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Towards Intelligent Continuous Assistance

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Abstract Technology supported assistance is a research area dedicated to support both older adults and, at some level, their caregivers in a variety of situations and contexts. A number of projects doing detailed evaluation both with robots and/or ICT-based intelligent devices have identified as open challenges the need to guarantee both continuity and variability of service according to context interpretation. This paper starts from the willingness to study how both continuity and variability can be pursued by leveraging and integrating results from research areas like Artificial Intelligence (AI), Cognitive Systems, Psychology and Sensor Networks. Some of these technological skills are needed for example by an assistive robot and still represent open challenges in AI. This paper presents a medium term research initiative aiming at synthesizing an enhanced (intelligent) control architecture for assistive robots that take advantage from the continuous flow of information provided by a sensor network. The paper presents two main results: (a) starting from the analysis of requirements coming from the real world, it envisages a conceptual cognitive architecture highlighting the functional requirements and the key capabilities characterizing an "ideal" intelligent assistive robot; (b) it presents a prototype of a testbed architecture called KOaLa (Knowledge-based cOntinuous Loop) which integrates sensor data representation, knowledge reasoning and decision making capabilities showing its novelty in a realistic scenario.

Keywords Artificial Intelligence · Human-Assistive Robotics · Human-Robot Interaction · Ambient Intelligence

1 Introduction

Nowadays there are many widely diffused commercial robotic solutions like e.g., robot vacuums or industrial lightweight robots, while a new generation of intelli-

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gent robots is entering working and living environments, taking care of human-level tasks. Such robotic systems could be increasingly important especially in older people healthcare assistance. Several studies show that life expectation is increasing[1]. An increasing in life expectation means that the number of people who will need support to cope with age-related impairments in the next future will also increase. The main goal for such a target population is to maintain both a good quality of life and a level of autonomy as long as possible.

Research studies like e.g., the ones made by (Klein et al. 2005; Iwarsson 2005; Allen et al. 2001; Hellstrom and Hallberg 2001) show that ageing is one of the most relevant factors for frailty, dependency and level of received care. The objective of fostering a good quality of life in elderly people basically means to cope with age-related health and cognitive impairments and the consequent decrease of independence. Already in early 00s, the work made by (Charness 2003) pointed out the importance of innovative technologies for preserving the autonomy of elderly people in their own domestic environment. Since then, a growing number of research initiatives and projects have been investigated with the aim of realizing intelligent robotic solutions for healthcare and/or social assistance. Works on Pearl, e.g., (Pollack et al. 2002; Pineau et al. 2003; Pollack 2005) and works on the RoboCare project, e.g., (Cesta et al. 2007, 2011), represent some of the first reference results in this field, whereas, projects like Nestore-coach (El Kamali et al. 2018), Robot-Era (Fiorini et al. 2017; Bertolini et al. 2016) or GiraffPlus (Coradeschi et al. 2013; Cesta et al. 2016), are example of more recent research initiatives that have shown progresses in realistic scenarios with real users.

Recent advancements in Artificial Intelligence and Robotics are fostering the diffusion of intelligent robotic agents capable of supporting both older adults and caregivers in a variety of common life situations. Such robotic agents must be capable of monitoring and internally representing information coming from the environment, interacting with humans in a flexible and *human-compliant* way, autonomously performing tasks inside the environment and also personalizing interactions and services according to the specific needs of an assisted person. Let us consider for example the case of an assisted person with limited interaction abilities like e.g., limited hearing functionalities. In this case, an assistive robot should mainly interact with the assisted person through visual messages. Analogously, the interactions between an assistive robot and an assisted person must mainly rely on audio messages if the assisted person is affected by low vision. Therefore, a significant number of advanced cognitive capabilities are needed to allow an intelligent robot to provide a variety of effective assistive services and to adapt these services to the specific needs of the assisted person as well as the specific operating context.

Works like (Azimi et al. 2017; Castillo et al. 2017; Foresti et al. 2015) show that IoT and general sensor devices can be used to gather information about the environment and the health status of a person and accordingly recognize/detect critical situations and emergencies. The ability of dealing with different and heterogeneous sources and types of information constitutes a key feature to enable intelligent robotic assistants to *recognize* health-related states and needs of older

[1] See for example the 2012 ageing report showing economic and budget projections of EU member states between 2010 and 2060 - https://ec.europa.eu/eip/ageing/news/2012-ageing-report-europe-needs-prepare_en

persons as well as the states of the environment it acts in. Also, the need of supporting daily and personalized assistance entails the exploitation of IoT devices to gather information about the living environment of the assisted person as well as his/her physiological parameters in order to figure out which assistive task or set of tasks is more suited for the detected situation. It is necessary to endow newly social robots like for example the rather popular Pepper from SoftBank Robotics with advanced cognitive capabilities to provide well suited and effective impact in healthcare assistance and achieve the challenging objective of prolonging elderly independence as well as increasing their quality of life.

There are several research issues and open problems that must be properly addressed to achieve such challenging objectives. In our view, a number of advanced *cognitive capabilities* that range from knowledge representation and learning to decision making and acting need to be integrated. Many AI techniques and technologies can give a precious contribution and play an important role in this context if properly integrated in a uniform control approach. The survey by Langley et al. (2009) takes into account some key contributions from research in cognitive architectures and defines some guidelines and methodologies concerning the integration of the envisaged cognitive capabilities and the underlying techniques.

This Paper. This work takes inspiration from previous experience of our group within the GiraffPlus project (Coradeschi et al. 2013), a research project ended in 2014[2]. That project represented a successful example of the use of AI in domestic care scenarios and a precious experience with respect to the deployment of AI-based robots and assistive services in real domestic home environments. Although successful, the outcomes of the projects and the assessments of the pilot case-studies performed in different countries (Cesta et al. 2016) showed some limitations concerning the autonomy, the interactions of the robot with the patients, and, most of all, *the continuity of the assistive services.*

This paper, an extended version of (Cesta et al. 2019), aims at selecting a set of cognitive features needed to address the most relevant requirements that an intelligent assistive robot should satisfy to effectively take care with continuity of older adults inside their domestic home environment.

The paper identifies the most promising AI techniques that can help realising the considered features (Section 2), then proposes (Section 3) a cognitive architecture called AI^3 showing how the identified AI techniques can be integrated into the envisaged control approach, and the relationships among the functional elements composing the cognitive architecture. Furthermore, the paper describes (Section 4) a partial instantiation of AI^3 called KOaLa (*Knowledge-based cOntinuous Loop*) and then (Section 5) proposes a conceptual scenario exemplifying the use of KOaLa in daily-home assistance applications. Conclusions and future work directions are described in Section 6.

[2] GiraffPlus was funded by the European Community's Framework Programme Seven (FP7) under contract m. 288173. FP7 - ICT - Challenge 5: ICT for Health, Ageing Well, Inclusion and Governance. Duration: 01-01-2012 to 31-12-2014.

