Human-Agent Groups: Studies, Algorithms and Challenges:
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Contextual Knowledge Representation and Reasoning Models for Autonomous Robots

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Abstract

To provide, anywhere and anytime, smart assistive services to people, cognitive robots and agents need to be endowed with advanced spatio-temporal knowledge representation and reasoning capabilities. In this paper, a semantic approach for cloud-assisted robotics integrating entities of the ambient environment is proposed. Its principle consists of advanced contextual knowledge representation and reasoning models based on the hybridization of metric, topological and semantic information. A scenario dedicated to the cognitive assistance of frail people is implemented and analyzed for validation purposes of the proposed approach.

Introduction

Robots and smart objects are increasingly populating our everyday life environments where 20.8 billion objects are estimed, by Gartner company, to be connected in 2020. The ambition of the ambient assisted living (AAL) domain is to provide intelligent assistive services, with a high level of performance and acceptability, in order to increase the autonomy of dependent people and to improve their safety and well-being (Chibani et al. 2015).

The emergence of new smart objects such as smartphones, smart sensors and companion robots with the cloud computing systems is strongly contributing to extend ambient intelligent (AmI) environments (Kehoe et al. 2015). These environments will be composed of cognitive entities that are capable of perceiving their environments, reasoning, proactively executing tasks and adapting themselves to the user's context. According to the paradigm of context awareness, such robots will be able to better monitor dependent people, and provide them assistive services according to their context (Henricksen and Indulska 2006). For example, a companion robot that can assist visually impaired humans by describing them objects' location in dynamic environment. Such a robot must be able to communicate and to exchange knowledge with other entities, and then to adapt these knowledge in the humans' context, as illustrated in Figure 1. More generally, to provide, anywhere and anytime, smart assistive services to people, robots need to be endowed with advanced spatio-temporal knowledge representation and reasoning capabilities. One of the most important challenges in assistive robotics is to have complete, generic and expressive models for knowledge representation and reasoning, adapted to the dynamic nature of an ambient intelligent environment (Tapus, Maja, and Scassellati 2007; Hodges et al. 2012). Existing cognitive architectures usually emphasize uniformity in representation and reasoning mechanisms (Loutfi et al. 2008; Lemaignan et al. 2010; Riazuelo et al. 2015). They have dealt with the use of binary relationship-based ontology language such as *OWL, DOLCE, Cyc*. However, representing dynamic environment requires that all constituents of an event, an action, a fluent, etc. must necessarily be managed at the same time as a unique and coherent block (Zarri 2009).

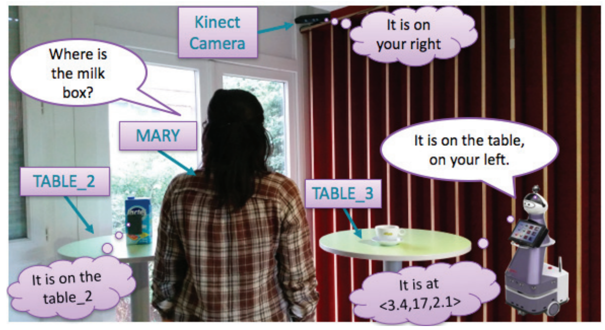

Figure 1: Interaction issue between Mary, visually impaired person, and cognitive entities in AmI environment.

To address these challenges, expressive representation models of contextual knowledge associated with the entities characterizing an ambient intelligent environment (human, robot, sensors, actuators, etc.) are required. These models will be able to represent spatial entities, their properties and spatial relationships between them at a specific time. Building efficient cognitive models for better modeling a dynamic environment requires a suitable architecture.

In terms of application, this study focuses on cognitive assistance of dependent people at home. Such a service aims to help a person to prepare his/her meal.

