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Ubiquitous robotics: Recent challenges and future trends

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H I G H L I G H T S

- Overview of the cloud robotics concept and a state of the art of the current projects in this domain.
- Challenges related to context modeling, situation awareness and semantic reasoning.
- Human–robot interaction based on ubirobots.
- Challenges concerning the ubiquitous robots' engineering.
- Future applications of ubirobots.

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A B S T R A C T

Ambient intelligence, ubiquitous and networked robots, and cloud robotics are new research hot topics that have started to gain popularity among the robotics community. They enable robots to acquire richer functionalities and open the way for the composition of a variety of robotic services with three functions: semantic perception, reasoning and actuation. Ubiquitous robots (ubirobots) overcome the limitations of stand-alone robots by integrating them with web services and ambient intelligence technologies. The overlap that exists now between ubirobots and ambient intelligence makes their integration worthwhile. It targets to create a hybrid physical–digital space rich with a myriad of proactive intelligent services that enhance the quality and the way of our living and working. Furthermore, the emergence of cloud computing initiates the massive use of a new generation of ubirobots that enrich their cognitive capabilities and share their knowledge by connecting themselves to cloud infrastructures. The future of ubirobots will certainly be open to an unlimited space of applications such as physical and virtual companions assisting people in their daily living, ubirobots that are able to co-work alongside people and cooperate with them in the same environment, and physical and virtual autonomic guards that are able to protect people, monitor their security and safety, and rescue them in indoor and outdoor spaces. This paper introduces the recent challenges and future trends on these topics.

1. Introduction

The ubiquitous computing revolution has further manifested itself in the new multidisciplinary research area of ubiquitous robots (ubirobots), also called networked robots [1,2]. Ubirobots overcome the limitations of stand-alone robots, such as mobile robots, walkers, and wearable exoskeletons, by integrating them together with ambient intelligence (AmI) and web services' technologies [3]. The emergence of new smart computing devices such as smartphones or smart sensors is strongly contributing to extend ubirobots' interaction and perception capabilities. So far, ubirobots are cognitive entities that are capable of moving around, sensing, reasoning, and proactively executing tasks and adapting themselves to the situation they may face anywhere and anytime [4,5]. Ubirobots are not only limited to physical mobile robots but can also be any software agent running on daily living objects such as smartphone, TV, oven, bed, office, etc. In fact, the overlap that exists now between ubirobots and AmI makes their

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integration valuable to create a rich hybrid physical–digital space with a myriad of proactive intelligent services that enhance the quality and the way of our living and working. These services have distinguishable characteristics such as ability to coordinate autonomously their activities with other physical or logical entities in order to provide assistive and monitoring services with add value compared to traditional centralized multi agent systems. Moreover, the emergence of cloud computing initiates the massive use of a new generation of ubirobots that enrich their cognitive capabilities and share their knowledge by connecting to cloud infrastructures.

For today, the major trends and challenges in ubirobotics research concern three main topics. The first one aims at making ubirobots more autonomic by endowing the robots with the following fundamental features: context and activity recognition, context and intention awareness, semantic reasoning, multi agent coordination and organizations, and autonomic (self-*) properties. The second one regards social awareness and affective interaction. This topic concerns the following research issues: natural language dialogs' automation, social coordination protocols, affects' measurement and recognition, ethical aspects of social interactions such as how to enforce a privacy policy in ubirobots to avoid the disclosure of private information, etc. The last topic concerns the ubirobots' engineering, in particular, the following issues: (i) the design of new engineering tools and middleware to create ubirobot services as plug and play applications; (ii) interoperability among robots and smart devices, i.e., going beyond remote control, voice and web services, abstracting the robotic functionalities and providing means for utilizing them; (iii) extending ubirobots' sensors and actuators through the network; (iv) how ubirobots will get their intelligence from the cloud.

These challenges are the enablers that will drive ubiquitous computing and robotics joint research in the next decade and beyond. For instance, the research on ubiquitous interaction techniques, such as smart displays, tangible and touch-less interfaces, and 3D cameras, is valuable to enhance service engineering and augment the interaction capabilities of robotic services with environment and users. The use of these technologies, combined with ontologies and advanced logic reasoning techniques, will make possible the development of cognitive robots that are able to carry out spatio-temporal perception with common sense understanding and reasoning about the real world. Such a reasoning goes beyond the use of common terms and description of objects. Recent works on recommendation systems focus on not merely a filtering system, but also on the use of software agents or robots that attempt to persuasively influence the consumer in choosing items [6]. Implementing such systems in ubirobots requires advanced social interaction enablers that integrate ambient intelligence sensors, actuators and multi media devices. Such an integration will enhance robots' coordination capabilities. Moreover, it will render robots' recognition of situations, activities and also user's intentions and affects more reliable and efficient [3,7,8]. This work was presented in part at [9]. The paper is organized as follows: Section 2 presents an overview of the cloud robotics concept and an up-to-date summary of the state of the art of the current projects in this domain. Section 3 presents some challenges related to context modeling, situation awareness and semantic reasoning. Human–robot interaction schemes based on ubirobots are discussed in Section 4. Section 5 presents some challenges concerning the ubirobots' engineering. The paper is concluded with a discussion about the significant future applications of ubirobots.

2. Cloud robotics

Without going into fictional considerations, enabling intelligent interactions between robots, humans, and ubiquitous computing systems, within ambient intelligence and cloud environments, can be envisioned for the near future. In [10], it is stated that the concept of cloud-driven robots means that there is the possibility for a robot to cast off complex computation tasks that its internal resources cannot handle or it can free up resources for other tasks.

