Spatio-Temporal Ontological Query Processing in IoE Environments

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Abstract

purpose: Leveraging ontologies to manage, analyze and understand the semantic context surrounding data generated by interconnected devices, sensors, and people in the Internet of Everything ecosystem. Provide early warnings for potential risks, such as health deterioration or unsafe behaviours.

Methodes: Ontology-based querying using chronological events enhances activity recognition and predicts future issues. Using temporal ontology and semantic reasoning ensures that queries are accurate and relevant.

Results: Combining spatial and temporal data with contextual awareness allows the system to assess the environment dynamically, perform adaptive processing, predict, and adjust its context-sensitive analyses.

conclusion: Contrary to the temporal Description Logic frameworks for dynamic context/event recognition and spatiotemporal concept representation, our Spatio-temporal querying approach further refines the system's responsiveness, enhances efficiency, and personalises relevant human-machine interaction.

KeyWords: Temporal ontology, activity recognition, context-aware, ontology-based querying, description logic, intelligent system, IoE ecosystem

1 Introduction

The promising research trends in Internet of Everything applications areas have led to the emergence of the known Internet of Robotic Things. In these environments, robots are designed to ensure complex cognitive tasks such as assisting and supervising dependent persons. These tasks require the manipulation of knowledge about the properties of objects and performing complex actions. An intelligent system must have advanced cognitive abilities to interpret context, recognize user activities and intentions, and make adequate decisions. Therefore, it is necessary to delve in human behaviour and understand why actions occur in specific sequences (i.e., time points and intervals) and spaces. As stated by the philosopher, Noël Carroll [1], the causality of later events and/or states of affairs depends on the earlier events. Consequently, finding correlations between events over time is an important aspect that leverages ambiguities of interpretation, which allows building up a kind of causal explanation automatically. Recent studies have addressed ontologies as a de facto solution for implementing intelligent systems for activity recognition and planning functions, tasks, and service composition ([2], [3], [4], [5]). Indeed, ontologies provide a vocabulary of concepts and properties, fostering a shared understanding of semantics among humans and machines. Although various methods for representation and reasoning over temporal data ([6], [7], [8], [9]) developed, they only deal with specific time intervals or time points. Even so, time points and semantic relationships between two- or a-time interval and a time point are not what they are designed for. Furthermore, we must handle that connectivity, such as event causality and goal. Despite this, no proposals for n-ary relations are included in OWL . Due to significant issues that remain unhandled by Ontology Web Language, it remains unsuitable for dynamic context/event recognition and spatiotemporal concept representation, expressing a chronological ordering between events and contexts. These points highlight the limitations of current methods ([10], [11], [12], [13]) and underscore the limitations of temporal description logic frameworks. One method to address this issue would be to use n-ary predicates to represent the evolution of knowledge and the chronological relationships between events and their contexts in both present and past. A statement like: "The robot observed that a person turned on the stovetop and left the kitchen towards the bathroom where he spent more than 25 minutes" is a complex task requiring consideration as a single indivisible entity. So, it can be challenging to fully describe this type of information using the usual binary Semantic Web languages such as Ressource Description Framework

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and OWL. However, explanatory role properties should then be necessarily introduced to represent a context fully. This paper has three contributions. First, the semantic annotation layer aims to describe an approach that permits the semantic description of heterogeneous entities that can change over time and interact with each other. Moreover, this layer deals with the semantic modelling of raw sensor data extracted from different sources, facilitating better analysis and reasoning. The second contribution is the usefulness of the narrative model of the narrative knowledge representation (NKRL) used for the first time in ambient intelligence ([14], [15]). It consists of adding to the usual ontologies of concept HClass (Hierarchical Class) as generalisation/specialisation structure, the ontology of events called HTemp (hierarchical Temporal) ontology. The third contribution is designing a Query-Processing Mechanism (QPM) about activity recognition and dynamic events/contexts,figure1. The QPM uses hierarchical structures of semantic predicates and functional roles in HTemp. Therefore, NKRL overcomes the disadvantages of Semantic Web Language by providing the HTemp ontology.

