing systems and by defining a common roadmap for complementary but until today largely independent research strands.

References

[1] Companionable, "Integrated Cognitive Assistive & Domotic Companion Robotic Systems for Ability and Security," http://www.companionable.net/, Last referenced on 27th of January, 2014, 2008.

[2] KSERA, "Knowledgeable Service Robots for Ageing," http://ksera.ieis.tue.nl/, Last referenced on 27th of January, 2014, 2010.

[3] Florence, "Multi-Purpose Mobile Robot for Ambient Assisted Living," http://www.florence-project.eu/, Last referenced on 27th of January, 2014, 2010.

[4] Mobiserve, "A buddy in your home," http://www.smart-homes.nl/innovatie/europees-onderzoek/mobiserv.aspx?lang$=$en-US, Last referenced on 27th of January, 2014, 2009.

[5] Hobbit, "The Mutual Care Robot," http://hobbit.acin.tuwien.ac.at/, Last referenced on 27th of January, 2014, 2011.

[6] Alias, "Adaptable Ambient Living Assistant," http://www.aal-alias.eu/, Last referenced on 27th of January, 2014, 2010.

[7] ACCOMPANY, "Acceptable roboticCs COMPanions for AgeiNg Years," http://accompanyproject.eu/, Last referenced 27th July 2014, 2012.

[8] K. Yamazaki, R. Ueda, S. Nozawa, M. Kojima, K. Okada, K. Matsumoto, M. Ishikawa, I. Shimoyama, M. Inaba, "Home-Assistant Robot for an Aging Society", Proceedigns of The IEEE, Centennial Year, Special Issue, Quality of Life Technology, Vol.100, No.8, pp.2429–2441, 2012.

[9] Robot-ERA, "Implementation and integration of Advanced Robotic systems and intellgent Environments in real scenarios for the ageing population," http://www.robot-era.eu/robotera/, Last referenced on 27th of January, 2014, 2012.

[10] G. Cortellessa, M. Scopelliti, L. Tiberio, G. K. Svedberg, A. Loutfi, and F. Pecora, "A cross-cultural evaluation of domestic assistive robots," in AAAI Fall Symposium on AI and Eldercare, Washington, USA, 2008.

[11] D. Bacciu, C. Gallicchio, A. Micheli, M. Di Rocco, A. Saffiotti, "Learning context-aware mobile robot navigation in home environments", in Information, Intelligence, Systems and Applications, The 5th International Conference on (IISA 2014), 2014, pp. 57-62.

[12] K. Dautenhahn, "Robots we like to live with?! - a developmental perspective on a personalized, life-long robot companion," in Proc. 13th IEEE International Workshop on Robot and Human Interactive Communication (ROMAN'14) – Kurashiki, Japan, 2004, pp. 17–22.

[13] M. K. Lee, J. Forlizzi, S. Kiesler, P. Rybski, J. Antanitis, and S. Savetsila, "Personalization in HRI: A longitudinal field experiment," in Proceedings of the Seventh Annual ACM/IEEE International Conference on Human-Robot Interaction. New York, NY, USA: ACM, 2012, pp. 319–326.

[14] "Network Robot Forum," http://www.scat.or.jp/nrf/English/, last referenced on 23rd January 2014.

[15] F. Dressler, Self-organization in Autonomous Sensor and Actuator Networks. John Wiley & Sons, 2007.

[16] J.-H. Kim, Y.-D. Kim, and K.-H. Lee, "The third generation of robotics: Ubiquitous robot," in Proc. of 2nd International Conference on Autonomous Robots and Agents, Palmerston North, New Zealand, 2004.

[17] R. Lundh, L. Karlsson, and A. Saffiotti, "Dynamic self-configuration of an ecology of robots," in Proc. of the 2007 IEEE/RSJ International Conference on Intelligent Robots and Systems, San Diego, USA, 2007, pp. 3404–3409.

[18] M. Broxvall, "A middleware for ecologies of robotic devices," in Proc. of the 1st International Conference on Robot Communication and Coordination. IEEE Press, 2007, pp. 30:1–30:8.

[19] "Alderbaran Robotics," http://www.aldebaran-robotics.com/en/Home/welcome.html?language$=$en-GB, last referenced on 23rd January 2014.

[20] J. O. Blom and A. F. Monk, "Theory of personalization of appearance: Why users personalize their PCs and mobile phones," Hum.-Comput. Interact., vol. 18, no. 3, pp. 193–228, 2003.

[21] E. T. Hall, The Hidden Dimension, 1966.