Applying the current cloud computing technology provides numerous advantages that can be valuable for the composition and running of new ubiquitous robot services. For instance, all of the complex computations can be offloaded in the cloud like what is done for Apple's voice recognition service "Siri". In addition, the cloud will provide any robot with the ability to quickly acquire cognitive functionalities and knowledge in a short bounded time and to guarantee continuous evolving of robot services' performance, accessibility and flexibility and also cost savings. Moreover, connecting the robots to semantic knowledge databases hosted in the cloud will allow a large number of heterogeneous robots to share common sense knowledge.

The term "cloud robotics" was coined in 2010 referring to the usage of cloud computing facilities to enhance networked robots' capabilities. Network robots can be teleoperated by a human or comprised of a set of robots that act collectively to accomplish a given task. In both scenarios, there are some constraints related to communication, resource capacity and information storage/manipulation that represent challenging problems nowadays. Cloud computing is able to provide on-demand access to processing and storage resources, as well as to specific frameworks and applications. Regarding robotics, cloud computing can be used to (i) store information collected and/or produced by robots, allowing an easy sharing of such information among different types of robots and (ii) perform real-time, on-demand processing of data provided by robots. The main idea is to apply the technologies and delivery models leveraged by cloud computing platforms to overcome the limitations presented by current networked robots, resulting in a new paradigm for robotic applications.

The concept of "robot-as-a-service" (RaaS) refers to robots that can be dynamically combined to give support to the execution of specific applications. They correspond to the hardware layer within a traditional cloud computing stack, using well-defined robot–robot interaction protocols based on their own resources. Above such a layer, a set of specialized services can be used by RaaS to perform functionality, brokering for service discovery and publishing, and executing applications on behalf of a client, among other tasks. Fig. 1 exemplifies such a cloud-based approach to robotics.

For the last two years, we have been observing the emergence of cloud robotics platforms and application proposals. For instance, RoboEarth is a web platform that is intended to provide a complete cloud robotics infrastructure for robot-to-robot interactions. RoboEarth [11,12] also addresses semantic knowledge sharing among different types of robots. In this platform, the knowledge about robot tasks as well as operation strategies and targets is aggregated and accumulated into web servers so that robots can automatically generate operation commands required for providing services by referring to the shared information. Willow garage launched the "Heaphy Project", which is a cloud robotic system that allows controlling a robot remotely using just a web browser. An experiment was conducted through the virtual working market place "Amazon Mechanical Turk". In the same way as remote surgery, the concept of this project is to hire human operators over the world, to control the robot's sensors and actuators in order to perform real life tasks such as taking out the trash or moving heavy objects, etc. In this system, all the computations are pushed into the cloud instead of equipping the robot with high cost computing and memory power. Quintas et al. proposed a new conceptual design for a service robot system supported by cloud services. These latter are dedicated for the

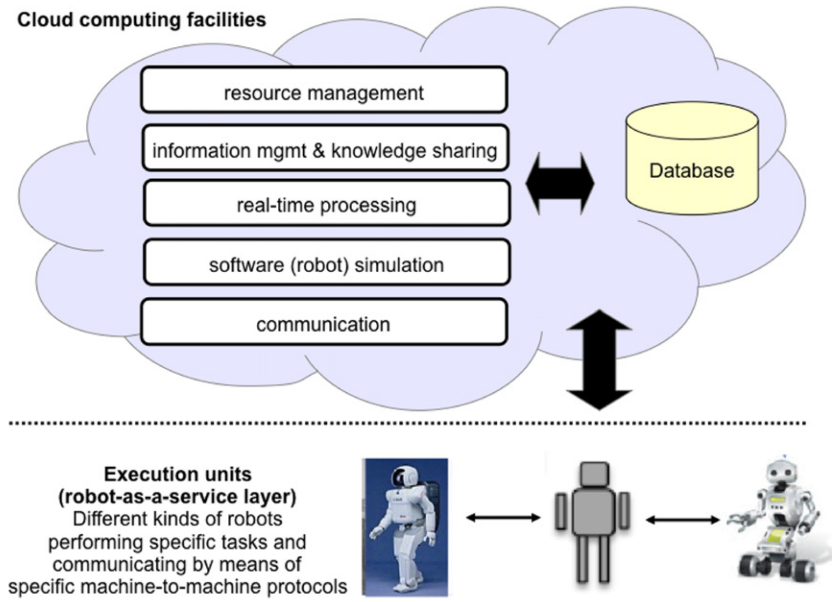

Fig. 1. A typical architecture for cloud robotics.

exchange and learning of relevant information that might be applied in human–robot cooperative tasks [13].

Davinci is another cloud robotic project, from ASORO (A-Star Social Robotics Laboratory), with the objective of providing cognitive robot services. DaVinCi [14] can be regarded as a platform-as-a-service (PaaS) system built with Hadoop and ROS (Robotic Operating System) that shares a set of algorithms and data within a robotic network. Each unit can share its sensor data and also upload data to be processed in the cloud. For instance, the robots are able to perform simultaneous localization (SLAM) and generation of their 3-D environment maps using the cloud infrastructure instead of using their onboard systems [14]. In [15], the concept of elastic cloud computing architecture for cloud robotics is proposed. It is built on the combination of a virtual ad-hoc cloud formed by a group of networked robots and a centralized cloud. Three elastic computing models are used for running robots. In the peer-based model, each robot and each virtual machine (VM) in the cloud are considered as a single computing unit, while in the proxy-based model, a group of networked robots are communicating with a proxy VM in the cloud infrastructure. In the clone-based model, each robot corresponds to a system level clone in the cloud. A task can be executed in the robot or in its clone in the cloud [15].