2 Key Ingredients for an Effective Daily-Home Assistance

The development of reliable AI and robotic technologies aimed at supporting the daily-home life of persons at home is a really challenging research goal. Such scenarios require a number of complex and heterogeneous capabilities that are not trivial to integrate into robotic systems. A possible approach is to identify and focus on a restricted set of well-defined capabilities and *skills* that are really necessary to achieve the desired (assistive) objectives.

What emerged from GiraffPlus is that the realization of intelligent and continuous behaviors providing end-users with adapted and personalized assistive services requires the characterization of an “assistive context” from different perspectives.

The features of a (domestic) environment, the health-related needs of an assisted person and the technical skills of the used (social) robot strongly influence the type and “shape” of the obtained assistive behaviors. As shown in GiraffPlus, the use of IoT devices organized into a sensor network allows an assistive robot to *perceive* the domestic environment. The analysis of environmental information in combination with social capabilities of a telepresence robot (e.g., videoconference functionalities) are well-suited to support monitoring and socialization services and therefore facilitate the communication between end-users and “external” entities like e.g., formal and informal caregivers, doctors or relatives.

Also, the technical skills and capabilities of a robot strongly influence the assistive services that can be actually realized as well as the possible impairments of end-users influence the way assistive services are “delivered” and the preferred interaction modalities. These aspects are crucial to realize an effective and personalized assistance. For example, end-users with short-term memory loss may desire to frequently receive reminders about his/her personal agenda or his/her therapy to follow. Conversely, end-users that do not have short-term memory loss may found useful a reminding service but they may prefer a “less-invasive interaction”.

Figure 1 characterizes this ”multi-dimensional” perspective and shows the aspects that in our opinion are the most relevant to realize a contextualized and intelligence assistance.

On the one hand (the left side of the Figure 1) there is the environment a robot interacts with and monitors/observers over time. IoT devices represent a precious source of information to characterize the status of the house (e.g., the temperature or the luminosity in a particular room), the status of the elements inside the house (e.g., whether the TV is consuming energy or not or whether the window of the bedroom is open or closed) and the physiological parameters of an assisted person (e.g., the heart rate or the body weight).

On the other hand (the right side of Figure 1) there is the expected behaviors of an assistive robot. A robot is supposed to “act” in a contextualized way by taking into account particular features of the environment and the health-related needs of the assisted person (i.e., the particular *assistive context*).

The work by (Cesta et al. 2018a) provides a quite relevant and exhaustive analysis made within GiraffPlus, showing the requirements and expected behaviors of domestic care assistive robots from end-user perspective. We here focus on a set of key requirements that are in our opinion fundamental for achieving our (research) objectives of continuous and autonomous assistance. These requirements can be organized according to following four perspectives: (i) environment per-

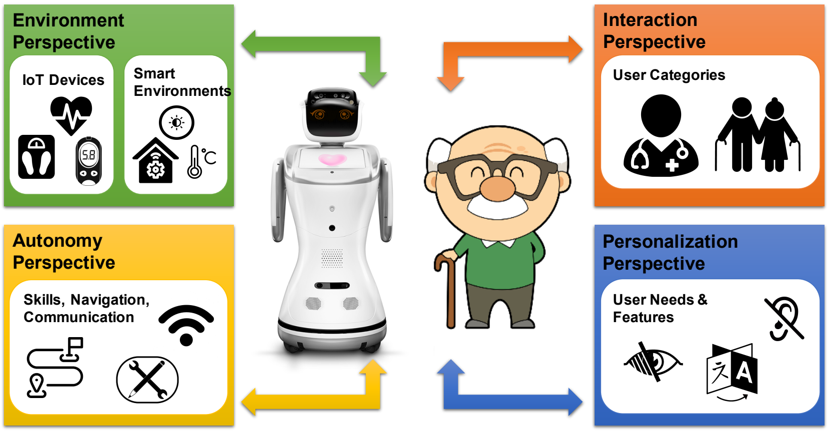

Fig. 1 The key ingredients characterizing a cognitive architecture for assistive robots

spective; (ii) autonomy perspective; (iii) interaction perspective; (iv) adaptation perspective.

- **Environment perspective.** Pursuing the idea of GiraffPlus different IoT devices are used to gather information about the environment and the health status of an assisted person. Broadly speaking, there are two categories of sensing devices that are relevant in domestic assistance scenarios: (i) *environmental sensors*; (ii) *physiological sensors*.
  Environmental sensors (or ambient sensors) produce data about the state of a particular area of the house like e.g., the kitchen, the living-room and so on. Physiological sensors produce data about physiological parameters of a person like e.g., blood pressure, hearth rate and so on. The envisaged assistive robot must properly deal with this information to monitor and characterize the status of the different features that compose the environment. Specifically, it must implement *perception* capabilities to process data gathered from IoT sensing devices and recognize activities the assisted person is performing inside the house as well as the health status of the assisted person.
- **Autonomy perspective.** There can be different situations that may require the execution of some supportive task by the system. For example, as often stated, the system can remind the dietary restrictions when a person is preparing his/her meal, can remind the therapy when a person wakes up or can make a phone call to a relative of the assisted person when asked. This means that the envisaged intelligent assistive robot must know the set of possible behaviors that enable safe and correct (autonomous) interactions with the environment. Such additional source of information called *causal knowledge* characterizes "basic rules" guiding the execution of possible behaviors. These rules describe the (internal) capabilities of the system and enable *decision making processes* that synthesize sequences of operations that carry out complex assistive tasks if executed according to some operational constraints.
  More in general, it is necessary to distinguish between proactive and passive behaviors. Proactive behaviors determine the need of autonomously deciding the assistive tasks to perform according to the observed evolving state of the

environment or the assisted person. Passive behaviors instead determine the capability of interacting with the assisted person and directly receive *commands* (i.e., requests of executing some assistive tasks) through some kind of communication/interaction channel.

- **Interaction perspective.** The capability of receiving commands from a person as well as the capability of reminding the therapy imply a bidirectional communication "channel" between the assistive robot and the assisted person. An assistive robot can interact with humans at different levels and with different modalities like e.g., gestures and/or voice commands. It is important to realize human-robot interactions as much natural and safe as possible. This is crucial to avoid that end-users perceive the robot as a threat or a not useful or too complex "tool".
  To achieve this, an assistive robot should correctly understand commands and instructions coming from humans and show behaviors that are both safe and socially acceptable by humans. Namely, the behaviors of an assistive robot should be compliant with so-called *social norms* that are necessary to effectively take part to "social life". An example is the work by (Awaad et al. 2015) which represents an interesting contribution in this context addressing the "social task" of a robot serving coffee to a guest. Even for a "simple task" like this, a robot should follow "social norms" to realize human-compliant behaviors. As shown by (Awaad et al. 2015) indeed, although the *functional affordance* of cups and watering cans is the same of "containing some fluid", a human-guest would hardly accept the robot behavior of serving coffe using a watering can.
- **Adaptation perspective.** Another dimension that must be taken into account is the personal attitude and preferences. Different persons have different habits and different needs that can also change over time. Assistive robots must tightly interact with persons during their daily-home living and therefore a general and "static behavior" would not be so effective in the long run. Indeed, a recent survey made by (Rossi et al. 2017) shows that *adaptation* and *personalization* represent two key *qualities* of social robots and that a good level of these qualities is crucial are crucial to achieve *user acceptance* and carry out an effective assistance.