[22] M. L. Walters, M. A. Oskoei, D. S. Syrdal, and K. Dautenhahn, "A long-term human-robot proxemic study," in Proc. of 20th IEEE International Symposium on Robot and Human Interactive Communication, RO-MAN 2011, Atlanta, USA, 2011, pp. 137–142.

[23] E. Pacchierotti, H. I. Christensen, and P. Jensfelt, "Embodied social interaction for service robots in hallway environments," in Proc. of Field and Service Robotics, Results of the 5th International Conference, FSR 2005, Port Douglas, Australia, 2005, pp. 293–304.

[24] K. Dautenhahn, M. L. Walters, S. Woods, K. L. Koay, C. L. Nehaniv, E. A. Sisbot, R. Alami, and T. Siméon, "How may I serve you?: a robot companion approaching a seated person in a helping context," in Proc. of the 1st ACM SIGCHI/SIGART Conference on Human-Robot Interaction, HRI 2006, Salt Lake City, USA, 2006, pp. 172–179.

[25] J. Mumm and B. Mutlu, "Human-robot proxemics: Physical and psychological distancing in human-robot interaction," in Proc. of the 6th International Conference on Human-robot Interaction. ACM, 2011, pp. 331–338.

[26] M. L. Walters, D. S. Syrdal, K. Dautenhahn, I. R. J. A. te Boekhorst, and K. L. Koay, "Avoiding the uncanny valley: robot appearance, personality and consistency of behavior in an attention-seeking home scenario for a robot companion," Auton. Robots, vol. 24, no. 2, pp. 159–178, 2008.

[27] D. Li, P.-L. P. Rau, and Y. Li, "A cross-cultural study: Effect of robot appearance and task," Int. Jrnl. Social Robotics, vol. 2, no. 2, pp. 175–186, 2010.

[28] J. Goetz, S. Kiesler, and A. Powers, "Matching robot appearance and behavior to tasks to improve human-robot cooperation," in Proc. of 12th IEEE International Workshop on Robot and Human Interactive Communication. RO-MAN'03. IEEE, 2003, pp. 55–60.

[29] Pleo, "http://www.pleoworld.com/pleo_rb/eng/index.php," Last referenced on 27th of January, 2014.

[30] AIBO, "http://www.sony-europe.com/support/aibo/1_1_3_aibo_story.asp?language$=$en," Last referenced on 27th of January, 2014.

[31] Roomba, "http://www.irobot.com/global/en/store/Roomba.aspx?gclid$=$CJjunOysnrwCFSbnwgodEiwAFA," Last referenced on 27th of January, 2014.

[32] K. Dautenhahn, S. Woods, C. Kaouri, M. L. Walters, K. L. Koay, and I. Werry, "What is a robot companion - friend, assistant or butler," in In Proc. IEEE IROS, 2005, pp. 1488–1493.

[33] F. Amirabdollahian, S. Bedaf, R. Bormann, H. Draper, V. Evers, J. G. Pérez, G. J. Gelderblom, C. G. Ruiz, D. Hewson, N. Hu et al., "Assistive technology design and development for acceptable robotics companions for ageing years," Paladyn, Journal of Be-

havioral Robotics, pp. 1–19, 2013.

[34] J. Saunders, N. Burke, K. L. Koay, and K. Dautenhahn, "A user friendly robot architecture for re-ablement and co-learning in a sensorised homes," in *Proc. 12th European Conf. Advancement Assistive Technology in Europe, (AAATE13)*, 2013.

[35] U. Reiser, C. Connette, J. Fischer, J. Kubacki, A. Bubeck, F. Weisshardt, T. Jacobs, C. Parlitz, M. Hagele, and A. Verl, "Care-o-bot®creating a product vision for service robot applications by integrating design and technology," in *Intelligent Robots and Systems, 2009. IROS 2009. IEEE/RSJ International Conference on*. IEEE, 2009, pp. 1992–1998.

[36] J. Stienstra, P. Marti, and M. Tittarelli, "Exploring dynamic expression in human-system interaction," in *Proceedings of CHI 2013, Paris*, 2013.

[37] P. Marti and J. Stienstra, "Engaging through her eyes: embodying the perspective of a robot companion," in *Proceedings of the 18th International Symposium on Artificial Life and Robotics, AROB 2013., Daejeon, Korea*, 2013.

[38] A. Saffiotti and M. Broxvall, "PEIS ecologies: Ambient intelligence meets autonomous robotics," in *Proc. of the 2005 joint conference on Smart objects and ambient intelligence: innovative context-aware services: usages and technologies*. ACM, pp. 277–281, 2005.

[39] Rubicon, "A Self-learning Robotic Ecology," http://fp7rubicon.eu/, Last referenced on 28th of September, 2014, 2014.

