Internet of Robot Things in a Dynamic Environment: Narrative-Based Knowledge Representation and Reasoning

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Abstract. Internet of Things (IoT) technologies interconnect increasing numbers of artifacts (e.g., robots, sensors) and individuals, allowing the setting up of Internet of Robotic Things (IoRT) systems in a dynamic environment (e.g., homes, hospitals). Semantic heterogeneity is among the main challenges that arise for developing those systems. Particularly to deal with the dynamic knowledge extraction from the heterogeneity of sensors and data that are spatially and temporally distributed, the sporadic occurrence of events, and also if there is a causality chain that explains an ordered occurrence of these events. Ontologies constitute de facto an ineluctable design to reduce this ambiguity by creating a semantic link between low-level digital data, allowing: i) dynamic knowledge management, and ii) enhancing environmental perception and anchoring functions.

This approach uses a model that overcomes the disadvantages of the semantic Web standards such as OWL/RDF-S. An IoRT system dedicated to monitoring and assisting the elderly in their everyday living is described and evaluated.

Keywords: Ontology · OWL · Narrative · Reasoning · Spatial-temporal representation · IoRT · IoT · Distributed systems

1 Introduction and Motivation

Joined into the Internet of Robot Things (IoRT) environment, robots are designed to ensure complex cognitive tasks such as assistance and monitoring dependent persons [5]. Fundamental requirements within such dynamic environments are dynamic knowledge management, handle the nontrivial aspects of spatial-temporal reasoning based on chronological and semantic analysis, about past and ongoing events. Robots endowed with formal ontological models and

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capabilities to i) deal with the dynamic knowledge extraction and processing from the heterogeneity of sensors spatially and temporally distributed, ii) perceiving and correlating events' semantic relationships (i.e., causal explanation and ordered occurrence) can accomplish tasks under different environmental conditions. To show the effectiveness of the proposed approach in an IoRT environment, let's start with the following motivating scenario that influenced the overall of our approach.

Consider an elderly named John, living alone. He has been using his laptop in the living room when someone rang. John moves towards the entrance to open the door. Using the sensor fixed on the door, the open-door event can be detected. John and his guest are heading towards the living room. A few minutes later, John goes to the kitchen and tries to prepare some coffee. At this moment, the presence sensor detects a motion in the living room. From the observations that can be perceived and correlated in this scenario, a reasoning system designed to control the habitat of John should be able to recognize particularly: John interrupts the activity (the use of a PC), and John is not alone. The latter knowledge is deduced since John cannot be present in two different spaces simultaneously. In this scenario, let us assume that John is wearing physiological sensors (e.g., the bracelet) that notify hospital staff if John feels bad or falls. After John's guest left, we suppose that John falls and does not push the emergency button. In this case, a robot has to localize and check John's status and evaluate his health state. Handling the semantic link between the real world abstraction and the knowledge bases through ontologies allows enhancing robot' environmental perception, interaction, actuation, control, and anchoring functions. Consequently, finding correlations between events over time is still an open issue and an important aspect that automatically builds up a causal explanation for an event/situation.

The best approach is to create a semantic link between low-level digital data derived from perception systems with high-level semantic representations of ontology to meet those requirements [3]. The aim here is to implement a process of grounding concepts defined in ontologies with the entities present in the real environment. The approach presented here enables the semantic description of heterogeneous entities that can change over time and interact with each other. The representation and reasoning about dynamics events/contexts use hierarchical structures of semantic predicates and functional roles of the Narrative Knowledge Representation Language (NKRL) [1]. NKRL overcomes the disadvantages of semantic Web ontological such as OWL/RDF-S by providing HTemp ontology. The latter uses n-ary hierarchical structures of predicates and n-ary semantic roles to represent dynamic events, spatial-temporal dependencies, and context knowledge.