In this paper, novel contextual representation models based on n-ary ontologies and inference mechanisms are proposed. The expressiveness of the n-ary ontologies on which the narrative knowledge representation language (NKRL) is based, is exploited in this paper. It overcomes the problems encountered in the spatial and dynamic knowledge representation approaches based on binary ontologies such as (Walter et al. 2013; Riazuelo et al. 2015), commonly used in ambient intelligence and robotics. The contributions of the paper can be summarized as follows: (i) a cognitive architecture for cloud-assisted robots to endow robots and agents with new capabilities in order to better understand the context of an entity and consequently to improve the decision making; (ii) a spatiotemporal knowledge representation model based on the hybridization of metric, topological and semantic information, and associated reasoning mechanisms. By exploiting both the NKRL language (Zarri 2009) and a semantic graph describing the spatial entities and their relationships, a complete, coherent and expressive spatio-temporal knowledge representation is guaranteed allowing a group of agents and robots to reason over representations of dynamic environment. An extension of NKRL based on a new structure of the templates of the HTemp (hierarchy of templates) ontology is proposed; (iii) a representation model of properties of entities and reasoning about the status of these entities populating the environment. By representing changes of context, the proposed model improves the perception of the context and ensures better adaptation of assistive services. By exploiting these models, the goal is to make inferences on knowledge about user's context in the dynamic environment. This knowledge may relate to the entities populating the environment, their relationships, and their status to improve context awareness.

The paper presents, first, a review of related works concerning the representation of a dynamic environment and reasoning in the robotics field. Then, it describes the different layers of the cloud-assisted robot cognitive architecture for human-environment interaction and introduces the novel approach for contextual knowledge representation and reasoning. Finally, this paper evaluates the proposed approach. It is concluded with a short review of the proposed approach and a summary of the ongoing works.

Related work

In the field of robotics, the symbolic representation of a dynamic environment has been the subject of many research projects in recent years. Several works have dealt with the use of semantic web ontologies to implement robotic knowledge management platforms without supporting spatial reasoning at the ontology level. For example, the *RobotEarth* platform based on binary representations using the language owl doesn't support spatial reasoning or temporal reasoning at the ontology level, (Riazuelo et al. 2015). The *ORO* platform is limited to geometric reasoning (Lemaignan et al. 2010). *PEIS Ecology* uses the DOLCE language to describe static knowledge and doesn't support spatial reasoning in the ontology (Loutfi et al. 2008).

To provide an expressive description of the environment, several researchers have proposed alternatives to metric maps by developing approaches to represent the environment as topological maps and/or semantic maps (Riazuelo et al. 2015; Hemachandra et al. 2011). Thus, Zender et al. (Zender et al. 2008) propose a framework to represent environments such as offices. Semantic models are proposed to represent categories of offices and spatial relationships between these offices. Pronobis and Jensfelt (Pronobis and Jensfelt 2012) propose a multimodal representation incorporating semantic knowledge from identified objects, and spatial information provided by humans. The two approaches are related to the establishment and exploitation of semantic maps rather than the exploitation of both metric and semantic representations of the environment.

The idea of merging the metric, topological and semantic maps, has been proposed by several researchers such as Walter et al. (Walter et al. 2013). However, the languages used for the semantic representation of the environment such as *OWL*, are limited to the use of binary and unary relationships. Representing a dynamic environment with complex spatial relationships requires that all constituents (spatial entities and these relationships) must necessarily be managed at the same time as a unique and coherent block (Zarri 2009). Thus, the binary representation doesn't guarantee the coherence of the relationships.

Cloud-assisted robot cognitive architecture

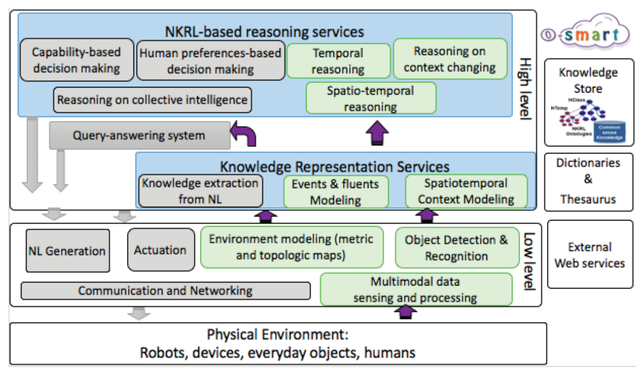

Figure 2: Cognitive architecture for cloud-assisted robotics

An extension of the cognitive architecture presented in (Ayari et al. 2015), is proposed for cloud-assisted robotics in this paper. To render robots and agents able to better understand the context and consequently to improve their decision-making, this extension endows robots and agents with new capabilities. These latter concern the expressive and efficient contextual knowledge representation and reasoning models for a richer and complete description of the environment. An overview of the proposed architecture is shown in figure 2.

