Self-Sustaining Learning for Robotic Ecologies

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Abstract: The most common use of wireless sensor networks (WSNs) is to collect environmental data from a specific area, and to channel it to a central processing node for on-line or off-line analysis. The WSN technology, however, can be used for much more ambitious goals. We claim that merging the concepts and technology of WSN with the concepts and technology of distributed robotics and multi-agent systems can open new ways to design systems able to provide intelligent services in our homes and working places. We also claim that endowing these systems with learning capabilities can greatly increase their viability and acceptability, by simplifying design, customization and adaptation to changing user needs. To support these claims, we illustrate our architecture for an adaptive robotic ecology, named RUBICON, consisting of a network of sensors, effectors and mobile robots.

1 INTRODUCTION

Wireless Sensor Networks (WSNs) play an important role in applications ranging from environmental monitoring to ambient intelligence and AAL solutions. So far, WSNs have been mostly used to acquire environmental readings and to send them to a central powerful processing node for analysis. Pushing forward this approach, we want to integrate robotic and WSN devices into a smart robotic ecology, aiming to achieve higher-level and more sophisticated objectives. Sensor nodes have limited computational power, yet sufficient to perform an in-network analysis on the sensor information. Therefore, we can devise a distributed learning system comprising both sensor nodes and robots that cooperatively process the sensed data to facilitate the achievement of a global goal. In particular, WSNs and robots are not seen anymore as separate entities that act in an independent way. Rather, they cooperate, as a smart robotic ecology, to process raw data to deduce higher-level information and to achieve a smart goal.

Building systems out of multiple networked robotic and WSN devices extends the type of applications 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. However, current integration techniques strictly rely on models of the environment, of their components, and of their associated dynamics. Based on these models, they can be used to find strategies to coordinate the participants of a robotic ecology and react to perceived changes in the environment but they lack the ability to proactively and smoothly adapt to an evolving situation.

Much work has been undertaken in the WSN and multi-agent communities to apply machine learning methods to ease the development of systems that adapt to changing conditions in their operative environment, reducing the programming effort before and after deployment, and enabling to process sensory data from non-stationary environments or for which a precise model is not available. However, these learning approaches typically pose strong computational requirements and the available solutions are strongly tailored to very specific tasks. All these limitations make robotic ecologies still difficult to deploy in real world applications, as they must be tailored to the specific environment, hardware configuration, application, and users, and they can soon become unmanageably complex and expensive.

We argue that these problems must be addressed by developing novel methodologies that couple communication and control to learning for robotic ecologies. Specifically, we claim that extending WSN with the concepts and technology of distributed robotics and multi-agent systems can can open new ways to design systems able to provide intelligent services in our homes and working places. We also claim that endowing these systems with learning capabilities can greatly increase their viability and acceptability, by simplifying the design, customization and adaptation to changing user needs. In particular, the learning infrastructure should provide a *general purpose* service, capable of addressing a large number of different tasks, rather than solving a fairly specific, though highly optimized, duty.

As part of the EU FP7 project RUBICON (Robotic UBIquitous COgnitive Network), we tackle these challenges by building on existing solutions to develop the concept of self-sustaining learning for robotic ecologies. Specifically, we investigate how all the participants in the RUBICON 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 needs. We propose a *general purpose* learning infrastructure distributed over the ecology. Moreover, by building on the ecology concept, we make the learned knowledge and the learning infrastructure available and accessible to novel participants that dynamically join the ecology.

2 LEARNING IN WSNS

Learning in WSNs introduces unseen challenges with respect to adaptive control and data processing in centralized systems, mostly due to the severe computational limitations of the sensory nodes and to its distributed architecture. Artificial Neural Networks (ANNs) (Haykin, 1998) are one of the most important learning paradigms, also characterized by interesting analogies with the distributed nature of WSNs. This has partly motivated the research on ANNs applications to WSNs, which can be broadly categorized into two classes, comprising *centralized* and *distributed* models. The former comprises approaches where the ANN resides only in selected nodes of the WSN, typically the sink or the clusterheads. Recurrent ANN (RNN), better suited to dynamical modeling of WSN, have been exploited in (Moustapha and Selmic, 2008) to achieve centralized fault isolation by learning predictive models of healthy and faulty nodes. The distributed approach comprises models where learning units are replicated on each sensor node and are characterized by variable degrees of learning cooperation.