[40] R. Lundh, L. Karlsson, and A. Saffiotti, "Dynamic self-configuration of an ecology of robots," in *Proc. of the International Conference on Intelligent Robots and Systems, 2007. IROS 2007. IEEE/RSJ*, 2007, pp. 3403–3409.

[41] J. F. Allen, "Maintaining knowledge about temporal intervals," *Communications of the ACM*, vol. 26, no. 11, pp. 832–843, 1983.

[42] D. Bacciu, S. Chessa, C. Gallicchio, A. Lenzi, A. Micheli, and S. Pelagatti, "A general purpose distributed learning model for robotic ecologies," in *Proceedings of the 10th International IFAC Symposium on Robot Control (SYROCO'12)*, vol. 10, 2012, pp. 435–440.

[43] M. LukošEvičIus and H. Jaeger, "Survey: Reservoir computing approaches to recurrent neural network training," *Comput. Sci. Rev.*, vol. 3, no. 3, pp. 127–149, Aug. 2009.

[44] C. Gallicchio, A. Micheli, P. Barsocchi, and S. Chessa, "User movements forecasting by reservoir computing using signal streams produced by mote-class sensors," in *Mobile Lightweight Wireless Systems - Third International ICST Conference, MOBILIGHT 2011, Bilbao, Spain, May 9-10, 2011, Revised Selected Papers*, ser. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering. Springer, 2011, pp. 151–168.

[45] D. Bacciu, C. Gallicchio, A. Lenzi, S. Chessa, A. Micheli, S. Pelagatti, and C. Vairo, "Distributed neural computation over wsn in ambient intelligence," in *Ambient Intelligence - Software and Applications*, ser. Advances in Intelligent Systems and Computing, A. Berlo, K. Hallenborg, J. M. C. Rodríguez, D. I. Tapia, and P. Novais, Eds. Springer International Publishing, 2013, vol. 219, pp. 147–154.

[46] A. K. Ray, G. Leng, T. McGinnity, S. Coleman, and L. Maguire, "Development of cognitive capabilities for smart home using a self-organizing fuzzy neural network," in *10th IFAC Symposium on Robot Control, Dubrovnik, Croatia*, 2012.

[47] G. Prasad, G. Leng, T. McGinnity, and D. Coyle, "Online identification of self-organizing fuzzy neural networks for modelling

time-varying complex systems," in *Evolving Intelligent Systems: Methodology and Applications*, ser. Computational Intelligence. IEEE, 2010.

[48] B. Shneiderman and P. Maes, "Direct manipulation vs. interface agents," *Interactions*, vol. 4, no. 6, pp. 42–61, Nov. 1997.

[49] M. Di Rocco and F. Pecora and P. Kumar and A. Saffiotti, "Configuration Planning with Multiple Dynamic Goals," in *Proc. of the AAAI Spring Symposium on Designing Intelligent Robots, Stanford, California*, March 2013.

[50] D. Bacciu and P. Barsocchi and S. Chessa and C. Gallicchio and A. Micheli, "An experimental characterization of reservoir computing in ambient assisted living applications," *Neural Computing and Applications*, Springer-Verlag, 2013, pp. 1–14.

[51] K. Eunju, H. Sumi, D. Cook, "Human Activity Recognition and Pattern Discovery," *Neural Computing and Applications*, Pervasive Computing, IEEE , vol.9, no.1, pp.48-53, Jan. March 2010.

[52] M. Kurz, G. Hoelzl, A. Ferscha, A. Calatroni, D. Roggen, G. Troester, H. Sagha, R. Chavarriaga, J. Millán, D. Banach, K. Kunze, P. Lukowicz, "The OPPORTUNITY Framework and Data Processing Ecosystem for Opportunistic Activity and Context Recognition," *International Journal of Sensors, Wireless Communications and Control*, vol. 1, num. 2, p. 102-125, 2012.

[53] J. Ye and S. Dobson, and S. McKeever, "Situation identification techniques in pervasive computing: A review," *Pervasive and mobile computing*, Elsevier, vol. 8, num. 1, p. 36-66, 2012.

[54] P. Rashidi DJC, "The resident in the loop: Adapting the smart home to the user," *IEEE Transactions on Systems, Man, and Cybernetics journal*, Part A. 2009 September;39(5):949–959.

[55] S. Szewcyzk, K. Dwan, B. Minor, B. Swedlove, D. Cook, "Annotating smart environment sensor data for activity learning," *Technology and Health Care, Special issue on Smart environments: Technology to support health care*, 2009.

[56] S. Helal, W. Mann, H. El-Zabadani, J. King, Y. Kaddoura, E. Jansen, "The gator tech smart house: A programmable pervasive space," *Computer*, 2005;38(3):50–60.