The challenging aspects in cloud-networked robotics (CNR) should be focused on scalability and dependability. The resource allocation problem in the real world will become more complicated with system complexity. Since robotic services are related to both real world and cyber spaces, CNR often encounters privacy, security and ethical issues. To deal with security and privacy issues of ubirobots, the robot middleware should include encryption and usage control based on policies and digital identities to avoid intruders that can take control on the robot or get access to a person's private information. Middleware implementations based on the Device Profile Web Service (DPWS) standard offer sufficient security functionalities that can be valuable for making the robot web service more secure and interoperable. Ongoing research projects like Web Of Objects[1] or A2Nets[2] are dealing with the integration of the DPWS standard in the different levels of the cloud computing architecture: IaaS, PaaS, SaaS. The benefits of applying SOA principles in the design of cloud networked robots with capabilities are inline with the challenges addressed in the roadmap given by Cangelosi et al. on the future of developmental robotics [16]. An SOA-based design is used by Chen et al. [17] to allow a RaaS unit to act as a service provider, broker, and client at the same time. The same SOA approach is used by Quintas et al. [13] to implement a service robotic system in which a cloud is used to store knowledge (learned skills) that can be shared among distant groups of robots, while improving the interaction with human agents.

The major concerns regarding cloud robotics today refer to communication, computation and security. The choice of performing a given task locally in a RaaS or remotely in the cloud depends on the timeout defined for such a task (i.e., its delay sensitivity). We must consider wireless network characteristics, message manipulation (packing and transmission), and energy consumption, among other issues, in order to decide where to execute a task: by on-board processors (RaaS resources) or offloaded to the cloud.

As any cloud application, security is another issue to be addressed, specially if we consider virtual resources provided by public clouds. Hu et al. [15] address such challenges through a very interesting architecture in which robots can communicate among themselves by means of a machine-to-machine protocol, being able to interact with the cloud by means of a machine-to-cloud protocol. They also investigate techniques and models to deal with computational, communication, and security issues. Their architecture also foresees an optimization framework that will be used to decide where to execute tasks: locally within the network of robots or remotely in the cloud, and also the best computing model (peer, proxy or cloud-based), according to application requirements and network characteristics.

Kamei et al. [18] discuss some key problems in realizing continuous robotic support for daily activities of disabled and elderly people. They present a case study based on a shopping mall in which robots help in several tasks (reminders of what a person must buy, carrying bags, and navigating inside the shopping mall, among others). The robot's operation is based on a set of functionalities to manage multi-robots and multi-area information, which are implemented on the Ubiquitous Network Robot Platform (UNR-PF) [19]. The Google Object Recognition Engine, among other tools,

[1] http://www.itea2.org/project/index/view/?project=10097.
[2] http://www.itea2.org/project/index/view/?project=10033.

is used by Goldberg et al. [20] to implement a prototype architecture for object recognition, pose estimation and grasping. Photos of objects are recorded in the Google cloud, together with some semantic data (weight, texture, CAD model, etc.) and a candidate grasp set for each object. A robot can take a photo of a given object and send it to an object recognition server running in the cloud. If recognized, the server sends the stored data for that object, allowing the robot performing pose estimation and selecting a grasp from their grasp set associated with that object.

Despite those already cited, there are a lot of additional significant cloud-based robotics platforms. Roboswarm[3] is a European project that aims to develop an open environment that allows a robot swarm to share knowledge on domestic and public area applications. The project focuses on self-adaptation, cost efficiency and elasticity of functionality within the swarm. It employs a set of techniques for multi-robot orchestration and service composition based on ontologies and workflows. The idea of robot swarms was also applied to other areas [21]. Started in early 2012, the European Project RoboHow[4] proposes to set new frontiers in the cognitive robotics field, i.e., a robot "that autonomously performs complex everyday manipulation tasks and extends its repertoire of such by acquiring new skills using web-enabled and experience-based learning as well as by observing humans".

3. Activity recognition, semantic reasoning and context awareness

Enhancing ubirobots with autonomic capabilities to execute complex tasks, in a dynamic real world, requires them to have advanced cognitive capabilities to understand what exists and what happens in the environment. This also includes understanding the description of objects, the purpose of the services provided by each object and how the objects are interacting and behaving. Such capabilities are often called context/situation awareness. Situation and context awareness are widely used concepts in pervasive computing and ambient intelligence that are used to get a better understanding of living persons and their surrounding's objects, activities, or to adapt the behavior of the services according to the context [22]. In general, the context and situation are too closed concepts that refer to the observation and interpretation of a set of interrelated physical objects. The most adopted definition is the one given by Dey et al. in [23] that we summarize as follows: context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves. The meaningful interpretation of the context is done by observation components (i.e., agents), rather than from sensors. Contextual information pieces such as location, identity, time, and activity are considered as the primary context types for characterizing the situation of an entity [5]. The recent progress in wireless sensing and mobile computing technologies have resulted in some interesting context awareness approaches, which have been surveyed in [24]. Most of these approaches provide middleware functionalities for context representation and interpretation. These latter can be used by any software agent to capture context attributes, the changes occurring on these attributes in order to adapt its behavior. The recent middleware allows, in addition, a combination of rule-based reasoning procedures and ontologies to deliberate on high-level context, recognize objects and activities, and adapt the system to the user preferences and needs. We consider two categories of context interpretation approaches, namely numerical approaches and symbolic approaches. The numerical approaches are usually used for human activity and pattern recognition, for instance, daily physical activities. The mostly used sensors are the ones based on wireless technologies (or motes) that range from sensors that measure temperature, humidity and light, to sensors that measure the pressure on surface, detection of a human posture, to infrared motion sensors that detect physical intrusion, or RFID sensors that identify the presence of persons/objects in a given area. Wireless sensor networks allow the continuous observation of activities in fixed or mobility situations and provide a rich set of context data that allow an easy recognition of the ongoing activity.