Going back to Figure 1, the *cognitive architecture* represents a sort of *middleware* responsible for integrating the skills an assistive robot needs to satisfy all the requirements and provide effective assistive services. The envisaged assistive robot integrates a significant amount of heterogeneous and advanced capabilities according to the requirements discussed above. There are several AI techniques that can address a subset of these capabilities, when taken individually. However, the integration of these techniques and the coordination of the related processes within a unified control approach is challenging and represents an open research problem.

The design of such advanced control approaches has been typically tackled by researchers in *cognitive architectures*. Consequently, we introduce a conceptual cognitive architecture to propose a possible integration of the AI technologies that in our opinion are the most promising to achieve our long-term research objective. We call this architecture AI^3 and further describe it in the next section.

3 Conceptual AI^3 Architecture for Assistive Robots

Research in cognitive architectures aims at endowing an artificial agent with a hybrid set of cognitive capabilities that range from learning and perception to problem solving and acting. As stated by (Langley et al. 2009), research in cognitive architecture is important because it enables the creation and understanding of (synthetic) agents that support the same capabilities as humans by integrating results in cognitive sciences and AI.

A key point in the design of cognitive architectures is the management of different source of knowledge and the basic capabilities needed to access and process such knowledge. For example, knowledge from environment comes through perception, knowledge about opportunities of a particular state of the environment comes through planning, reasoning and prediction. The survey made by (Ye et al. 2018) provide an exhaustive list of existing cognitive architectures and supported capabilities. The works on ACT-R (Anderson et al. 1997, 2004), the works on SOAR (Laird 2008; Laird et al. 1987), and the work on ICARUS (Langley et al. 2004) are some examples of the most known cognitive systems realized in this field. Although not so recent, the work by Langley et al. (2009) provides a good and complete discussion of cognitive capabilities that are relevant for the the design of our cognitive system.

As shown in the previous section, the envisaged assistive (cognitive) robot must be capable of *knowing* the environment it operates in, *autonomously deciding* the operations that must be performed and how and, *adapting* its behavior according to the different features and needs of assisted persons. Thus, the cognitive capabilities elicited in (Langley et al. 2009) that are particular relevant for our purpose are the following: (i) *recognition and categorization*; (ii) *reasoning and belief maintenance*; (iii) *prediction and monitoring*; (iv) *problem solving and planning*; (v) *decision making and choices*; (vi) *execution and action*.

Besides cognitive architecture also research in AI and Robotics (Rajan and Saffiotti 2017; Ingrand and Ghallab 2017) has tackled the problem of designing intelligent systems capable of both interacting with the real-world and solve complex problems through the autonomous synthesis execution of actions (planning and acting according to (Ghallab et al. 2014)). *Machine learning*, *knowledge representation and reasoning*, *automated planning and execution* represent three well-established field of AI that can play an important role in this context. Following the *sense-reason-act* AI pipeline and taking into account contributions from cognitive architecture design, we here propose a cognitive architecture for assistive robots pursuing the tight integration of three AI areas. We call this architecture the *three-core AI-based cognitive architecture* - AI^3.

Figure 2 provides a conceptual view of the AI^3 pointing out the relationships between the identified cognitive capabilities and the three phases of the sense-reason-act cycle. It shows correlations between cognitive capabilities and AI cores that are involved with the sense-reason-act cycle.

The *Machine Learning Core* concerns techniques that are responsible for realizing perception capabilities and learning useful information from the interactions between the robot and the assisted person (i.e., the *experience*). AI techniques belonging to this core support *Prediction & Monitoring* and *Representation & Categorization* by learning predictive models of the daily-home habits as well as the evolving health-related needs and features of an assisted person. They support ab-

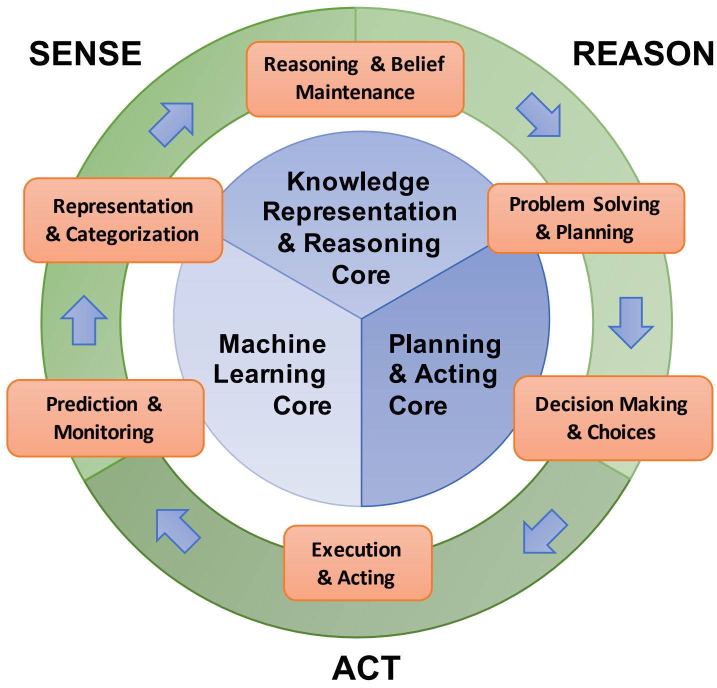

Fig. 2 The three-core AI-based conceptual architecture.

straction processing of outputs coming from of different sensory sources providing an assistive robot with a continuous flow of heterogeneous information that must be properly integrated.

Therefore, *Representation & Categorization* relies on the integration of *Machine Learning Core* and *Knowledge Representation & Reasoning Core* to uniformly represent and process gathered information. Specifically, ontology-based approaches support the representation and integration of different sources of information (*data fusion*) by providing a clear and uniform semantics to guide knowledge processing mechanisms.

The *Knowledge Representation and Reasoning Core* concerns AI techniques that are responsible for implementing such knowledge processing mechanisms and elaborating information coming from the environment. They build and maintaining an internal abstract representation of the "working environment" i.e., the internal *knowledge* of the assistive robot. Such knowledge is central to the envisaged architecture and represents the synchronization point of the AI-cores.