NKRL provides a means to reconstruct the context from the potential semantic relationships about events occurrences in both past and present time, as well as their spatial-temporal dependencies, demonstrating its adaptability to various scenarios in Internet of Everything ecosystems. The QPM relies on two kinds of rules: transformations and hypothesis to determine contexts and recognise human activities and intentions. The rules are concisely described based on the application domain and specific sensor outputs. When it is impossible to find explicit knowledge within the knowledge base using hypothesis rules, the QPM combines the two classes of rules to discover all the possible implicit information associated with the original context. Transformation rules try to adapt the search pattern (*query1 = intial query*) by automatically transforming *query1* into one or more sub-queries *q11, q12 , ..., q1n* that are not strictly equivalent but only semantically close to the initial query. The paper is structured as follows: Section 2 presents a general-related work on ontology-based knowledge representation and query processing for activity recognition. Section 3 introduces a novel knowledge representation and query processing for IoE ecosystems. Section 4 describes the method for recognising activities using specific scenarios. Section 5 presents an evaluation and scalability of the proposed approach. Finally, section 6 outlines discussion, a conclusion.

2 Related work

Some significant conceptual and practical issues still plague the use of W3C languages regarding the creation and processing of rules. Despite the important contribution these languages have made, for example, in simplifying the management and interpretation of contexts through the use of semantic representations and querying/reasoning tools. Description Logic (DL) has become a formalism in symbolic knowledge representation because it offers complete reasoning and is supported by tools (e.g., Pellet)). OWL 2 have extended the original OWL 1 with a few practical features. The three OWL 2 profiles can offer some advantages in particular application scenarios but are more restrictive than the full OWL 2 DL. OWL 2 QL enables conjunctive queries to be answered similarly to the standard relation database principle. In this last case, reasoning will always be sound, but it may not be complete (that is, it is not guaranteed that all correct answers to queries will be computed). Researchers have explored expanding the DL is syntax to include the OWL language.

2.1 Knowledge representation

Key-value-based techniques have been proposed by [16] using a simple data structure to describe a sensor's outputs and, therefore, trying to represent an activity. Moreover, [17] proposed hierarchical structures relying on deep neural networks. Unfortunately, all those approaches are very limited in handling the interoperability in activity recognition systems. Various research for activity recognition approaches combining ontolgies and rule-based models or machine learning, such as [18]. Authors have relied on naive Bayesian models to represent objects to infer the possible actions on these objects and, thus, deduce the associated activity. This approach is based on the semantic relations between everyday actions that can be executed through these objects. However, the authors did not use an ontology but a taxonomy of concepts and did not implement an ontology of roles. A several symbolic representations of the user environment and ontological reasoning have been proposed in the literature to deduce activities according to a set of preselected actions using the OWL ontology. They exploited human-object interaction and, therefore, events using the flow of sensors for activity recognition. These systems are excellent at contextualising activities by establishing connections between objects, actors, and environments, a skill that is essential for accurately interpreting human behaviour. However, the ontology paradigm historically emphasises structure and lacks behavioural components such as role. Recent research underscores the pivotal role of ontologies in enhancing robotic autonomy. An in-depth review delves in to their contribution to knowledge representation, task planning, and adaptability in dynamic environments, empowering robots to reason about their environment and act reliably [19]. In the Internet of Things (IoT), a context-aware edge computing framework, CONTESS, harnesses context to optimize resources by reducing latency and adapting processing at the network's edge [20]. The semantic representation of robotic manipulations has also made significant strides through knowledge graphs. A multi-layer model describes objects, actions, and effects, facilitating automatic task planning [21]. In parallel, motion planning in dynamic environments benefits from context-aware human trajectory prediction, enabling robots to anticipate behaviors and avoid collisions [22]. This idea is extended to autonomous driving, where a multimodal framework uses neural networks to