Recently, activity recognition has gained increasing attention with the technological advances and the emergence of novel adapted technologies such as wearable and ubiquitous technologies with considerable reduction in size, cost and energy consumption. Research fields concern mainly robotics and pervasive computing that ranges from low-level data collection and information processing to high-level service delivery and applications within intelligent and smart environments. Applications regard chiefly the behavior and situation recognition for ambient assisted living such as Daily Living Activities (sitting, standing, walking, sleeping, eating, drinking, cooking, washing in a bath, using a toothbrush, watching TV, using mobile phone, etc.), emergency situations for healthcare, well-being and security (fall detection and alarm trigger, monitoring of heart rate, blood pressure, etc.) and habitat monitoring in smart environments (home temperature, humidity, luminosity, security, etc.). Several techniques have been used for activity recognition such as video-based sensors [25], wearable sensors, environmental and object sensors (smartphones, RFID, etc.). Recently, body worn sensors have become commonly used as an important paradigm in wearable computing as they are used to infer the user's intention [7,8]. User acceptance, novel applications, sensor type and placement, calibration and sensor deployment make challengeable the use of robust methods to recognize activities. Accordingly, different approaches and algorithms have been proposed and studied in the literature as a function of the activities' modeling, representation or information reasoning. Activity recognition is generally considered as a machine learning problem. A ground-truth data set describing the user activities is used to train the system by mapping between the wearer's activity and the associated signals [26]. We consider two main classification techniques that have been used so far for activity recognition; the first one consists of supervised activity classification approaches, while the second one consists of unsupervised ones. The major drawback of the use of supervised techniques is the collection of sufficient amounts of labeled data for a representative set of free-living activities which may be sometimes difficult to achieve and computationally expensive. Typical classifiers include mainly *k*-Means, DBSCAN (Density-Based Spatial Clustering of Applications with Noise), and the approaches based on Gaussian Mixture Models (GMM).

On the other hand, complex daily living activities consist of a sequence of action steps that are executed in a given order to fulfill the final goal. Consequently, monitoring the temporal evolution of the elementary activities should be modeled. In such a temporal ordering of the activity, fulfillment of the preceding activities should be used as a critical indicator of the execution of the whole task. Regarding the temporal classifications, state-space models are typically used to enable the inference of hidden states given the observations. The Hidden Markov Model (HMM) is one of the main temporal classification techniques used in human physical activity recognition [27]. Fig. 2 shows the activity recognition process from the data acquisition towards the context and high-level activity inference including data preprocessing, segmentation, feature extraction, classification, data fusion and reasoning information processing [26].

3 http://roboswarm.eu/index.html.

4 http://robohow.eu/.

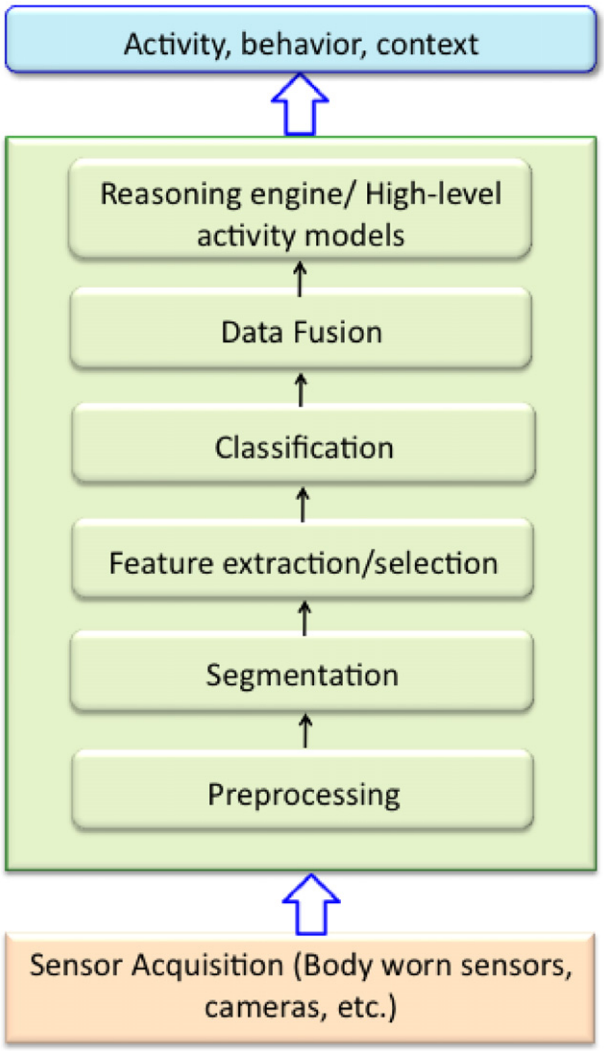

Fig. 2. Activity recognition process.