At the low level, a *communication service* enables the entities populating the environment to connect and subscribe to the cloud services using the standardized middleware technologies (XMPP, REST, etc.). The communication service enables also the basic exchange capability between any entity by more focusing on the encoding of messages' content, which is defined by elements such as lexicon, grammar, speech acts, and semantics.

A *knowledge base* connects most of the services such as the knowledge representation service and the reasoning service, enabling cognitive agents or robots to be endowed with large general purpose commonsense knowledge for human-environment interaction. When connected to the cloud, a robot or an agent can benefit from the powerful computational, storage, and communications resources of modern data center in the cloud, which can process and share information from various robots or agents (other machines, smart objects, humans, etc.). The ontology representing commonsense knowledge relies on a central server and is shared between all the entities populating the environment when each entity has its own instantiations of dynamic knowledge. Sharing a commonsense knowledge and common language guarantee the semantic interoperability of these entities and enables them to communicate between each other.

At the high level, the cloud enables robotic systems to be endowed with robustness, resources elasticity, and computational power according to the definition of cloud robotics paradigm. Thus, it is possible to build lightweight, low cost, smarter robots, which intelligent ”brain” is in the cloud. The ”brain” here consists of information processing, knowledge representing, environment models, reasoning engine, etc. In this study, a brain is designed to provide the following services:

- The knowledge representation services exploit the expressiveness of the n-ary ontologies on which the narrative knowledge representation language (NKRL) is based. The natural language (NL)/NKRL service provides a set of common techniques, algorithms and technologies introduced in previous work (Ayari, Chibani, and Amirat 2013). It allows robots to understand statements by converting these latter into NKRL predicates occurrences. The *spatiotemporal context modeling service*, proposed in this paper, produces symbolic descriptions of the spatio-temporal context of the entities populating the environment. The event and fluent modeling service represents what is occurring in the environment such as states of the entities populating the environment. The generated NKRL predicates occurrences within these services are stored in the knowledge base, and queried back, when necessary by reasoning techniques or query-answering system;
- The *online NKRL context-aware reasoning* is based on the inference engine of Narrative Knowledge Representation Language (NKRL). This engine was extended, in previous work, by context-aware reasoning models including human preferences (Ayari et al. 2015), reasoning model based on collective intelligence (Ayari et al. 2016). In this work, this engine is extended by new spatio-temporal reasoning models including reasoning on topological, orientation and proximity relationships, and reasoning models for context and entities properties values changing.

The main design principle of the proposed architecture is to integrate seamlessly the entities populating an ambient environment. In particular, it consists of the integration at the representation level to manage the rich semantics of natural interactions with humans and to ensure that all entities populating the ambient intelligent environment share a commonsense knowledge and common language. The proposed architecture aims to develop intelligent and autonomous robots in dynamic environment that are able to serve and interact seamlessly with humans by providing assistive services.

Contextual knowledge representation and reasoning: hybrid models

To take into account both the ’static’ and ’dynamic’ characteristics of any entity populating the environment and to overcome the problems encountered in the dynamic knowledge representation approaches based on binary ontologies, an ontological model based on the Narrative Knowledge Representation Language (NKRL) is proposed.

Narrative Knowledge Representation Language

The NKRL language (Zarri 2009) is based on:

- *HClass ontology*: an upper ontology that consists of a hierarchy of binary classes. It allows describing plain/static commonsense knowledge for human-environment interaction such as *person*, *object*, etc. This ontology is characterized by the subsumption relationship describing generalization/specialization among concepts;
- *HTemp ontology*: an $n - ary$ ontology that allows to define templates for representing dynamic entities based on the notions of ”*conceptual predicate*” and ”*functional role*”. To each role, arguments and the property *”location”* can be associated. The $HClass$ ontology has an autonomous existence, with respect to the description of the dynamic entities in the $HTemp$ ontology. This allows to take into account well-defined classes of cognitive phenomena without considering the specificities of their contexts, figure 3;
- *Inference engine:* high-level inference procedures are based on NKRL *transformation* and *hypothesis rules*, which allow the inference of implicit relations between predicative occurrences and consequently the chronological context of a given event such as the inference of the new robot’s location and the related spatial relationships when the robot moves;
- *Query-answering system:* the queries are operated directly on explicit predicative occurrences stored in the knowledge base by means of search patterns p_i, which are processed by the Filtering Unification Module (FUM) (Zarri 2009).