1.1 NKRL Vs OWL-SWRL

Several ambient intelligence and robotics applications have been implemented using W3C approaches such as [4,6]. Even if these approaches offer a high level of expressiveness, their major disadvantages lie in generating a redundant description of temporal knowledge, the difficulty of defining predicates of any arity to represent the temporal dimension of properties, and rewriting most existing ontologies. Moreover, reasoning about the semantics of temporal relationships expressed with these ontologies can only be done with OWL-DL's reasoning engines [2]. Furthermore, standard OWL-like languages offer little support for building up rules. Indeed, the lack of the notion of variable in OWL makes it impossible to rely on this language in its native form to build real inference engines for rule processing and does not support rules and rule processing introduced in its specifications at the time of its conception.

Note that the argument often raised in a W3C context and stating that any n-ary representation can always be converted to one, making use only of binary relations without any loss of expressiveness is incorrect. A statement like: "the robot moves towards the place where John is localized and tries to check if he is conscious or not" requires being considered a single indivisible entity. So, it can be tough to describe this type of information in full, using the usual binary Semantic Web (SW) languages in the W3C style (RDF, OWL). Nevertheless, there are proposals for n-ary relations and n-ary datatypes; however, they are definitely excluded in OWL 2. Indeed, these proposals have unnecessarily increased the complexity of reasoning in different ontological layers. Therefore, it remains significant issues that are not handled by OWL 2 that make it unsuitable in terms of dynamic context/events recognition and spatial-temporal concept representation and thereby express a chronological ordering between events/context.

1.2 Spatio-Temporal Representation and Semantic Correlation Between Events

Based on time instant, NKRL uses two temporal attributes: date-1 and date-2, allowing annotating an event/context to reconstruct the logic of Allen interval. The temporal attribute, date-1, represents the event that begins to be true at the timestamp t1-the second date-2, which denotes the end of the same event at the timestamp t2. The time interval is organized into nine lists corresponding to three categories: precedence, coincidence, subsequence, see Fig. 1. The preceding category represents the events that appeared before the date indicated in the date-1 attribute. The subsequence category represents events that occurred after date-2. The coincidence category makes it possible to represent events using the obs(erve) modulator used to denote the beginning of an event. These three categories each consist of three lists. Each list is divided into three sections corresponding to period 1, period 2, and period 3. Finally, bound 1 and bound 2 delimit these periods.

Another possibility is that only an intermediate timestamp t3, between t1 and t2, is known. In all these cases, NKRL requires that we use only the first temporal attribute, date-1, i.e., the single timestamp available is systematically associated with date-1, the second attribute, date-2, being empty.

For example, the *home control system* observes that ENTITY_1 is sitting but does not give any information about the end of this event or its duration.

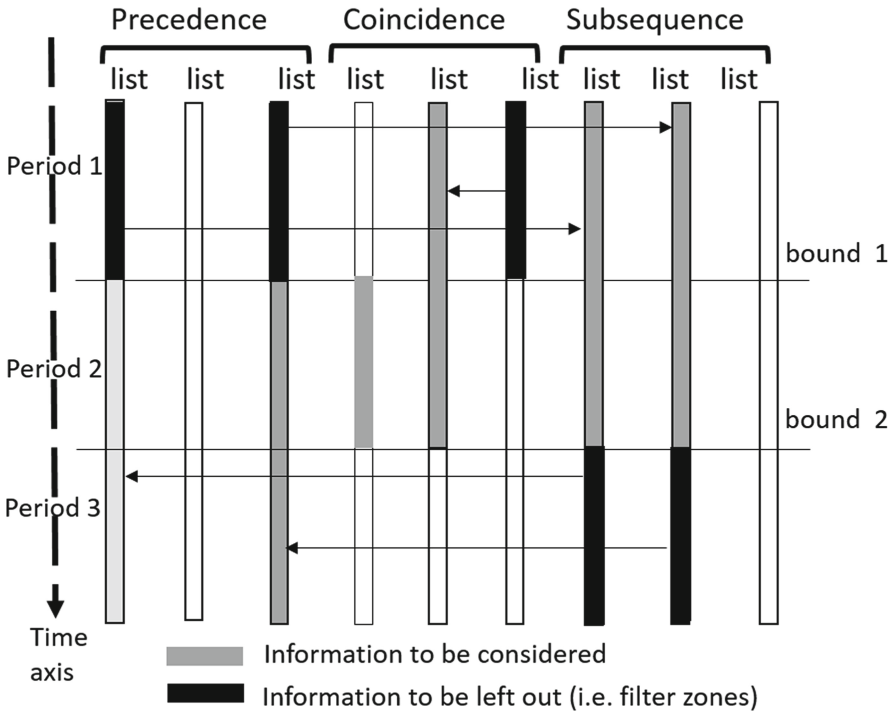

Fig. 1. The temporal index algorithm.