With respect to symbolic reasoning approaches, context interpretation is a rule-based inference process that is used for reasoning on complex contexts and situations. Using first-order logic approaches with powerful inference engines such as Prolog or Jess to implement such an inference is the initial approach. However, the complexity and heterogeneity of context information and sensors are very high. Therefore, the use of first-order predicates to model context knowledge is not sufficient, and higher order logics are required for modeling the AmI environment dynamics. In fact, the current trend in symbolic representing and reasoning in context aware systems relies largely on the use of ontology standard languages and also, on the use of rule-based inference for modeling the semantics of the context in the AmI environment (i.e. users, objects and their corresponding events). Some ontology models have gained much popularity such as SOUPA or CONON [28]. These models are built using the most popular ontology language called Ontology Web Language (OWL) [29]. OWL is a W3C standard ontology language for publishing and sharing ontologies using RDF (the Resource Description Framework). The current version is OWL 2, which extends the standard version OWL 1 with a set of meta-modeling and reasoning features that helps, for instance, to disambiguate the exact meaning of a name (e.g., a name like Person can be used as a class, an individual or a property) [29]. Indeed, the main advantage of OWL is that it ensures semantic interoperability and common sense understanding of objects' and services' descriptions during the interaction between heterogeneous entities. The reasoning capabilities of OWL are based on the open world assumption (OWA) that does not make any hypothesis about the truth or falsity of a fact unless it can be proven. Thus, if the truth or falsity of some facts is unknown, nothing can be inferred about these facts and both cases must be considered in the description of the ontology [30]. Such a reasoning allows one to build effective rules for the maintenance of symbolic representation of the real world and to translate any event to knowledge management operations. For instance, when an event occurs in the environment, such as switching on the light spot or a robot enters into the kitchen, the reasoning system will translate these events to ontology management actions such as the creation, modification or removal of instances from the ABox part of the ontological-knowledge base, or the classification of this event as being an instance of concept that corresponds to a new object of more specific type. Subsumption or satisfiability reasoning operations can be used, according to the open world assumption, for different practical issues that are valuable in ubirobotics such as object anchoring and classification [29]. OWL reasoning is also useful for implementing techniques for match-making of user queries with objects' and services' description. With respect to robotics, some interesting ontology-based approaches have been proposed to increase the cognitive capabilities of robots. For instance, the SURF approach uses OWL-S ontologies to model robot services [31]. All of the robot's interfaces, actuators, and sensors are implemented as web services. In [32], the Cognitive Robot Abstract Machine (CRAM) approach is proposed for the implementation and control of complex mobile manipulation robotic tasks. The core of CRAM allows first-order reasoning using Prolog and OWL-DL representation of the environment. Ontology-based Multi-layered Robot Knowledge Framework (OMRKF) [33] is a similar approach to the previous one with complex knowledge management structured into four classes of knowledge modules: perception, model, activity and context. The work aims to endow the robot with semantic capabilities by relying on a richer multi-ontology approach where two different hierarchies are used for the description of spatial information and real world objects. The information in the two hierarchies is combined in different ways to provide the robot with more advanced reasoning and planning capabilities. In these approaches, OWL is used for querying purposes rather than decision-making reasoning. The recovery technique was the implementation of specific software glue that makes combination of the query results as inputs or outputs of traditional inference systems such as Prolog in the context of specific applications. However, the OWA assumption of OWL cannot be applied for all the reasoning operations needed for ubirobots, because OWA may induce logical inconsistencies that can happen due to conflicts in modeling ontologies and reactive inference rules, given that these two formalisms are completely independent and it is up to the designer to take care about such conflicts. For instance, two different instances can refer to the same real world object, raising, in some cases, conflicts or incoherence in decision making using two independent reactive reasoning rules. The other shortcoming of using DL-based OWL reasoners is their limitation to the inference by an inheritance paradigm. This latter is more useful in solving the most common classification (subsumption) problem than in executing real reasoning operations where new knowledge must be produced from the existing one. The advent of SWRL, a Horn-like rule language, does not provide the reasoning capabilities required for dynamic environments. Moreover, SWRL does not support 'negation as failure', as well as classical negation, disjunctions and non-monotonicity. In addition, designing rules in SWRL to handle a dynamic context remain too complicated to be used in real world applications. In spite of the advantages of the high expressivity supplied by RDF, OWL 1 and its successor OWL 2, the approaches presented above cannot be used to apply reactive reasoning for bounded systems such as ubirobots. Sometimes, defining complex reasoning on situations and activities needs to define complex recognition patterns of dynamic events that are too difficult to model due to the binary relations that can be used in OWL. For instance, it is difficult to model in the same predicate that a robot moved an object from place A to place B. Using OWL, the system will produce independent instances using independent concepts and properties such as robot action, action effect, object location, location change, etc. In addition, applying ontology reasoning in ambient intelligence environments needs to take up some challenges concerning the distribution of context reasoning on smart devices, building common sense knowledge bases, and taking into account the spatio-temporal parameters of the context. In our opinion, the appropriate way to deal with reactive reasoning in ubirobots is the use of Closed World Assumption (CWA) reasoning that combines ontologies with production rules. Sabri et al. proposed a framework that deals with context reasoning according to CWA, by preserving on the one hand, the structural expressiveness provided by ontologies and on the other hand, by exploiting in full all the possible benefits of production rules' reasoning. Using CWA reasoning renders the inference non-monotonic, i.e., the presence of a new factual instance can invalidate the previously drawn conclusions, while the name of the concept must be unique to avoid any possible contradiction.

4. Human–robot interaction based on ubirobots

The measure of ubiquity of robots, in the lives of humans, can somewhat be measured by the level of interaction and participation in the everyday lives of humans. The participation in the lives of humans requires that robots have a number of capabilities, similar to humans, but also complementary in scope to capabilities commonly lacking in humans. Complementary skills and capabilities provide an extension to humans, which we cannot provide for ourselves, similar to that of common tools. In this case, the robotic tools are autonomous and human-like, in form.

While it is conceptually promising to consider the usefulness of seamless human–robot interaction, it is a matter of practical complexity. Interfaces between humans are complex in terms of language, meaning and understanding. These are amplified when robots are considered in the equation. The necessity to interface requires networking, communication and interaction.

In this section, applications and research areas linking humans and robots through interaction are described. Examples of this include networked robot interaction techniques, natural and social–natural interactions driven by interaction architectures, such as those integrating humans, agents, robots, machines and sensors (HARMS) together seamlessly. Extension to these architectures, where computation is conducted in the cloud, is shown as a viable component of complex human–robot interaction strategies. The combination of natural language (NL) is necessary and vital to humans, driving the need for NL interaction and the inclusion of ontological structures to store the meaning and intelligence of interaction. Finally, humans and robots constantly and necessarily interact with their surrounding environments. The seamless, symbiotic interaction of ubiquitous robots and their ambient environment is described.