Dynamic environment Representation

Acting and interacting in AmI environments requires a spatial representation model that enable heterogeneous entities populating this environment such as, mobile robots and humans, to be integrated seamlessly. To deal with that, a spatiotemporal knowledge representation model based on the hybridization of metric, topological and semantic information, and associated reasoning mechanisms is proposed in this paper. This model exploits both the NKRL language (Zarri 2009) and a semantic graph (Walter et al. 2013) to describe the spatial entities and their relationships at specific

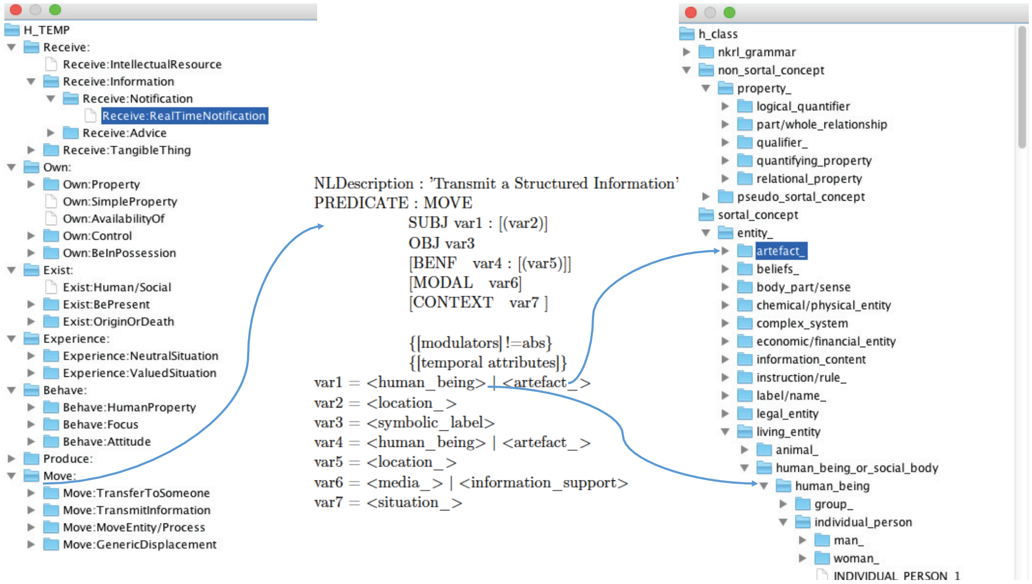

Figure 3: The *HClass* and the *HTemp* ontologies

time. The *HTemp* ontology of NKRL complete the semantic graph with temporal knowledge to be adapted to represent a dynamic environment. Formally, a *dynamic environment* is then described as a semantic graph $\mathcal{G}\left(\mathcal{E}, \mathcal{R}, t\right)$ composed of:

- A set $\mathcal{E}$ of entities; each entity is represented, at time t, by its situation vector $\mathcal{X}$ and a conceptual instance $\mathcal{I}$ in the *HClass* ontology, such as kitchen, table, etc.;
- A set $\mathcal{R}$ of relationships between these entities; each relationship is represented using the predicate NKRL *"EXIST"* of the *HTemp* ontology. This predicate is used to represent spatial relationships between the entities of the environment by associating the time dimension to these relationships.

Figure 4 shows the semantic graph representing a scene from an ambient environment.

Spatial entity representation: To represent static and dynamic spatial entities, both of semantic and geometric representation models are introduced in this work. Semantic representation enables robots to conceptualize human-made environments similar to the way humans do where geometric representation enables them to navigate autonomously.

- *Semantic Representation:* Each spatial entity e, denoted by $e \in \mathcal{E}$, is represented by an instance $\mathcal{I}$ of the concept '*entity_*' of the *HClass* ontology and denoted by $\mathcal{I} \sqsubseteq entity\_$, figure 5.

  A *static entity* is a fixed element of the environment whose position doesn't evolve through time, for example, a house, a bedroom, a kitchen, etc. This type of entity is described by the concept *"location_"* of the HClass ontology and denoted by $\mathcal{I} \sqsubseteq location\_$.