As shown in Figure 2, AI techniques belonging to this core mainly support *Recognition & Categorization*, *Reasoning & Belief Maintenance* and *Problem Solving & Planning*. As said *Recognition & Categorization* relies on the integration of *Knowledge Representation & Reasoning* and *Machine Learning* AI cores. Similarly, *Problem solving & Planning* is supported by both *Knowledge Representation & Reasoning* and *Planning & Acting* AI cores that are integrated through the internal knowledge of the assistive robot (i.e., the KB).

The *Planning and Acting Core* concerns AI techniques that are responsible for actually interacting with a patient and the related environment. These techniques rely on the internal knowledge to characterize and execute the operations/actions that can be performed as well as the set of observable events and/or activities that need support and proactive assistance. Below, we give a more detailed description of AI^3 by taking into account the cognitive capabilities elicited by (Langley et al. 2009) we mentioned so far. For each elicited capability we describe the elements of the cores of AI^3 that are involved and how they interact to satisfy the functional requirements.

3.1 Recognition and categorization

An intelligent agent must make some contact between the environment and its internal knowledge. This capability is closely related to *perception* and usually requires to process information/data gathered from perceptual systems like e.g., sensing devices, in some way. It is necessary to recognize situations or events as instances of known pattern to build knowledge from perceptual outputs. Thus, an assistive robot must internally represent these patterns and the relationships that hold across different situations in some way.

Knowledge Acquisition and *Sensor Data Processing* are architectural elements responsible for dealing with perceptual output received through either sensing devices or interacting commands. This allows an assistive robot to deal with both data coming from the deployed sensors and data coming from interactions with the assisted person. Data processing and integration rely on the *Ontology-based Reasoning* which is an architectural element encapsulating general properties and relationships (i.e., *semantics*) that guide the interpretation process of perceptual outputs. Namely, the ontology defines general concepts and properties in shape of general rules that characterize the possible situations and events assistive robots deal with.

In our view, the ontology is the key element providing a semantics for interpreting and processing data in a uniform way. The ontology is an integration point between the sense phase and the reason phase of the control loop. It guides the reasoning processes elaborating “external” information and building the internal knowledge of the robot (i.e., the *Robot Knowledge Representation*). Then, this knowledge is continuously maintained and refined through *Reasoning & Belief Maintenance* capabilities.

3.2 Reasoning and belief maintenance

Reasoning is a central capability of a cognitive system like the envisaged assistive robot. It allows an agent to incrementally build and refine its internal knowledge about the “world”. The maintenance and refinement of such knowledge over time is then closely related to problem solving and other “acting” capabilities of a cognitive agent as it will be shown next.

Reasoning draws theoretical conclusions from other beliefs assumptions that an agent already holds or dynamically build over time according to gathered data or *experience*. To support such capabilities, a cognitive system explicitly represents relationships among beliefs and reason about them. An assistive robot for example should be able to internally represent and reason about the health-related features and needs of the assisted person. The element *User Modeling* in Figure 2 could enrich the internal knowledge by representing the "profile" of an assisted person.

Relationships and beliefs are usually represented through logical or probabilistic formalisms that can be more or less expressive according to the specific application needs. Therefore reasoning and belief maintenance capabilities use mechanisms that draw inferences using these formalisms and related knowledge structures.

This capability is crucial to realize an ontology-based knowledge processing mechanism encapsulated by the element *Ontology-based Reasoning* which guides other architectural elements like e.g., *Knowledge Acquisition*, *User Modeling* and *Behavior Prediction* in the continuous refinement and maintenance of the internal knowledge of the assistive robot. Also, reasoning plays an important role not only when inferring new beliefs but also when deciding whether to maintain existing ones or not. Such *belief maintenance* is especially important for dynamic environments in which situations may change in unexpected ways, with implications for the possible behaviors of an agent.

The knowledge is encapsulated by the architectural element *Robot Knowledge Representation* which represents the integration point between the abstract reasoning and the "acting reasoning" capabilities.

3.3 Prediction and monitoring

A cognitive system like the envisaged assistive robot exists over time. It must be capable of predicting future situations and events accurately in order to dynamically adapt its behavior to changing situations. For example, the health-state of an assisted person as well as his/her daily-home routines may change over time and an assistive robot should be able to capture such changes and behave accordingly.

Prediction requires some model of the environment and the effects that actions have on it. Therefore, a cognitive system should also include the capability of *learning predictive models* from experience and refining them over time. The *Machine Learning Core* of the AI^3 cognitive architecture encapsulates the basic functionalities needed. The architectural element *Behavior Learning* enriches the *Recognition & Categorization* capability by providing functionalities to identify relevant features and information useful to characterize the evolving state of the "world" (i.e., the evolving behaviors and needs of the assisted person in the case of assistive robots). Then, the architectural element *Behavior Prediction* supports *Reasoning & Belief Maintenance* by elaborating learned data and dynamically generating *predicative models* of the assistive context.

3.4 Problem solving and planning

A model characterizing the effects of actions and functional capabilities of *domain entities* is needed to support planning. Reasoning processes use this knowledge to autonomously decide a sequence of actions which is encapsulated into a *plan*.

However, problem solving represents a more abstract notion than planning. This capability implies a more abstract way of reasoning which may require to take into account also "external resources" to solve a problem or carry out a particular task. It means that internal knowledge of the assistive robot must characterize *functional capabilities* of other agents and/or "acting elements" of the environment such that as assistive robot can *delegate* the execution of some assistive tasks (or part of them).

Such a higher level of problem solving can be achieved by integrating meta-reasoning mechanisms capable of analyzing and inferring the functional capabilities of external "agentive objects" of the environment. This can be achieved by leveraging formal representation like e.g., an *ontology of functions* as seen in (Borgo et al. 2009, 2016, 2019). In this way, an assistive robot can dynamically infer which operation/function can be performed by which agent/object of the assistive context and adapt the (abstract) decision making process accordingly.

The architectural element *Online Task Reasoning* anlyzes the particular situations and health-related information encapsulated by the internal knowledge to dynamically identify *opportunities* and integrate assistive tasks into the plan. Namely, it realizes *goal recognition* functionalities that trigger assistive tasks (i.e., planning goals) according to the current knowledge of the agent.

3.5 Decision making and choices

To operate and concretely support a person an assistive robot must make decisions and select among possible alternatives. Such decisions are often associated with the recognition of particular situations and/or patterns (i.e., known states of the environment).

AI^3 supports the recognition-act cycle through the *Knowledge Representation and Reasoning Core* and the *Planning and Acting Core*. The former processes information from the environment and refine the internal knowledge accordingly as seen above. The latter interacts with the environment by executing the operations needed to perform supportive tasks.

The internal knowledge encapsulates a "causal model" of the assistive context characterizing possible choices and capabilities of an assistive robot as well as possible interactions with the environment. The description of these interactions usually consists of a description of the *effects* that actions have on the environment when executed (i.e., the induced state transitions) and the *conditions* under which actions can be executed/applied. According to this knowledge, the *Planning and Acting Core* provides the deliberative and decision making processes needed to autonomously synthesize and execute assistive tasks.

