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Robotic UBIquitous COgnitive Network

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Abstract Robotic ecologies are networks of heterogeneous robotic devices pervasively embedded in everyday environments, where they cooperate to perform complex tasks. While their potential makes them increasingly popular, one fundamental problem is how to make them self-adaptive, so as to reduce the amount of preparation, pre-programming and human supervision that they require in real world applications. The EU FP7 project RUBICON develops self-sustaining learning solutions yielding cheaper, adaptive and efficient coordination of robotic ecologies. The approach we pursue builds upon a unique combination of methods from cognitive robotics, agent control systems, wireless sensor networks and machine learning. This paper briefly illustrates how these techniques are being extended, integrated, and applied to AAL applications.

1 Introduction

Building smart environments out of multiple robotic devices extends the type of application that can be considered, reduces their complexity, and enhances the individual values of the devices involved by enabling new services that cannot be performed by any device by itself. Consider for instance the case of an automatic vacuum cleaner that avoids cleaning when any of the inhabitants are home after receiving information from the home alarm system.

Current robotic ecologies [1] strictly rely on models of the environment and of its associated dynamics. For instance, in AAL settings, they require pre-defined models of both the activities of the user they try to assist and the services that should be carried out to assist them. Crucially, they lack the ability to proactively and smoothly adapt to evolving situations and to subtle changes in user's habits and preferences.

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All of these limitations make such systems difficult to deploy in real world applications, as they are tailored to the specific environments, hardware configurations, applications and users, and they can soon become unmanageablely complex.

Multi-agent and robotics applications have often relied on machine learning solutions to free the developer from having to specify the details and consequences of the interaction between each agent and its environment, and to deal with noisy and uncertain sensor data. However, until now, strict computational constraints have posed a major obstacle to translating the full potential benefits of these results in robotic ecologies. Furthermore, even when they are successfully applied, they usually require expensive training sessions and costly human supervision to drive each adaptation step.

The EU FP7 project RUBICON (Robotic UBIquitous COgnitive Network) builds on existing solutions to develop the concept of self-sustaining learning for robotic ecologies. Specifically, RUBICON investigates how all the participants in a robotic ecology can cooperate in using their past experience to improve their performance by autonomously and proactively adjusting their behaviour and perception capabilities in response to a changing environment and user's needs.

2 The RUBICON Approach

In order to test and develop RUBICON, we use a smart home test-bed laboratory - a fully functional apartment of over $40m^2$ equipped with automated doors and blinds, and sensors such as gas/water/smoke/movement detectors and microphones. In addition, the test-bed is being extended with mobile robots and with wireless sensor networks (WSN) nodes, each comprising a computational unit with radio and sensors.

The resulting RUBICON ecology is required to:

- Assist the users in their daily living and also alert relevant stakeholders of potentially dangerous or anomalous behaviour and/or situations.
- Learn to leverage and enhance its context awareness and reasoning abilities (e.g. including the ability to recognize user's activities, to locate humans and/or robots as well as dangerous situations);
- Adapt and tune its abilities to the characteristics of the environment where it is deployed and to the behaviour of its inhabitants, for instance, adapting to the fitting of new furniture and new carpets, and to changes in the user's preferences and needs.
- Exhibit robustness, reliability and graceful degradation of performance when some of its devices are removed or replaced, as well as the ability to seamlessly incorporate additional ones.

The RUBICON layered architecture, illustrated in Fig. 1, builds upon the PEIS middleware [1] to provide a de-centralized Communication Layer for collaboration between functional processes (such as those used to classify household sounds, lo-

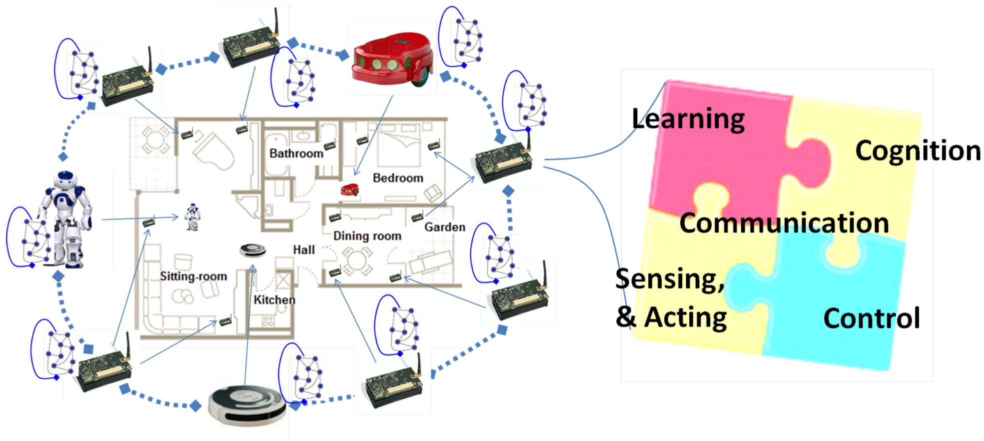

Fig. 1 Left: System Diagram, Right: RUBICON Layered Architecture.

calize users and/or robots, as well as navigation and other robotic skills) running on separate and heterogeneous devices. In order to enable simple and effective access to the transducer and actuator hardware on wireless nodes, all of these resources are abstracted and accessed as communication channels built over the MadWise Stream System framework [2].

In order to achieve necessary and meaningful tasks in a goal-oriented, coordinated fashion, the nodes participating in a RUBICON system are controlled by a Control Layer built on agent [3] and timeline-based planning [4] technologies. In this manner, a robotic ecology is capable of finding and using alternative means to accomplish its goals when multiple courses of action/configuration are available. For instance, a robot may decide to localize itself with its on-board sensors, or to avail itself of the more accurate location information from an environmental camera.

The key to enabling adaptive behaviour is to learn to extract meaning from noisy and imprecise sensed data, and also to learn what goals to pursue, and how to pursue them, from experience, rather than by relying on pre-defined strategies.

These issues are tackled by exploiting a distributed learning infrastructure and *flexible environmental memory* - the RUBICON Learning Layer. In particular, the Learning Layer is used to: (i) provide predictions which depend on the temporal history of the input signals (e.g. the users future location [5], or the probability of success of performing an action or using a device in a given situation), and (ii) analyze, process and fuse sensed information to extract refined goal-significant information (e.g. recognize that the user is cooking by monitoring its location as well as the sensors signalling when kitchen appliances are in use). To these ends, we make use of *Recurrent Neural Networks* (RNN), and specifically of *Reservoir Computing* (RC) models [6], due to their modular, networked structure, which can be naturally distributed and overlaid on top of the RUBICON ecology, as represented in Fig. 1.

Finally, a Cognitive Layer drives the reasoning and self-sustaining capabilities of the ecology by analysing current events, as determined by the Learning Layer, reasoning across this information and historical data and behaviours, and deciding on appropriate goals and priorities for the Control Layer. To this end, the Cognitive Layer is based on *Self-Organizing Fuzzy Neural Network* (SOFNN) [7] - hybrid systems where neural networks are used to learn fuzzy membership functions and create fuzzy rules that may be easily interpreted. The particular appeal of SOFFN is their capacity for self-organizing structural growth through the addition and the pruning of neurons driven by novelty detection and habituation mechanisms [8].

3 Conclusion and Future Work

We believe that the extension and integration of the techniques we discussed along the lines illustrated in this paper promises to solve many of the problems that still obstruct the implementation and diffusion of smart robotic environments outside research laboratories. Future work within the project RUBICON will refine and implement RUBICONs high-level architecture and validate it in realistic settings.

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