  A *dynamic entity* represents an element of the environment whose position evolves over time. Two categories of dynamic entities are distinguished:

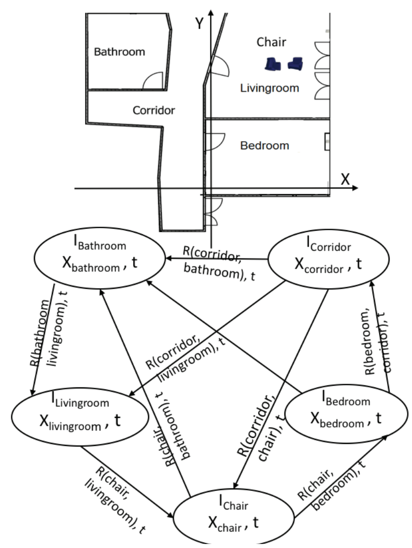

Figure 4: Typical scene of ambient environment with its semantic graph

  - The *living entities* (person, animal) that are described by the concept *"living_entity"* of the HClass ontology and denoted by $\mathcal{I} \sqsubseteq living\_entity$;
  - The entities *"objects"* whose position changes as a result of an action performed by an agent. For example, the *"vase"* is moved by John (the agent). This type of entity is described by the concept *"artefact_"* of the *HClass* ontology and denoted by $\mathcal{I} \sqsubseteq artefact\_$.

- *Geometric representation: "Spatial entity"* represents an element of the environment that is characterized by its position, its orientation and its dimensions (eg width, length,

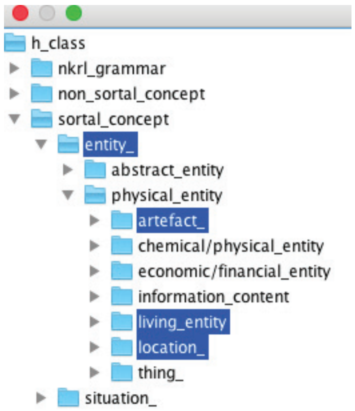

Figure 5: Entities representation in *HClass* ontology

height). In this work, each spatial entity, static or dynamic, is represented by its situation vector $\mathcal{X}(x, y, \theta)$ where x and y are the cartesian coordinates of its center of gravity, and θ its orientation. A static entity is represented also by its region $REG(x_{min}, y_{min}, x_{max}, y_{max})$ defined by an enclosing rectangle, where x_{min}, y_{min}, x_{max} et y_{max} represent the coordinates of the lower-left and upper-right vertices of the rectangle.

Extension of NKRL for spatial relationship representation: Although the $NKRL$ language allows a complete, coherent and expressive knowledge representation, it doesn't support spatial reasoning in its original version.

Among the most representative works in spatial knowledge representation domain, we can mention those handling topological representations by exploiting the notion of labeling of the spatial relations, as proposed in the Region Connection Calculus (RCC) algebras. *RCC-8* is one of the most used algebras for semantic representation of entities and spatial relations based on the language OWL. These relations cover, however not, all the spatial relations such as orientation relationship (*"left of"*, *"right of"*), proximity relationship (*"close"*, *"far"*), etc.

In this paper, the proposed spatial representation model is mainly focused on topological, orientation and proximity relationships. The formalism ABLR (Above Below Left Right) (Laborie 2008) is exploited to represent topological and orientation relationships between spatial entities. On all the relations proposed by Laborie et al. (Laborie 2008), the following 11 spatial relationships (topological and orientation relationships) are exploited for their expressiveness: ABOVE, BEHIND, BELOW, BETWEEN, FRONTOF, ONE, LEFTOF, RIGHTOF, INSIDE, OUTSIDE and INCLUDE. To model the notion of proximity, four linguistic variables characterizing the proximity between two objects are considered: CLOSE, FARENOUGH, FAR and VERYFAR. These relationships can be composed using $AECS$ operators (for Alternative Enumeration Coordination Specification) of the NKRL language for a richer spatial description of the environment.

Example: Consider the following statement: **E4:** *John is near to the refrigerator*. Its representation in NKRL is:

E.occ4: EXIST
SUBJ JOHN: CLOSE(REFRIGERATOR_1)
date-1: 14/02/2017 11:30
date-2:
Exist: HumanPresentAutonomously

Extension of NKRL with fluents for entities properties representation In this work, we focus on the context changing through the changes of the entities properties of the environment following the occurrence of events. The study of the state of the art has shown that the theory of the Event Calculus or the Situation Calculus proposed by *McCarthy* and *Hayes* is a logical approach well adapted for representing knowledge and reasoning about changes of context and changes of values of entities properties (McCarthy and Hayes 1969). In this theory, the notion of fluent is introduced to represent the entity properties whose values change over time. A fluent associated to an entity property is true, if this entity acquires a specific value for this property.