Task Planning and *Plan Dispatching* are the architectural elements in charge of online synthesizing and deciding the actions that must be performed. They rely on the internal model of the assistive robot, the environment and the expected behavior of the assisted person to provide a personalized interaction plan achieving assistive objectives.

3.6 Executing and acting

Interactions entail the execution of skills and operations in a real environment. In some frameworks, this happens in a completely reactive manner. The agent selects one or more primitive actions on each decision cycle, executes them and repeats the process on the next cycle. This approach is usually associated with closed-loop execution strategies, since the agent can also sense the environment.

Plan Dispatching, *Plan Monitoring* and *Plan Adaptation and Repair* are the architectural elements responsible for managing the execution of synthesized plans by actually performing operations into the real environment. The closed-loop approach allows an agent to receive *feedbacks* about the execution of actions in the real-world.

These feedbacks provide information about the outcome of the execution of an operation. Failures or more in general, the recognition of an unexpected or even an unknown state of the environment represent *exogenous events* that may occur during the execution of a plan. The architectural element *Plan Adaptation and Repair* is specifically responsible for handling this kind of events to achieve a robust execution of plans and reliable assistive behaviors.

Replanning is a typical execution strategy used to manage such exogenous events. Replanning mechanisms allow an agent to dynamically generate new plans every time the nominal execution is “altered”. The envisaged assistive robot can then modify its behaviors according to the detected status of the environment and carry out assistive tasks in different *contingent situations.*

Assistive robots usually operate in a dynamic environments whose uncontrollable evolutions can make planned assistive tasks unfeasible. This is especially true in non ideal environments like the home of an older person. Therefore, it is necessary to properly manage such situations and properly react to exogenous (and uncontrollable) events.

4 The KOaLa Cognitive Architecture

The AI^3 architecture and the discussed capabilities represent a sort of blueprint or roadmap of an ideal assistive robot strongly using AI features. Of course, the realization of such an intelligent assistive robot is a challenge for a long-term perspective. Still an amount of work is needed to develop and make operational the envisaged AI-based cores and concretely integrate these capabilities within a flexible and reliable control process. However, we have already paved the way realizing a partial prototype of AI^3, called KOaLa (*Knowledge-based cOntinuous Loop*), introduced in (Cesta et al. 2018).

KOaLa is an instantiation of AI^3 covering a significant subset of the pursued capabilities. Currently, it pursues the integration of knowledge representation & reasoning with automated planning and execution. A tight integration between these two technologies and related capabilities is crucial to achieve a continuous and personalized interaction between a user and an intelligent system (either a robot or an intelligent software). Relevant examples are the works (Bacon et al. 2013; Cesta et al. 2014; Cortellessa et al. 2013) that integrate knowledge reasoning and planning for realizing personalized crisis management training.

Specifically, KOaLa relies on the tight integration of an ontology-based knowledge processing module and a timeline-based planning and execution module within a *sense-reason-act cycle*. These modules are called respectively the *KOaLa Semantic Module* and the *KOaLa Acting Module*. Figure 3 describes the architecture of the prototype highlighting the phases that compose the control flow and the relationships among components. As shown, the control flow starts with data gathering from the environment and ends with action execution involving robot actuators and/or sensor configurations. It instantiates many of the elements composing the *Knowledge Representation and Reasoning Core* and the *Planning and Acting Core* described in the previous section.

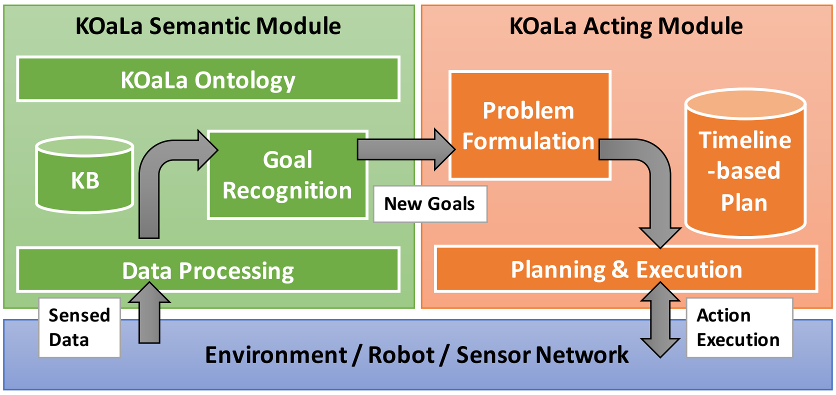

Fig. 3 The semantic and acting modules of composing the KOaLa *sense-reason-act* cycle

4.1 The Semantic Module

The *KOaLa Semantic Module* is responsible for the interpretation of sensor data and the management of the resulting *knowledge* of the robot. This module relies on the *KOaLa Ontology* to provide gathered data with semantics and incrementally build an abstract representation of the application context i.e., the *Knowledge Base* (KB). A *data processing mechanism* uses standard semantic technologies based on the Web Ontology Language (OWL), defined by (Bechhofer 2009), to build and continuously refine the KB. Then, a *goal recognition process* analyzes the KB in order to identify specific *situations* that require a proactive "intervention" of the robot and dynamically generates related *goals* for the acting module.

The KOaLa ontology has been defined by leveraging SSN, defined by (Compton et al. 2012), and DUL[3], two stable and publicly available ontologies. They define some useful concepts and properties that we have further extended for our assistive purposes. The ontology has been structured in different contexts that characterize the knowledge according to different levels of abstraction and perspectives: (i) the

[3] http://www.loa-cnr.it/ontologies/DUL.owl

sensor context; (ii) the *environment context*; (iii) the *observation context*.. Figure 4 below shows an excerpt of the KOaLa ontology[4].