[57] EM. Tapia, SS. Intille, K. Larson, "Activity recognition in the home using simple and ubiquitous sensors," *Pervasive Computing*, 2004:158–175.

[58] D. Cook and N. C. Krishnan and P. Rashidi, "Activity Discovery and Activity Recognition: A New Partnership," *IEEE T. Cybernetics*, vol. 43, num. 3, p. 820-828, 2013.

[59] P. Rashidi and D. Cook and L. B. Holder and M. Schmitter-Edgecombe, "Discovering Activities to Recognize and Track in a Smart Environment," *IEEE Trans. Knowl. Data Eng.*, vol. 23, num. 4, p. 527-539, 2011.

[60] KSERA Project: Deliverable D4.1 Learning & decision making algorithms in pervasive environments, "http://cms.ieis.tue.nl/ksera/documents/KSERA_D4.1.pdf,", November 2010, Last referenced on 9th of March, 2014.

[61] R.V. Kulkarni, A. Főrster, G.K. Venayagamoorthy, "Computational Intelligence in Wireless Sensor Networks: A Survey", *IEEE Communications Surveys & Tutorials*, 13(1), 2011.

[62] C.J.C.H. Watkins, "Learning from delayed rewards", PhD Thesis, University of Cambridge, England, 1989.

[63] M. Dragone, M. Di Rocco, F. Pecora, A. Saffiotti and D. Swords, "A Software Suite for the Control and the Monitoring of Adaptive Robotic Ecologies", in *Workshop on Towards Fully Decentralized Multi-Robot Systems: Hardware, Software and Integration 2013 IEEE International Conference on Robotics and Automation, ICRA 2013 Karlsruhe, Germany*, May 6 - 10, 2013.

[64] A. Khalili, C. Wu, and H. Aghajan, "Autonomous Learning of User's Preference of Music and Light Services in Smart Home Applications", in *Behavior Monitoring and Interpretation Workshop at German AI Conf*, Sept. 2009.

[65] A. Aztiria, J. C. Augusto, R. Basagoiti, A. Izaguirre, D.J. Cook, "Learning Frequent Behaviors of the Users in Intelligent Environments", in *IEEE T. Systems, Man, and Cybernetics: Systems*, vol. 43, num. 6, p. 1265-1278, 2013.

[66] H. Lieberman, "Your Wish is My Command: Programming by Example", *Morgan Kaufmann Publishers Inc.*, San Francisco, CA, USA, 2001.

[67] Y. Sugiura, D. Sakamoto, A. Withana, M. Inami, and T. Igarashi, "Cooking with Robots: Designing a Household System Working in Open Environments", in *CHI 2010*, p. 2427-2430, 2010.

[68] H. Dang and P.K. Allen, "Robot learning of everyday object manipulations via human demonstration", in *Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on*, p. 1284 -1289, 2010.

[69] R. Fung, S. Hashimoto, M. Inami, T. Igarashi, "An augmented reality system for teaching sequential tasks to a household robot", in *ROMAN 2011*, p. 282-287, 2011.

[70] N. Chen, Y. Hu, J. Zhang, "Robot Learning of Everyday Object Manipulation Using Kinect", in *Foundations and Practical Applications of Cognitive Systems and Information Processing: Advances in Intelligent Systems and Computing*, vol. 215, p. 665-674, 2014.

[71] G. Amato, M. Broxvall, S. Chessa, M Dragone, C Gennaro, C. Vairo, "When Wireless Sensor Networks Meet Robots", in *ICSNC 2012 : The Seventh International Conference on Systems and Networks Communications*, 2012.

[72] M. A. Goodrich and A. C. Schultz, "Human-robot Interaction: A Survey", in *Found. Trends Hum.-Comput. Interact.*, Now Publishers Inc, vol. 1, num. 3, pp. 203-275, 2007.

[73] T. S. Dahl and N. M. K. Boulos, "Robots in Health and Social Care: A Complementary Technology to Home Care and Telehealthcareż", in *Robotics*, vol 3, num 1, pp. 1-21, 2013.

[74] A. Dillon, "User Interface Design", MacMillan Encyclopedia of Cognitive Science, Vol. 4, London: MacMillan, pp. 453-458, 2003.

[75] N. A. Streitz: "From Human-Computer Interaction to Human-Environment Interaction: Ambient Intelligence and the Disappearing Computer", Universal Access in Ambient Intelligence Environments, pp. 3-13, 2006.