Event Calculus	*NKRL Language*
HoldsAt(closed,t_1)	F.occ1: OWN SUBJ DOOR_1 OBJ property_ TOPIC closed date-1 t_1 date-2 Own:SimpleProperty

Table 1: Example of a fluent representation in Event Calculus and in NKRL

To model entities properties values changing in *NKRL*, the notion of *fluent* used in the *Event Calculus theory* is exploited. The predicate *Holds(property, t)* of this theory is formalized using the *OWN* predicate of *NKRL*, cf. table1. The *OWN* meaning stands for '*being in possession of something*'. Specifically, the templates *Own:CompoundProperty* and *Own:SimpleProperty* represent the entity properties at specific time. They are well adapted for representing fluents. A symbolic label *"F"* is also used to identify a predicative occurrence that represents a fluent. Thus, the representation of the property of an entity through the predicate *OWN* means that the value of this property is true between the instants t_1 and t_2. The table 1 shows the fluent representation in *NKRL* and in *Event Calculus* corresponding to the state *"closed"* of the property *"opening state"* of the entity *"door"*, that is *true* starting from the instant t_1.

Context-aware reasoning

Spatio-temporal context recognition New spatial reasoning models extending NKRL inference engine are proposed in this work allowing to better understand the saptial/spatiotemporal context.

- *Reasoning on topological relationships:* To extend NKRL with spatial reasoning models, the principle of composition of topological relationships is exploited in this work. In the ABLR formalism, the composition of topological relations is based on the relations of Allen's temporal intervals (Allen 1983). In this paper, two categories of relations are used to infer new spatial relations: inverse relations and composed relations. Formally, a relation R can be obtained:

- *by inverting an existing relationship:* $R = r^{-1}$
- *by composing several existing relationships:* $R = r_1 \otimes r_2 \otimes ... \otimes r_n$

The inference of spatial relationships in *NKRL* is based on the principle of composition on which is founded the topological reasoning. This mechanism involves two steps: generation of inverse relationships and composition of spatial relationships.

- *Inverse relationships:* A set of rules is defined in NKRL to infer an inverse relationship. An inversion rule is composed of a condition, a consequent, and a set of variables, table 2.

Condition:
EXIST SUBJ var1: BEHIND (var2)
Consequent:
EXIST SUBJ var2: FRONTOF (var1)

Table 2: Example of inversion rule in NKRL

- *Composition relationships:* Using the *transitivity* property, a composition rule allows to infer a new spatial relationship from existing relationships. In this paper, a composition rule is built from the composition table proposed by Laborie et al. (Laborie 2008). Formally, for a topological relationship, defined by its label $\mathcal{L}$, involving a set of entities $\mathcal{E}$, the transitivity relationship is defined as follows:

$$\forall x, y, z \in \mathcal{E}, [(x\mathcal{L}(y) \wedge y\mathcal{L}(z)) \Rightarrow x\mathcal{L}z]$$

In NKRL, a composition rule is described by a condition consisting of a conjunction of two or more predicates, a consequent, and a set of variables, table 3.

Condition:
COORD(C1 C2)
C1. EXIST SUBJ var3: LeftOf (var1)
C2. EXIST SUBJ var1: LeftOf (var2)
Consequent:
EXIST SUBJ var3: LeftOf (var2)

Table 3: Example of composition rule in NKRL

- *Reasoning on orientation relationships:* To establish orientation relationships, defined in this paper, it is necessary to define a reference landmark. In the case of an ambient environment, the reference landmark corresponds to the landmark of an observer such as a robot, a Kinect camera or a person. The reasoning on the orientation consists, here, of transforming the spatial relation described in the reference landmark of the first observer, for example, the entity *"KINECT"*, into a new relation described in the reference landmark of the second observer, for example the entity *"MARY"*, by taking into account the situation vectors of these two entities.