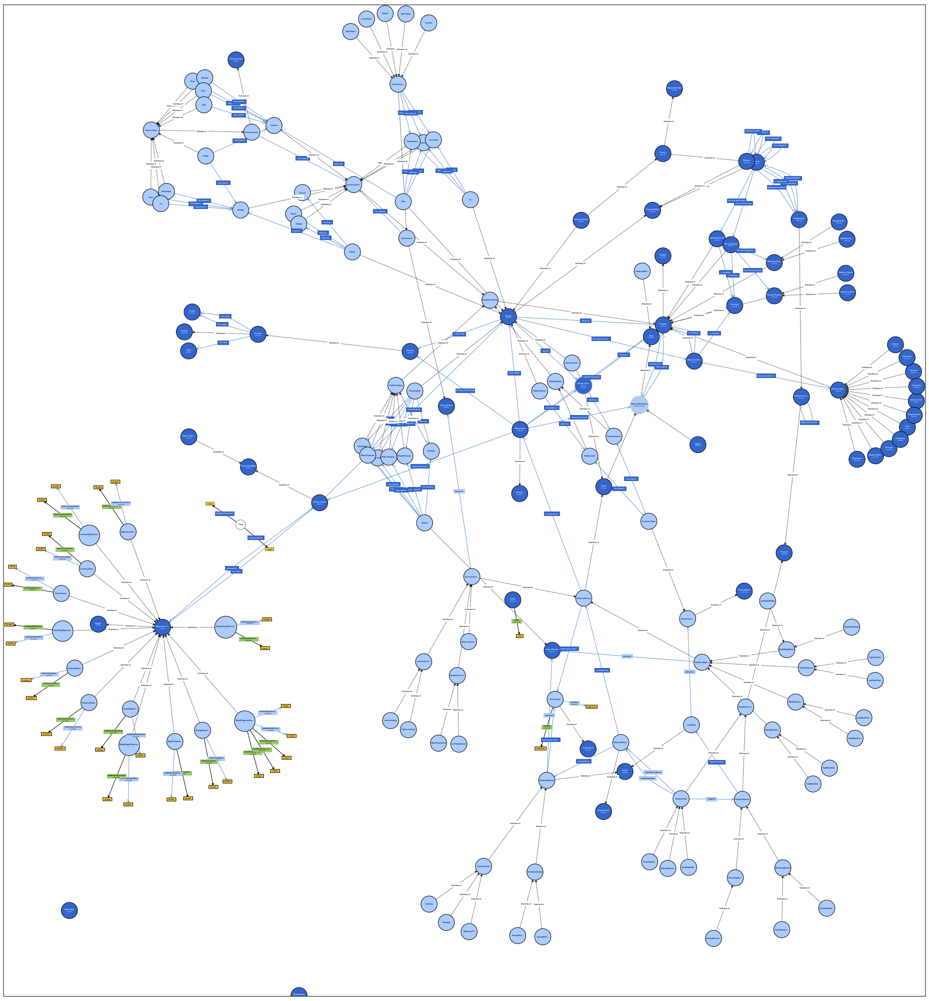

Fig. 4 Excerpt of the KOaLa ontology

The *sensor context* characterizes the knowledge about the sensing devices that compose a particular environment, their deployment and the properties they may observe. This context strictly relies on SSN by providing a more detailed representation of the different types of sensor that can compose an environment as well as the different types of properties that can be observed. Leveraging this general knowledge, it is possible to dynamically recognize the actual monitoring capabili-

[4] Visualization generated with TKIZ using alpha version of the TeX exporter of WebVOWL (version 1.1.3)

ties as well as the set of *operations* that can be performed according to the types of sensor available and their deployment.

The *environment context* characterizes the knowledge about the structure and physical elements that compose a home environment, and the deployment of sensors. This context models the different *physical objects* that may compose a *home environment*, their properties and the particular deployment of the sensors. Thus, this context provides a complete characterization of a domestic environment and the relate configuration of the sensor network.

The *observation context* characterizes the *features* that can actually produce information in a give configuration as well as the *events* and the *activities* that can be observed through them. This context identifies the *observable features* of a domestic environment as the physical elements that are actually capable of producing information through the deployed sensors. Similarly, it identifies the *observable properties* as the properties of the observable features that can be actually observed through the deployed sensors. In this way, the KB is capable of representing observations and processing/interpreting received data by taking into account the associated environmental information like e.g., the are of the house data comes from or the type of object data refers to.

A knowledge processing mechanism elaborates sensor data following the semantics defined by the KOaLa ontology. Figure 5 shows the main steps of the data processing pipeline realizing such processing mechanism. Each step is managed through a dedicated reasoning module which elaborates data and the KB at a specific level of abstraction (i.e., ontological context).

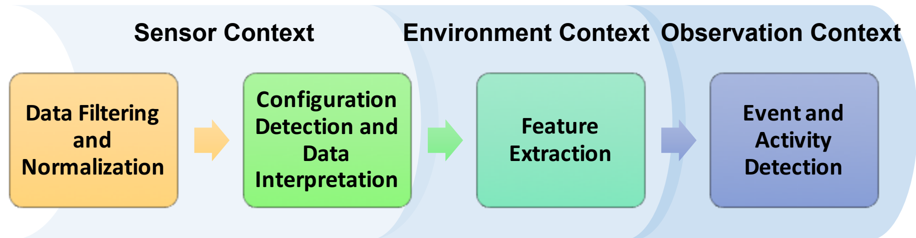

Fig. 5 Data processing pipeline for knowledge inference and maintenance

The KB is initialized on a configuration specification which describes the structure of the domestic environment, the set of sensors available and their deployment. The *Configuration Detection and Data Interpretation* module generates an initial KB by analyzing the configuration specification. The resulting KB is then continuously refined by interpreting sensor data coming from the environment.

The *Feature Extraction* module identifies the observable features of the environment and the related properties. It processes sensor data in order to infer *observations* and refine the KB accordingly. Then, the *Event and Activity Detection* module analyzes inferred observations by taking into account the knowledge about the environment. These reasoning modules are implemented by means of customized Jena rule-based engines [5]. Each rule-based engine is fed with a num-

[5] See Apache Jena software library - https://jena.apache.org/

ber of dedicated *inference rules* that encapsulate the semantics to contextualize processed data and connect ontological contexts as shown in (Cesta et al. 2018b).

4.2 The Acting Module

The *KOaLa Acting Module* is responsible for planning and executing operations according to the events or activities inferred by the semantic module. These events are inferred by the *Goal Recognition* module (GR) of the knowledge processing pipeline show in Fig. 5. GR is a key enabling feature of KOaLa for dynamically linking the semantic and the acting modules as shown in (Umbrico et al. 2018). It can be seen as a background process that monitors the updated KB and generates *assistive task signals* every time particular situations are recognized. GR is a key enabling feature for *proactivity*.

Assistive task signals are modeled as *planning goals* the *problem formulation* process encodes into a planning problem specification. The resulting problem specification is then given to a planner which synthesizes a temporal plan describing the sequences of operations needed to support the user. Planning and execution capabilities of KOaLa rely on a timeline-based framework called PLATINUm, which is integrated into the cognitive architecture.

The set of goals the Acting Module deals with depends on the particular configuration of the environment and the available *capabilities* of the deployed sensors. A *planning model* encapsulates the knowledge about the capabilities of the *controllable elements* that compose the environment and how such capabilities can be coordinated to realize the desired *assistive functionalities*. A planning model must describe the primitive capabilities of an assistive robot like e.g., make a call, send a message or move to a particular location, as well as the primitive capabilities of the available sensors like e.g., turn on, turn off a sensor or set a particular configuration on a sensor.

Goals represent high-level assistive tasks that can be performed by properly controlling and coordinating these primitive capabilities. The planning model can be dynamically configured by analyzing the “static” knowledge about the domestic environment. Fig. 6 shows the configuration process pipeline which generates a planning model description by leveraging mechanisms similar to those described in (Borgo et al. 2019, 2016) for a reconfigurable manufacturing system.