The recent human–robot interaction (HRI) based on ubiquitous networked robots encompasses a variety of research fields in social robot application, psychological and educational fields, robot behavior design, android science, etc. During the last decade, ATR Intelligent Robotics and Communication Laboratories in Japan conducted many field trials in real world, such as elementary school, science museum, train stations, elderly-care facilities, and shopping malls (Fig. 3). Through the experimentation, a number of critical requirements and useful techniques for implementing ubiquitous networked robot systems were studied. These ubirobot systems enable augmentation of a stand-alone robot's HRI capabilities and central planning and coordination between robots, human assistance for difficult recognition tasks, and flexibility in resource management. For instance, the ambient intelligence environment with WLAN and/or multiple laser-range finders helps a robot to find pedestrians from a distance and then enables it to approach them in a shopping mall [4]. The success or failure of ubiquitous robot services that will be put in the future market is greatly determined by their capacity to take into account user experience. Design user experience-oriented services have proven beneficial. However, a few efforts have been made to measure and respond to user experience after deploying the service for real use or in the context of living labs. The formula of providing good functionalities against a reasonable price is no longer sufficient to make the differentiation among the service providers and manufacturers. So actors should adopt new approaches to captivate and attract users by adopting a holistic approach taking into account user identity, profile, perception, emotion, social interaction and relations, etc.

As robots become more pervasive and ubiquitous in the lives of humans, they become increasingly involved in everyday tasks formerly executed by the humans. Humans should expect that robots will take on tasks to simplify our lives, by working with humans just as other humans do, in normal societies or organizations. This level of integration goes beyond that of defined robots. Other autonomous systems and machines have taken over parts of our lives through innovation. This labor specialization allows humans more comfort, time, or focus on higher-level desires or tasks. To further this unification of relationships, the defined line between humans and other actors must be reduced and made more indistinguishable [34]. In other words, it should form a general consciousness [35] of cooperation and teamwork. To further this innovation, the relationship between Humans, software Agents, Robots, Machines and Sensors (HARMS) must approach that of indistinguishability in multi agent systems' communication. In fact, the whole concept of indistinguishability is novel and useful in terms of capability-based organizations, where the system selects a task for execution, based on the capability of some agents (or other HARMS actor) given its capability to accomplish the selected task or solve a goal. All available actors with that specific capability allow the choice to be indistinguishable. Communication is the medium to enable indistinguishability, but is useful in an organization of setting where group rational decisions and choices are made.

When a human leaves the home to go to get groceries, he often forgets to check the need for items. For example, if while at the store he does not know the amount of milk available at home, he can call a human at home to ask for the status of milk. Why not connect to a robot or the refrigerator to determine this status? In this case, the task of determining the milk status is indistinguishable between another human, a robot, or a machine (the refrigerator). It does not matter which system actor gives the answer, only that there is sufficient system capability present to answer the question. This is not requiring the intelligence measured by a Turing test [36] but simply masking the interface between each of the actors in a complex cyber-physical system. Relationships between the actors will be defined by the need for capability, the ability of communication and understanding, not of simple homogeneous actor affiliation.

The use of natural language is the mechanism to carry out this interface. Talking with any actor in a cyber-physical system, in a common language of understanding, will enable the solution of many common problems. Conversing in natural language with another human is common, but if communication is also possible

Fig. 3. An example of a robot approaching a target person.

with software agents, robots, machines, and sensors, the human asking the question is not concerning with who or what answers the call of task execution. To extend this innovation, the non-human actors will communicate and interact in natural language, with each other, just as they will with a human. If all actors, human and non-human, converse in natural language, it will approach the level of a Turing similar consciousness. This is not to measure intelligence, but measure the indistinguishability between actors in complex cyber-physical task domains encountered every day in human life. The integration between human and non-human actors is the key to robotic and intelligent cyber-physical integration and ubiquity enabling all actors to work in cooperative societies, or organizations, to solve complex tasks.

The cloud presents an interesting strategic option for robots and the field of robotics. On the one hand, offloading computational requirements from the typically limited processors, and therefore the power requirements, presents an avenue of relief, specifically in scaled-up, larger robotic organizations or societies. On the other hand, the insecurity and potential risks of the cloud, open society up to a potential risk from malware and spurious acts, but also to potential loss of control of sometimes lethal robotic instances.

While there are obvious positives and negatives to using the cloud infrastructure to integrate robots and humans, the positive potential outweighs the negative aspects. The advantage to offload computation is dramatic, as the limiting factor for many robots is on-board power. Limiting computation cycles lessens the stress on on-board power.

The natural distributed nature of the cloud allows scaling of robotic teams to potentially dramatic levels, especially when combined with humans. Typically, networked robot teams can work in small groups. The cloud enables larger groups over potentially unlimited geography to connect. Also, the ability to provide services through the cloud infrastructure creates a virtually infinite supply or computational services, capability, and possibility for interaction and extension of collective behavior.

The combination of the HARMS models, or similar architectures, with cloud computing combines the strengths of distributed computation, indistinguishability, social organization, and collective intelligence. The combination of these particular elements creates a sum of human-like structure in robot and machine interfaces, but additionally allows humans to participate due to the integration of natural language and the lack of obvious differentiation between actors in the system other than that by capability. Making ubirobot services social aware and affective requires taking into account affects that can be inferred using physiological sensors. Several affective computing technologies of particular interest in ubirobotics are currently under development or on research progress. The advances in these technologies will make the interactions more human like and the ubirobots more sensitive to complex interactions and aware of human affects such as mood, stress, mental states, disorders, etc. [37,38]. Harnessing these technologies to become easy-to-integrate, validated, and well-documented components for existing and future ubiquitous computing applications in general is crucial for integrating them into the main stream of ubirobot service development. For these reasons, we need a design methodology that is well suited to capture specific needs of the users that will adopt ubirobots as a daily living companion and will use their services intensively. User categories will range from children to elderly, including people with physical disabilities or specific requirements.