Condition:
C1. EXIST SUBJ var1: RIGHTOF(var2)
Consequent:
EXIST SUBJ var1: LEFTOF(var2)

Table 4: Example of orientation rule in NKRL

To establish a spatial relationship, a set of metric transformation rules exploiting the situation vectors of the entities are used. Orientation rules expressed in NKRL are specified using these transformation rules. Reasoning on orientation relationships improves the interaction between agents, robots, and human by exploiting efficiently the spatial knowledge of each entity;

- *Proximity relationships:* The use of distance relationships in ontologies enables a richer representation of spatial knowledge. However, the semantics of these relationships vary depending on the application context. For example, at a city level, a distance of 50 meters can be characterized by the proximity level *"close"*, whereas at a building level, this distance is characterized by the proximity level *"far"*. In this work, reasoning model allowing to infer proximity relationships between entities from metric distances and vice versa, is proposed. To implement this reasoning, the distance is partitioned into four partitions configured using a parameter denoted by the variable α. This parameter depends on the class of the spatial entities. This type of representation was proposed by Hudelot (Hudelot, Atif, and Bloch 2008). Formally, a proximity level corresponding to a distance d between two spatial entities $\mathcal{E}_1$ and $\mathcal{E}_2$ is defined as follows:
  - close, if $d(\mathcal{E}_1, \mathcal{E}_2) \in [0, \alpha]$
  - far enough, if $d(\mathcal{E}_1, \mathcal{E}_2) \in]\alpha, \frac{3}{2}\alpha]$
  - far, if $d(\mathcal{E}_1, \mathcal{E}_2) \in]\frac{3}{2}\alpha, 2\alpha]$
  - very far, if $d(\mathcal{E}_1, \mathcal{E}_2) \in]2\alpha, +\infty]$

Reasoning on context and entities properties values changing: To deduce the values of fluent f, associated with the entity properties, following the occurrence of an event e at the instant t_2, the transformation rules $\mathcal{RT}$ of NKRL is used. A transformation rule allows to convert an event of changing from one state to another, described in *NKRL* using the predicate *MOVE*, into two fluents f_1 and f_2 described in NKRL using the predicate *OWN*. In *Event Calculus theory*, this transformation is represented by the predicates *Initiates (e, f, t)* and *Terminates (e, f, t)*. Unlike the *Event Calculus theory* where fluents and events are specific to each use case, the *NKRL* language allows greater abstraction thanks to the transformation rules allowing the deduction of different fluents from any event. Formally, an event e can make true or false a fluent f starting from an instant t_2 such as:

$$(f, t_2) \Leftarrow (e, t_2) \wedge \mathcal{RT}$$

$$\neg(f,t_2) \Leftarrow (e,t_2) \wedge \mathcal{RT} \wedge (f,t_1) \wedge t_1 < t_2$$

For example, the occurrence of the event *"open a door"* at the instant t_2 results from the fact that the fluent *"door opened"* becomes *true* starting from this instant while the fluent *"door closed"* becomes *false*.

Evaluation

To highlight the benefits of using the proposed approach, three dimensions are considered: the size of the knowledge base, its runtime performance, and examples showing how diverse entities benefit from the proposed cloud-based contextual knowledge representation and reasoning system.

Knowledge base

Nowadays, more than 9.000 concepts describing commensense knowledge covering a wide range of concepts about human-centric applications are included in the *HClass* ontology. Using commonsense knowledge is motivated by the possibility of an automatic extension of these knowledge by other upper ontologies such as wordnet. Each cognitive entity has its own knowledge base. This latter consists of instances of *HTemp* ontology that is growing during tests. Endowing entities with distributed knowledge base allows to reduce significantly the complexity of the system in dynamic environment and thus the processing time.

Runtime and scalability

The execution of each component (service) is independent of the size of the dynamic knowledge base but is dependent of the size of HClass ontology. The number of accesses to the HClass ontology is proportional to the search patterns, objects detected, etc. Since NKRL rules define the domain of variables, the access to the HClass ontology is limited to a specific segment. This avoids exploring all concepts of the ontology.

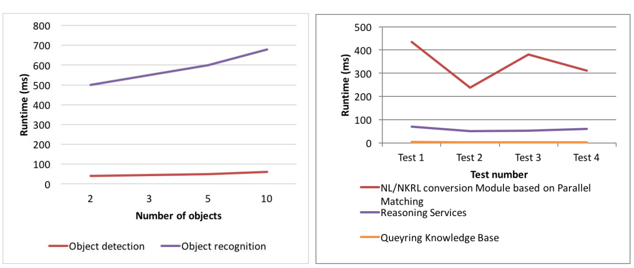

Figure 6: Response Time of each component

The use of the cloud for externalizing the expensive computation processes provides an improvement in the response time that make them useful in the context of group of agents and robots. Figure 6 shows that the response time of the reasoning and querying services remains constant during the tests. The response time of the parallel NL/NKRL conversion services is less than $500ms$ where the average time needed for querying the knowledge base to respond to a query is around $2ms$. These results show clearly the efficiency of the proposed cognitive architecture in terms of computation time, that is well adapted to natural human-environment interaction in ambient environment.