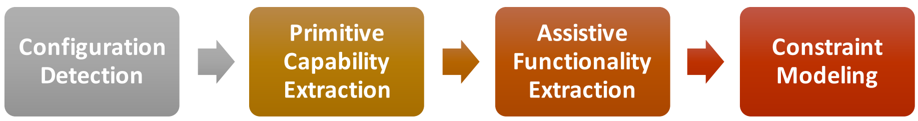

Fig. 6 Configuration pipeline for the generation of a timeline-based planning model

The *Configuration Detection* step extracts the configuration of the environment from the KB in order to identify the set and types of sensor and their deployment as well as information about the capabilities of the GiraffPlus robot. The *Primitive Capability Extraction* further analyzes these elements in order to extract the *environment primitives* and *robot primitives*.

Environment primitives represent the capabilities of the elements of the environment that can be controlled. They characterize the controllable elements of the environment and the operations that can be performed with them. It is important to note that they do not model directly the sensors of the environment, but rather they model the elements that can be controlled through the deployed sensors (i.e., the observable features). For example a sensor deployed on the socket where a TV is plugged in can be used to turn off and turn on the TV. In such a case, the TV becomes *controllable* and the related *turn on* and *turn off* capabilities are part of the *environment primitives.*

Robot primitives represent capabilities of the used assistive robot i.e., the GiraffPlus robot. They model the *functional layer* of the robot which provides the basic capabilities that can be used to perform assistive functionalities. For example, the GiraffPlus robot provides *navigation capabilities* that can be used to move the robot inside the domestic environment, *messaging capabilities* that can be used to send/receive messages to/from patient's relatives, *video-calling capabilities* that can be used to make calls or receive calls with or from doctors and patient's relatives. All these functionalities compose the *robot primitives.*

The *Assistive Functionality Extraction* step extracts the high-level assistive functionalities the system can perform. This step identifies the types of assistive task (i.e. planning goals) the goal recognition process could generate by analyzing the KB. Then, the *Constraint Modeling* step finalizes the control model by linking assistive functionalities to the environment and robot primitives. The result of this pipeline is a timeline-baed planning model characterizing the high-level assistive functionalities the GiraffPlus robot can perform as well as the operational constraints the system must satisfy to realize them.

4.3 Using PLATINUm for planning and acting

Planning and execution capabilities rely on PLATINUm which is a planning and acting framework defined by (Umbrico et al. 2017) and complies with the formal account of the timeline-based approach defined by (Cialdea Mayer et al. 2016).

A timeline-based model is composed by a set of *state variables* describing the possible temporal behaviors of the domain features that are relevant from the control perspective. Each state variable specifies a set of *values* that represent the states or actions the related feature may assume or perform over time. Each *value* is associated with a *flexible duration* and a *controllability tag* which specifies whether the value is controllable or not. A *state transition function* specifies the valid temporal behaviors of a state variable by modeling the allowed sequences of values (i.e., the transitions between the values of a state variable).

To coordinate the behaviors of different state variables a dedicated set of rules called *synchronization rules* is defined to model "global" constraints among values of different state variables. Such rules can be used also to specify *planning goals.* Given such a model, a PLATINUm planner synthesizes a number of timelines that allow an assistive robot to perform desired assistive tasks. Timelines represents envelopes of valid temporal behaviors of domain features.

A PLATINUm executive carries out the timelines by temporally instantiating the available sequences of values. Namely, an executive decides the exact *start time* of these values. The execution of these values not always can be controlled by the executive which must dynamically adapt the plan according to the *feedbacks* received during execution. For example, the time an assistive robot needs to navigate the environment and reach a particular location cannot be decided in advance. Indeed, the navigation can be slowed-down by obstacles and therefore the actual duration of a navigation operation is known only when the executive receives the associated feedback.

5 Conceptual Scenario

Although, KOaLa do not cover all the capabilities of AI^3 it already supports a number of interesting assistive services. Let us consider an assistive context consisting of an older person (John) who lives alone inside his apartment. The apartment is composed by a living room, a kitchen, a bathroom, a bedroom and a central corridor connecting all the rooms plus the entrance. A number of IoT devices are deployed all over the house to monitor the environment.

The windows and the entrance door are equipped with a sensor capable of checking whether they are open or closed. The rooms of the house are endowed with at least one sensor for detecting temperature, one sensor for detecting luminosity and one sensor for detecting motions inside the monitored area. Electronic devices like e.g., TVs, microwaves or ovens are equipped with sensors that detect the consumption of energy. In addition to these environmental sensors, other sensing devices are used to track physiological parameters of the assisted person like e.g., blood pressure, heart rate, blood glucose or body weight. All these IoT devices are connected together and realize a *sensor network* continuously producing a variety of data about the environment.

A telepresence mobile robot like e.g., the Giraff robot is endowed with KOaLa and deployed to John's apartment to support his daily-home living.

As shown in Section 4.1 data processing relies on the observable features and properties inferred by the analysis of the environment configuration and the related sensor network deployment (i.e., the sensor and environment contexts). The rules used to carry out this analysis are briefly shown below. According to the first rule below, observable features are defined as objects of the environment that can be observed through a sensing device deployed on them. Sensing devices have different "perception capabilities" that enable the observation of particular properties. According to this capabilities, each observable feature has a number of observable properties associated (see the second rule below).

$$
\begin{aligned}
\texttt{DUL:Object(o)} \wedge \\
\texttt{SSN:Platform(p)} \wedge \\
\texttt{SSN:Deployment(d)} \wedge \\
\texttt{DUL:hasPart(o, p)} \wedge \\
\texttt{SSN:hasDeployment(s, d)} \wedge \\
\texttt{SSN:deployedOn(d, p)} \rightarrow \quad & \texttt{ObservableFeature(x)} \wedge \\
& \texttt{hasObservableFeature(o, x)} \wedge \\
& \texttt{isObservableThrough(x, s)}
\end{aligned}
$$

```
            ObservableFeature(f) ∧
                   DUL:Object(o) ∧
                 DUL:Property(p) ∧
                   SSN:Sensor(s) ∧
     hasObservableFeature(o, f) ∧
          DUL:hasProperty(o, p) ∧
      isObservableThrough(f, s) ∧
             SSN:observes(s, p) →   ObservableProperty(x) ∧
                                    hasObservableProperty(f, x) ∧
                                    SSN:observes(x, p)
```

Knowledge inferred through these rules allows KOaLa to contextualize observations and better recognize events and activities occurring inside the environment.

Consider the case where Giraff is still inside the bedroom and John is moving to the kitchen to prepare his meal for lunch. As soon as John enters the kitchen and turns on the light the sensor network starts producing data. A sensor close to the door of the kitchen is activated by John's motions and Giraff receives this signal. The semantic module elaborates this data by applying the inference rules of the data processing mechanism.