5. Ubiquitous robots' engineering challenges

Since the concept of networked robots was proposed in 2002, several similar definitions have been proposed for both ubirobots and networked robots [2,39,1]. The challenges of networked robotic services throughout the daily activities clarify the necessity of a common platform to cope with problems, and difficulties remain for developing robotic services that support a wide range of human activities. To provide elderly and dependent people services such as shopping navigation/supports, healthcare services, etc., the following common functionalities are required [18]: multi-robot management, multi-area management, user attribute management and service coordination management. The common functionalities are implemented as a common middleware infrastructure. A robotic middleware is an important software layer that refers to the ability of a robot system to hide the heterogeneity of the low-level environment entities such as robot hardware and operating system, sensors and actuators. It refers also to the protocols

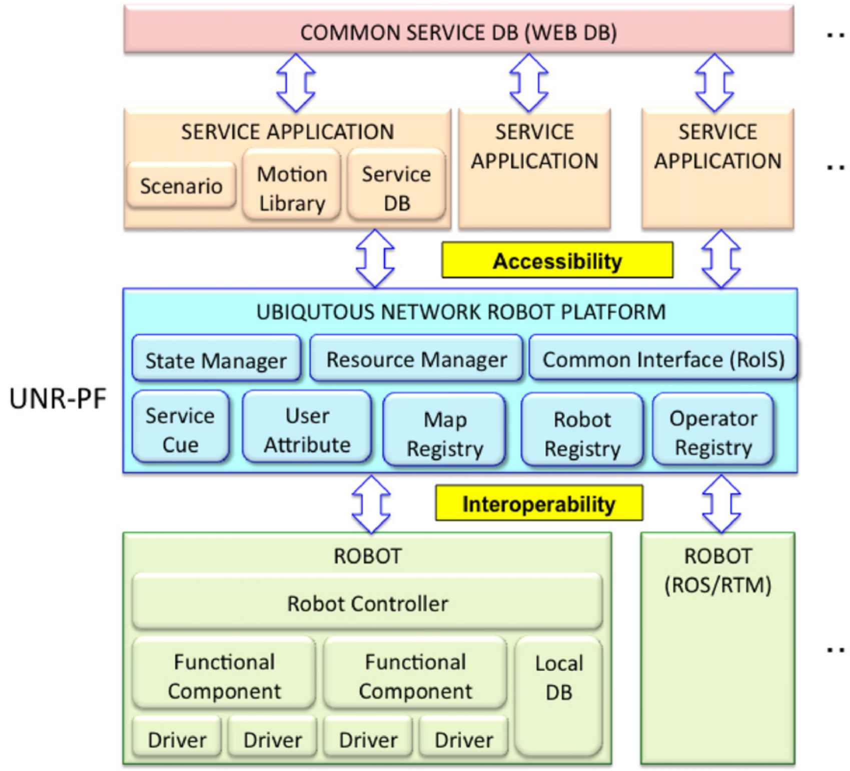

Fig. 4. Ubiquitous network robot platform (UNR-PF).

and functionalities that may be used by the robot to interact with the environment.

Building autonomic and self-evolving ubirobots needs to adapt the existing ubiquitous computing middleware or develop new ones that can take into account the specifics of robot behaviors and their interaction possibilities. Ubiquitous Network Robot Platform (UNR-PF) (Fig. 4) is an interesting middleware example, which is designed for ubirobot applications. This middleware consists of two platform layers: a local platform for the robotic system in a single area and a global one for the robotic system that ranges over multiple areas covered by a number of local ones (Fig. 5). These platforms serve as a middle-layer between the service application and the robotic component layers including smartphones, agents, sensor networks, etc. The platform is equipped with five database functions consisting of service cues, and user attribute, map, robot, and operator registries, and three management functions consisting of state, resource and message managers to provide common services to the service applications and robots. To share information among the robots and the service applications and achieve interoperability among different robots, the specifications of data structures and interfaces have been standardized. The Robotic Localization Service (RLS) specification was approved as a standard by the OMG (Object Management Group) in 2010. This standard proposes a new framework for robotic localization (RoLo) for the representation and treatment of location information specific to robotic usage. In addition, the Robotic Interaction Service (RoIS) Framework will be issued by the OMG in early 2013. The common platform architecture was discussed in the International Telecommunication Union Telecommunication Standardization Sector (ITU-T), study group 16 (SG16). The recommendation, F.USN-NRP, was accepted as a standardization work item in 2011 and is expected to be released in 2013 [18].

Today, the most practical integration techniques of ubirobots rely on the use of the web service middleware architecture such as SOAP and REST [5,31]. Thus, robots can publish their capabilities as services' description, and the problem of coordinating the robot with environment sensors and actuators of the AmI space can be seen as a pure SOA (Service-Oriented Architecture) design problem. In this context, Google proposed rosjava, an ROS (robot OS) middleware that is Android-based. This middleware adds to the robot's new capabilities, thanks to the integration of Google web services with the smartphone sensors. Google web services range from messaging and text translation to semantic web searching. Such services are processed out of the robot embedded system using the cloud infrastructure. Therefore, the software embedding cost of robots will be decreased and the robot becomes inexpensive. In this context, Google and iRobot have created together a software library for Android developers to write robotic apps that can be used for several application domains such as telepresence for telemedicine, mobile kiosks, etc. The apps are taking full control of iRobot Ava sensors and actuators wirelessly through a docked tablet.

From a service-oriented computing perspective, the Robot middleware should offer extensibility mechanisms to support the composition of new robot services by the combination and reuse of the existing services as building blocks. In general, service composition consists of creating complex services by combining the existing atomic services in order to take into account the evolution of a user's needs and its situation in the environment.