Assistance to prepare a meal

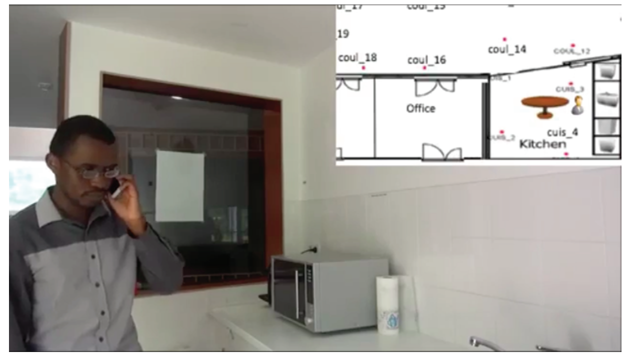

Figure 7: Scene extracted from the kitchen of the *livingLab*

The proposed scenario consists of implementing an assistive service to a person living alone and suffering from memory problems by providing contextual information to help him/her to prepare a meal, figure 7. This scenario is motivated by the problems of people with memory disorders. The objective of this demonstration is to show how a simple robot can reliably and efficiently update and exploit jointly the metric, topologic and semantic maps of other entities needed to perform daily tasks using the NKRL cloud services. To recognize the context *"prepare a meal"*, the person, called *John*, must be situated in front of the work plan in the kitchen during one of the following temporal references: "*morning*", "*midday*" and "*evening*". According to the scenario, a cognitive agent is able to detect that John is preparing a meal through the correlation of events concerning his location during breakfast, lunch or dinner time. To localize *John* in indoor environment, a localization system based on infrared beacons and an accelerometer placed at the chest of the person are used. The object detection service is implemented in the cloud infrastructure to extract objects situated on the work plan and their spatial relationships from an instant image detected by the kinect camera. These objects can be recognized then through the *Cloudsight service*[1] that provides their descriptions in natural language. The assistive service here consists of assisting John to prepare a meal; the robot turns on the hob and emits the recipe instructions. This work is reported in a multimedia video file[2].

Several experiments of this scenario have been conducted in the kitchen of the living-Lab of LISSI- UPEC[3]. 5 people agreed to test the proposed assistive service to prepare a meal involving the Kompai robot during the lunch break. In these experiments, we focus on the semantic and topologic mapping of a kitchen and the heterogenous data sources (camera, sensors, metric map and NL statements). These people have almost a similar daily agenda where they are

[1] http://cloudsight.ai/
[2] http://www.lissi.fr/videos/demo1.php
[3] http://youtu.be/XicBDjGSxYc

present in their office all day with a lunch break. Each person has foods in the refrigerator enabling him to prepare or to only warm up their meal. During these experiments, the queries are in natural language under the form of vocal message through the companion robot. *Speech recognition* turned out to be not robust enough due to the limited sensitivity of the microphone embedded into the companion robot. Participants repeat their utterances few times. *Person detection* was 100% reliable with a minor inaccuracy in terms of metric position. *Spatial reasoning model* needs significant enhancement to be intuitively usable. In very complex situation with ambiguous spatial relationship, this module cannot infer the right relationship. Therefore, a consistency checking of the proposed model is needed.

Conclusion

In this paper, a semantic approach for cloud-assisted robotics integrating entities of the ambient environment is proposed. Its principle consists of advanced contextual knowledge representation models based on the hybridization of metric, topological and semantic information. By exploiting both the NKRL language and a semantic graph describing the spatial entities and their relationships, the proposed approach overcomes the problems encountered in the spatial and dynamic knowledge representation approaches based on binary ontologies.

The scenario dedicated to the cognitive assistance of frail people showed promising results in terms of pertinence of the provided service where a better adaptation of the user's context is ensured. The ongoing works address the extension of the proposed approach for the represention and the reasoning on temporal context to improve context awareness and allow a better decision making.

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