[76] N. A. Streitz, T. Prante, C. Röcker, D. van Alphen, R. Stenzel, C. Magerkurth, S. Lahlou, V. Nosulenko, F. Jegou, F. Sonder, D. A. Plewe: "Smart Artefacts as Affordances for Awareness in Distributed Teams", The Disappearing Computer, pp. 3-29, 2007.

[77] T. W. Fong, C. Thorpe, C. Baur, "Robot, asker of questions", In Robotics and Autonomous Systems, vol. 42, No. 3-4, pp. 235–243, 2003.

[78] B. Graf, M. Hans, R. D. Schraft, "Mobile robot assistants: issues for dependable operation in direct cooperation with humans", IEEE Robotics and Automation Magazine, 11(2):67–77, 2004.

[79] E. A. Sisbot, L. F. Marin, R. Alami, "Spatial reasoning for human robot interaction", In Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems IROS 2007, pages 2281–2287, 2007.

[80] F. Broz, I. Nourbakhsh, R. Simmons, "Planning for human-robot interaction using time-state aggregated pomdps", In Proc. of the 23rd Conf. on Artificial Intelligence (AAAI), 2008.

[81] V. Montreuil, A. Clodic, R. Alami, "Planning human centered robot activities", In Proc. of the 2007 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 2007.

[82] M. Cirillo, L. Karlsson, and A. Saffiotti, "Human-aware task planning for mobile robots", In Proc. of the Int. Conf. on Advanced Robotics (ICAR), 2009.

[83] T. Kruse, A. Kirsch, "Towards Opportunistic Action Selection in Human-Robot Cooperation", In 33rd Annual German Conference on Artificial Intelligence (KI 2010), 2010.

[84] G. Amato, D. Bacciu, M. Broxvall, S. Chessa, S. Coleman, M. Di Rocco, M. Dragone, C. Gallicchio, C. Genaro, H. Lozano, T. M. McGinnity, A. Micheli, A. K. Ray, A. Renteria, A. Saffiotti, D. Swords, C. Vairo, P. Vance, "Robotic Ubiquitous Cognitive Ecology for Smart Homes", in Journal of Intelligent & Robotic Systems, pp. 1-25, Feb 2015.

[85] S. Coradeschi, A. Cesta, G. Cortellessa, L. Coraci, J. Gonzalez, L. Karlsson, F. Furfari, A. Loutfi, A. Orlandini, F. Palumbo, F. Pecora, S. von Rump, A. Štimec, J. Ullberg and B. Östlund, "GiraffPlus: Combining Social Interaction and Long Term Monitoring for Promoting Independent Living", In Proceedings of Human System Interaction (HSI) 2013, Gdansk, Poland, June, 2013.

[86] R. Borja, J.R. de la Pinta, A. Álvarez, J.M. Maestre "Robots in the smart home: a project towards interoperability", In International Journal of Ad Hoc and Ubiquitous Computing, vol. 7, No. 3, pp. 192-201, May 2011.

[87] M. Girolami, F. Palumbo, F. Furfari, S. Chessa, "The Integration of ZigBee with the GiraffPlus Robotic Framework", In Evolving Ambient Intelligence, Communications in Computer and Information Science Volume 413, pp. 86-101, 2013.

[88] Y. Ha, J. Sohn, Y. Cho and H. Yoon, "Towards Ubiquitous Robotic Companion: Design and Implementation of Ubiquitous Robotic Service Framework", ETRI Journal, vol. 27, no. 6, pp. 666-676, 2005.

[89] UniversAAL, "UNIVERsal open platform and reference Specifications for Ambient Assisted Living," http://universaal.org/, Last referenced on 28th of September, 2014, 2014.

[90] ROS, "Robotic Operating System," http://www.ros.org/, Last referenced on 28th of September, 2014, 2014.

[91] M. Auvray, C. Lenay, J. Stewart, "Perceptual interactions in a minimalist virtual environment", New Ideas in Psychology, 27(1), pp. 32-47, 2009.

[92] C, Parapar, J. Rey, J.R. Fernandez, M. Ruiz, "Informe sobre la I+D+I sobre envejecimiento", Fundacion CSIS, elder user responses regarding preferred functionalities of an assistive robot, 2010.

[93] A. Cesta, G. Cortellessa, F. Pecora, R. Rasconi, "Supporting Interaction in the RoboCare Intelligent Assistive Environment", In Proceedings of AAAI Spring Symposium on Interaction Challenges for Intelligent Assistants, 2007.

[94] J.N. Pereira, P. Silva, P. U. Lima, A. Martinoli, "SocialAware Coordination of Multi-Robot Systems Based on Institutions in Human Behaviour Understanding in Networked Sensing", Theory and applications of networks of sensors, 2014.