KOaLa knows that the received data must be interpreted as "something or someone is moving here". Also, KOaLa knows the *configuration* of the home environment and therefore it also knows that this sensor is installed into the kitchen of the apartment. Then, it can further elaborate the data and conclude that "someone is moving inside the kitchen". We are assuming here that only one person is being monitored/assisted. Therefore, it is possible to infer that "John is moving inside the kitchen" and add this *fact/belief* to the KB.

Similar processing mechanisms elaborate data about the luminosity of the kitchen. KOaLa detects that the observed value about the luminosity level of the kitchen is higher than a known threshold and consequently it can infer the fact that "the light of the kitchen has been turned on" and add it to the KB. Figure 7 shows a conceptual representation of these inference mechanisms.

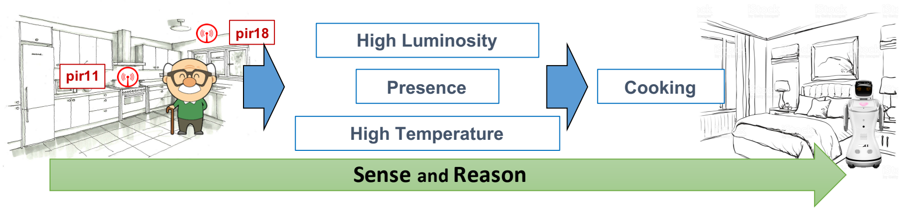

Fig. 7 KOaLa inference capabilities in action

This and other kinds of events are recognized by integrating knowledge inferred from different sensors and by contextualizing this knowledge with respect to the configuration and features of the environment. The rule below shows a general inference rule used to infer the "low temperature" event in a room of the house.

$$
\begin{array}{rl}
\texttt{SSN:Observation(o)} \wedge & \\
\texttt{SSN:FeatureOfInterest(f)} \wedge & \\
\texttt{SSN:featureOfInterest(o, f)} \wedge & \\
\texttt{Room(r)} \wedge & \\
\texttt{hasObservableFeature(r, f)} \wedge & \\
\texttt{SSN:SensorOutput(d)} \wedge & \\
\texttt{SSN:hasOutput(o, d)} \wedge & \\
\texttt{SSN:ObservedValue(v)} \wedge & \\
\texttt{SSN:hasValue(d, v)} \wedge & \\
\texttt{v} < \mathit{tempLowerBound} \rightarrow & \texttt{LowTemperature(x)} \wedge \\
& \texttt{concerns(x, r)} \wedge \\
& \texttt{SSN:isProducedBy(x, o)}
\end{array}
$$

After reaching the kitchen, John opens the window, turns on the stove and the TV and starts preparing his meal. The sensor attached to this window notifies a "loss of contact". KOaLa receives this data and knowing that the sensor is deployed to an object of type *Window*, it can infer that "a window of the kitchen is open". A similar process allows KOaLa to infer that "someone is watching the TV inside the kitchen".

Close to the hob, a temperature sensor has been installed in order to detect when the temperature is *high*. Knowing the deployment of IoT devices and the consequent configuration of the sensor network, KOaLa can infer that "someone is using the hob" when that sensor detects *high temperature* (i.e., when the observed value of the temperature close to the hob is higher than a known threshold).

Putting all the inferred facts together, KOaLa can further refine the internal knowledge and infer more general events or activities like e.g., "John is cooking". The inference rule below shows how *cooking* activities are inferred. Although simplified, this rule shows the basic idea of combining knowledge about recognized events (i.e., knowledge previously inferred) to infer even more abstract knowledge.

$$
\begin{array}{rl}
\texttt{Kitchen(r)} \wedge & \\
\texttt{HighTemperature(x)} \wedge & \\
\texttt{concerns(x, r)} \wedge & \\
\texttt{HighLuminosity(y)} \wedge & \\
\texttt{concerns(y, r)} \wedge & \\
\texttt{Presence(z)} \wedge & \\
\texttt{concerns(z, r)} \rightarrow & \texttt{Cooking(w)}
\end{array}
$$

Cooking represents a complex activity that may require some support by the assistive robot. The *goal reasoner* detects this *activity* and *triggers* a high-level planning goal which is internally sent/dispatched to the *acting module*.

KOaLa dynamically formulates a timeline-based planning problem by taking into account the known (physical) capabilities of the robot, the known state of the environment, the known state of John and his expected behavior within the rest of the day as well. The acting module synthesizes a timeline-based plan which integrates the sequence of operations needed to carry out the assistive task (*support meal preparation* - i.e., the goal triggered by the goal reasoner) with the (previously generated) daily plan.

Figure 8 above shows the synthesized timeline-based plan and the outcome of its execution. Following the plan, the assistive robot starts moving from the

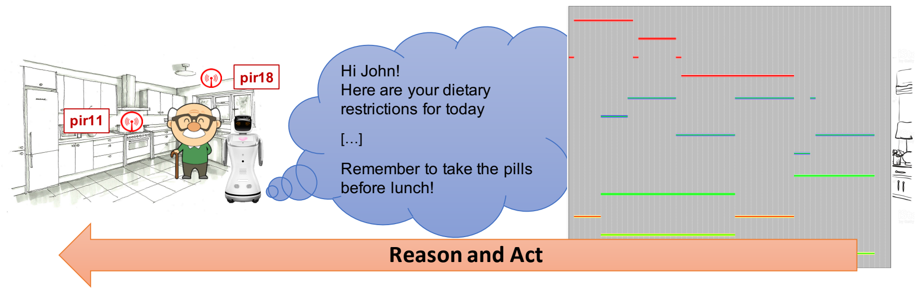

Fig. 8 KOaLa acting capabilities in use

bedroom towards John who is cooking. To do so, the robot autonomously navigates the home environment to reach the kitchen. KOaLa knows that John must follow some dietary restrictions and that he must take some pills just before eating. Also, KOaLa knows that John is affected by limited vision capabilities and therefore it decides to remind this information through (pre-recorded) audio messages. For this reasons, the robot starts interacting with John by reproducing the planned reminders once in the kitchen.

6 Conclusions and Future Works

This paper presented an AI-based cognitive architecture called KOaLa which integrates sensing, knowledge representation and automated planning techniques to constitute a high-level control loop to enhance proactivity features of an assistive robot designed to support an older persons living at home in her daily routine. A semantic module leverages a dedicated ontology to build a KB by properly processing data collected by means of a sensor network installed in the environment. An acting module takes advantage of the timeline-based planning approach to control robot behaviors. A goal triggering process acts as a bridge between the two modules and provides the key enabling feature to endow the robot with suitable proactivity levels.

KOaLa and the related long-term research objectives have been placed into a conceptual cognitive architecture called AI^3, designed according to general cognitive capabilities Langley et al. (2009). At this stage, some tests have been performed to show the feasibility of the approach. Further work is ongoing to deploy KOaLa in real world scenarios such as, e.g., modeling knowledge for elderly assistance cases (Umbrico et al. 2020) and to enable more extensive integrated tests.

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