Recently, Reservoir Computing (RC) (Jaeger and Haas, 2004) has gained interest for its ability in conjugating the power of RNN in capturing dynamic knowledge from sequential information with the computational feasibility of learning by linear models, resulting in suitable models for learning in the computationally constrained WSN scenario and for being embedded on-board the sensor nodes. For instance, (Gallicchio et al., 2011; Bacciu et al., 2011) have proposed an RC application to user's indoor movements forecasting using real-world data.

Overall, current work on neural applications to WSNs is fairly limited in exploitation of the distributed sensor architecture. Learning techniques are used to find approximated solutions to very specific tasks, mostly within static WSN configurations. Learning solutions have a narrow scope, resulting in poor scalability, given that different tasks are addressed by different learning models. Further, these solutions are centralized or characterized by little cooperation between the distributed learning units.

3 ADAPTIVE ROBOTIC ECOLOGY

We envision a robotic ecology, the RUBICON, that will exhibit tightly coupled interaction across the behaviour of all of its participants, including mobile robots, wireless sensor and effectors nodes, and also purely computing nodes. Each participant contributes to a shared collective knowledge and memory while engaging in collaborative learning with the other nodes by interacting through communication channels that are used to exchange both data and learning-specific signals, see Figure 1.

The self-improvement properties of RUBICON will be supported by creating a self-sustaining learning interaction dynamic between all its participants. In order to recognize situations and activities in the environment, the devices in the ecology will collectively learn to recognize, prioritize, aggregate and communicate meaningful events. In turn, novelty-detection and attention-focusing mechanisms will be used to drive the behaviour of all the different participants in the system, not only to satisfy applications objectives, but also to validate the performances of the system and thus provide crucial feedback to all the participants in the distributed learning.

The self-sustaining nature of our robotic ecology is seen in the layered architecture of each of its nodes, also represented in Figure 1. In addition to a Sensing, Acting & Functional Layer, which comprises sensors, actuators and existing functionalities, the ecology includes four layers, respectively: Communication, Learning, Control, and Cognitive.

The *Communication Layer* is mainly based on the two existing Software: the StreamSystem Mid-

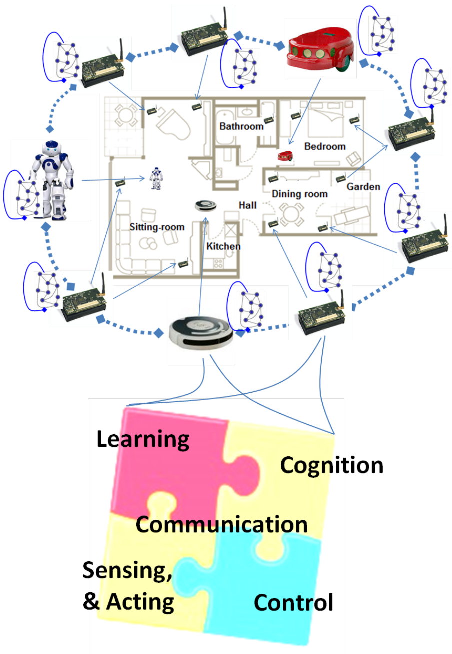

Figure 1: System Architecture

dleware (Amato et al., 2010) and the PEIS Ecology middleware (Saffiotti and Broxvall, 2007). These two background technologies implements partly overlapping services but with important differences in hardware requirements and with services targeted towards applications for robotics and for distributed WSNs, respectively. The PEIS middleware provides automatic discovery, dynamic establishment of P2P networks, self-configuration and high-level collaboration in robotic ecologies through subscription based connections and a *tuplespace* communication abstraction. The Stream System framework provides a simple and effective access to the transducer and actuator hardware on wireless nodes, and a communication abstraction based on channels.