Such information is expressed in NKRL with the predicative occurrence *aal8.c29*. The *BEHAVE* predicate is used to express an event where an entity is performing a task (i.e., manifests a given behavior directly). The *ENTITY_1* instance as "filler" of the $SUBJ(ect)$ role, the *sitting_position* property as filler of the $MODAL$ role, finally $date-1$ is the temporal attribute that marks the beginning of the event.

aal8.c29) PREDICATE: BEHAVE
SUBJ: ENTITY_1: LIVING_ROOM_1
MODAL: sitting_position
{ obs }
date-1:24/06/2021:19:20:785
is instance of Behave:HumanProperty (1.1)

aal8.c28) PREDICATE: PRODUCE
SUBJ: ROBOT_KOMPAI
OBJ: detection_: LIVING_ROOM_1
TOPIC: (SPECIF ENTITY_2(SPECIF different_from JOHN_))
date-1:24/06/2021:19:42:556
is instance of Produce: Assessment/Trial

The predicative occurrence aal8.c28 allows specifying that ROBOT_KOMPAI observes an entity different to John present in the living room. Before inferring that John cannot be at two different locations, the system must first verify that the space where the person is detected is part of the habitat of John.

1.3 The Commonsense Reasoning and Evaluations

Fig. 2. Depending on the knowledge analysis, The robot accomplishes tasks under different environmental conditions and recognizes situations/contexts. Moreover, distributed IoT devices assist the robot in localizing John. In fact, a concept defined in an ontology becomes identifiable from the data provided by the sensors.

Ensuring the homogeneity of the knowledge base and classifying each entity according to its role allow easily aggregating spatial-temporal events. Indeed, the conceptual representation at the design time of events by predicative occurrences requires the definition of a generic model making semantic matching between the NKRL templates and an event observed in the environment. This matching model can be seen as a function that takes input a syntactic description of the event and objects (role, properties, appearance, etc.) and computes as output an NKRL template. Therefore, the interface communication ensures a coherent representation of the world situations by handling the link between the real world abstraction and the knowledge base, Fig. 2. The experiments were conducted at the laboratory. The environment includes the following components: 1) A robot named Kompai. It has various sensors (i.e., 2 RGB cameras, one microphone, 6 ultrasound sensors, and 16 laser sensors), actuators, and a processing unit with a touchscreen display. This robot provides several high-level services, such as managing the medical agendas and the medical treatment; it can recognize and synthesize voice, enable speech interaction, send emails, and navigate in unknown environments, 2) Sensors for measuring brightness, moisture, and temperature; and 3) A bracelet for detecting falls and measuring the pulse of a person. Regarding the temporal performance of the NKRL model, the response time required to recognize the context in the scenario presented at the beginning of this document is 3.7 s. This time is acceptable for ambient intelligence applications.

2 Conclusion

NKRL addresses the lack of expressiveness linked with the binary nature of the W3C languages prevents them from representing correctly high-level information. In NKRL, concepts are represented in the (usual) binary way. Nevertheless, elementary events/situations (and general classes of events/situations) are represented using n-ary predicate/roles. Moreover, special conceptual structures have been conceived to take the temporal phenomena into account. Therefore, we claim that NKRL can play an important role in the AmI domain and cognitive robots. The symbolic modeling and reasoning at a high semantic level about space and time are fundamental for recognizing situations and providing customized assistive services. Indeed, the narrative-based approach we explore allows semantic descriptions of entities, events, and relationships between events, uses an n-ary hierarchical structure of semantic predicates and functional roles.

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