Three main middleware techniques referring to service composition are reported in the state of the art [39–41]: services' static assembly, services' orchestration using planning or workflows and services' choreography. As a consequence, using the service composition middleware should simplify for designers all of the complexity related to the design of new complex services, i.e. the configuration, the deployment and the management of the service and its constituents. The composition middleware should provide a good abstraction level that allows dealing with heterogeneous

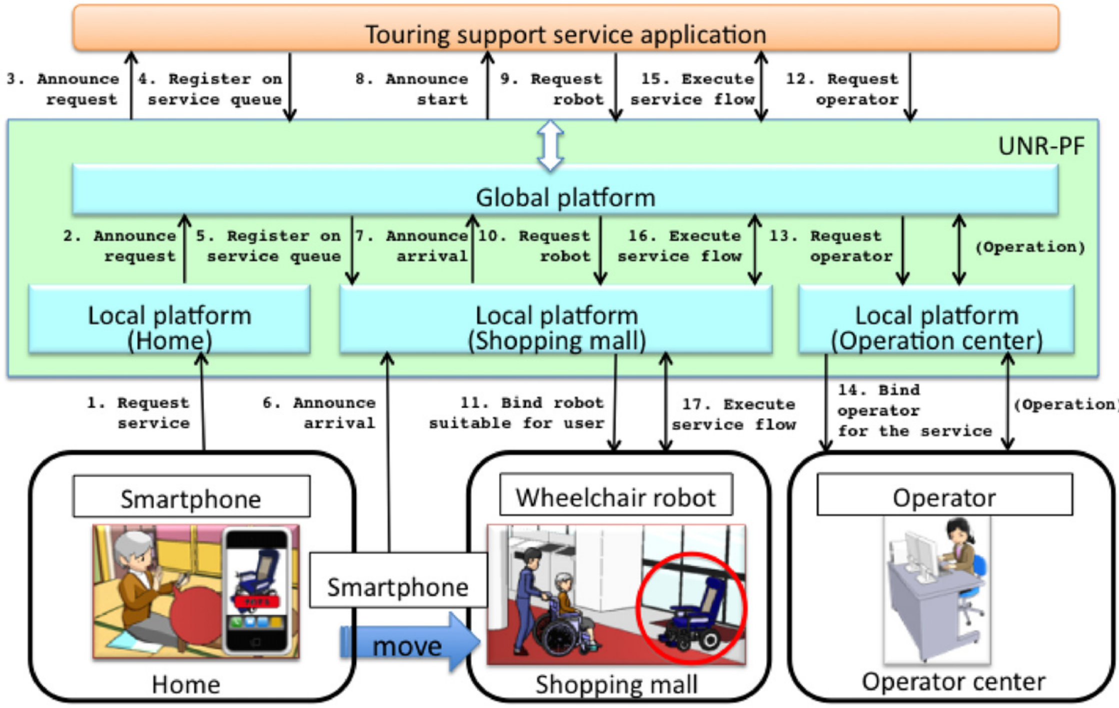

Fig. 5. UNR-PF for touring support service in a shopping mall.

services' technologies such as web services, OSGI bundles, etc. Using the paradigm of ontologies can greatly increase comprehension and interoperability among services. In this topic, service discovery and selection are the key functionalities that should be implemented within the robotic middleware.

The service discovery techniques that are proposed in the pervasive computing field can easily be reused and optimized for ubirobots. They span from device discovery using the Bluetooth/UPNP protocol called SDP to ontology-based semantic discovery protocols [3]. Service selection allows the selection of the best choice that matches with the composition plan, user preferences and current user situation [39]. Service selection must take into account network and service failures and execution environment dynamics. Several AI-based approaches can be applied to render service discovery and selection more intelligent by using reasoning tools such as description logics and case-based reasoning as well as by using machine learning techniques such as neural networks or Bayesian networks. Besides, we consider that all self* mechanisms, proposed in the autonomic computing field, can be valuable for the adaptation and the optimization of service composition such as self-configuration, self-adaptation, self-healing, self-management and self-optimization, etc. For instance, the self-configuration increases the degree of autonomy, flexibility and robustness toward the environmental dynamics and faults.

6. Conclusion

The future of ubirobots will be open to unlimited space of applications such as (i) physical and virtual companions assisting people in their daily living, (ii) ubirobots that are able to co-work alongside people and cooperate with them in the same environment, (iii) physical and virtual autonomic guards that are able to protect people, monitor their security and safety, and rescue them in indoor and outdoor spaces. With respect to the concept of smart cities, ubirobots will play various significant roles in urban situations. They will be the privileged actors on which we can rely to solve the major challenges that encounter the rapid development of our cities, such as handling humans and asset mobility within condensed population, making sustainable development tasks, or helping in decreasing and optimization energy consumption. For instance, they will assist dependent people in carrying out their daily tasks within the city, or act as safety guards, or collect our rubbish, etc. Medical robots and factory robots are considered among the success-stories of service robots. The future of these robots will be their design as co-worker ubirobots. These latter will enhance our working environments by making human and robots working together closely as a team, in a way that the robot can learn directly from its human co-worker and conversely the human can use the robot as his real assistant. This vision is inline with a new European research initiative called SMErobotics.[5] The ubirobots will reinvent factory robots to be co-workers that are able to 'think for themselves' within the tasks they are assigned to carry out so any repetitive tasks can be assigned to them. The use of ubiquitous technologies for both professional and personal healthcare is in continuous augmentation. The latest technologies can be connected to smartphones and are equipped with wireless connectivity to the internet. So, healthcare ubirobots will be one of the future generation of robots designed to play an important role as clinician co-workers.

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