The *Learning Layer* (LL) recognizes and detects relevant sensed information by providing predictions depending on the temporal history of the input signals (e.g. to predict user's future location depending on its movement pattern). It processes sensed information to extract refined goal-significant information, delivering such information to the Control and Cognitive layers to support single-node or multi-node control strategies and high-level reasoning. The LL builds a Learning Network (LN) on top of the robotic ecology, that is a *flexible environmental memory* serving as a task driven model of the environment that can readily be shared by new nodes connecting to the robotic ecology, allowing them to share the learned experience. The memory formation process in the LN is driven by task-specific supervised learning and feedbacks provided by the high-level reasoning implemented by the Control and Cognitive Layers. The LN design is founded on RC models (Jaeger and Haas, 2004), due to their networked structure, which naturally adapts to the distributed nature of the robotic ecology, and to their trade-off between computational efficiency and ability to deal with dynamic systems and noisy data. Each node of the LN hosts an RC network with a variable number of neurons, that are connected by remote synapses with neurons residing on other nodes, creating a distributed RNN.

The *Control Layer* (CL) ensures that the RUBICON nodes perform their actions in a coordinated and goal oriented fashion to achieve high-level tasks. One of the key strengths of a robotic ecology is to be capable of using alternative means to accomplish its goals when multiple courses of actions/configurations are available. However, while having multiple options is a potential source of robustness, efficiency, and adaptability, the combinatorial growth of possible execution traces makes difficult to scale to complex ecologies. Adapting, within tractable time frames, to dynamically changing goals and environmental conditions is made more challenging when these conditions fall outside those envisioned by the system designer. Finally, supporting varying computational constraints is a primary priority, as target environments will contain devices such as computers with large processing and bandwidth capacities, as well as much simpler devices. To these ends, the CL is framed as multiagent system (MAS) where each node in the ecology is controlled by an autonomous agent with timeline-based planning (Pecora and Cirillo, 2009), and embedded, agent-based plan monitoring, execution and co-ordination capabilities (Muldoon et al., 2006).

The key to enabling adaptive, and proactive behaviour in such a system will be to improve the ability of each agent to extract meaning from noisy and imprecise sensed data, and to learn what goals to pursue, and how to pursue them, from experience, rather than by relying on pre-defined strategies. To this end, we can leverage the vast literature of MAS learning methods (Sen and Weiss, 1999) (Busoniu et al., 2009) to use the learning services provided by the LL.

The *Cognitive Layer* (COG) is essential to close and animate the loop in our architecture by orchestrating the LL and the CL to drive the self-sustaining capabilities of the robotic ecology and reduce its reliance from pre-programmed models. While the LN provides learning functionalities that can be used to fuse and enhance existing perception abilities and to predict and classify events and human activities, each of these learning tasks must be precisely pre-defined, in terms of the data sources to be provided in input to each learning module as well as the examples needed for training their outputs. Similarly, while the CL can synthesize and coordinate the execution of strategies to achieve goals set for the whole ecology, its agents must be explicitly tasked, e.g. by the user, or by availing of pre-programmed service rules.

The COG is being built using *Self-Organizing Fuzzy Neural Networks* (SOFNNs) (Leng et al., 2004; Prasad et al., 2010) where fuzzy techniques are used to create or enhance neural networks and that can be used to learn membership functions and create fuzzy rules. Recently, research interests in self-organizing neural network systems have moved on from parameter learning to the structure learning phase, with a minimum of supervision. Our aim is to create SOFNNs that reflects the knowledge being obtained by the robotic ecology and autonomously map it to goals to be achieved by the CL in order to satisfy generic application requirements while also driving active exploration to gather new knowledge. The particular appeal of SOFNNs is their ability for structural modification through neuron addition and pruning. By linking such a structural adaptation to novelty detection and habituation mechanisms (Mannella et al., 2012), we aim to create a self-sustaining architecture that would start from using hand-coded neural fuzzy rules but that would soon be able to leverage past experiences to autonomously adapt them to the context where the robotic ecology is installed.

4 Conclusion and Future Work

The goal of this position paper was to put forward the concept of self-sustaining, learning robotic ecologies as a powerful extension of traditional WSNs. It has presented the rationale for the adoption and the integration of a number of techniques for the development of adaptive applications using this concept. While all the techniques illustrated in this paper have been tested in isolation, we believe that their extension and integration as discussed 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 will refine and implement our proposed architecture and exercise it in realistic settings.

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