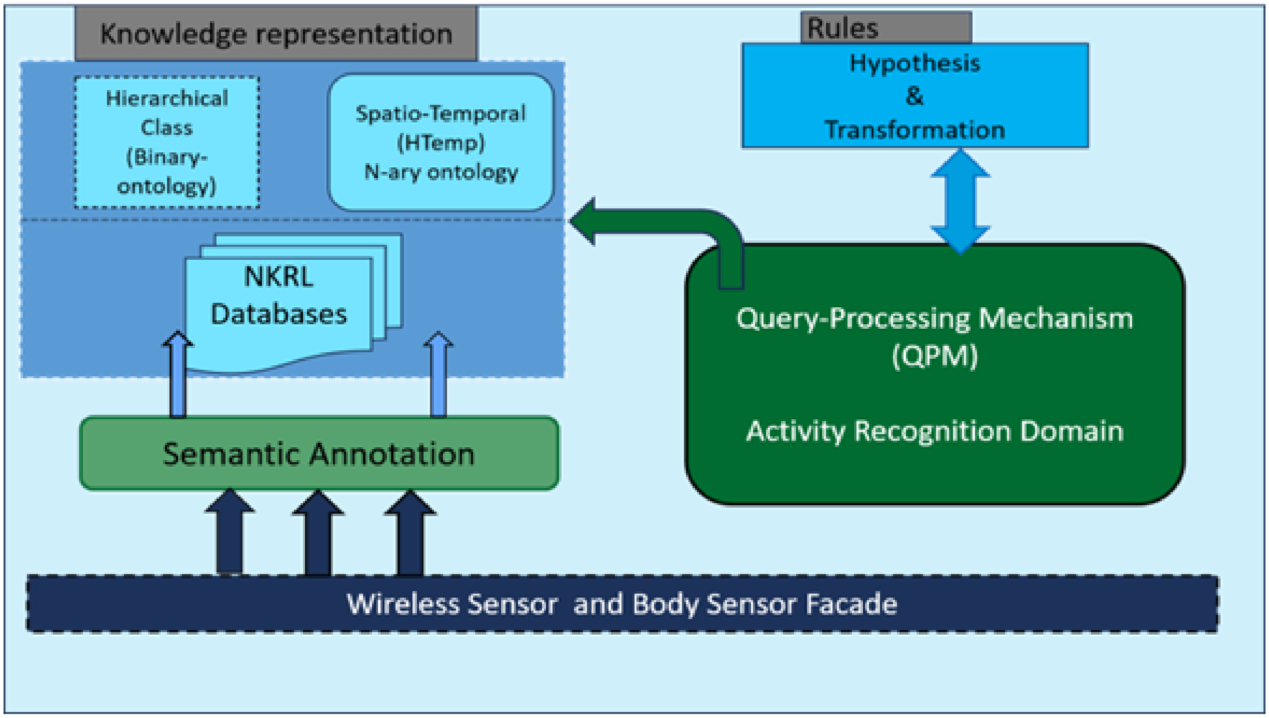


Figure 1: General activities and intentions recognition platform.

predict trajectories in heterogeneous environments, considering social intentions and interactions [23]. The integration of ontological frameworks in robotic task management is a significant advancement that promotes greater autonomy. For instance, one system proposes robotic task processing based on semantic modeling, which combines perception, reasoning, and execution [24]. This means that the robot can understand its environment, make decisions based on that understanding, and execute tasks accordingly. The ORKA ontology takes this a step further by formalizing the acquisition of knowledge from sensors and perceptions, enabling coherent information exploitation [25]. This work is further strengthened by approaches that combine ontologies and rules for collaborative task planning, such as disassembly in remanufacturing, where human and robotic roles are optimally coordinated [26]. In mixed reality, OWL ontologies have facilitated semantic mediation between humans and robots, enabling seamless and contextualized interaction during collaborative assembly [27]. This logic extends to ethical considerations, with proposals for the standardization of ontologies aimed at framing the decisions and behaviors of autonomous systems from a moral point of view [28]. This significant innovation also consists of integrating language models such as ChatGPT into robotic architectures (ROS), making possible a more intuitive and expressive interaction with users [29]. The latter is based on ontology formalism but does not integrate negation or define spatiotemporal relationships. Contextual gestural interactions also make an essential contribution. For instance, a dual-flow model allows the efficient recognition of control gestures. This model uses two streams of information, one for the hand's trajectory and the other for the hand's shape, to strengthen human-robot cooperation in complex environments [30]. Finally, an advanced approach to contextual indoor navigation for robots integrates semantic, spatial and temporal dimensions, allowing intelligent exploration of unknown environments with increased adaptability thanks to context modeling Incorporating ontological frameworks into robotic task management promotes greater autonomy. For example, one system proposes robotic task processing based on semantic modeling, combining perception, reasoning, and execution [31]. These contributions, derived from diverse work, demonstrate a convergence toward intelligent, adaptive, and human-centered robotic systems, supported by robust semantic structures and advanced contextual processing, and remain a relevant and promising avenue for better context management.

2.2 Query-processing mechanism

Few works have been done on developing query languages and inference rules based on temporal description logic, and Most of these works are based on Allen's temporal logic. Among these works, a temporal language TL-OWL an OWL-2 DL ontology of temporal concepts based on the idea of time interval and combing 4-D fluents [32]. Nevertheless, 4D-fluents maintain OWL expressiveness and reasoning support but still suffer from data redundancy [12]. Furthermore, unfortunately, TL-OWL ontology does not support temporal relations or consistency checking and is not compatible with OWL inferencing and querying tools. The authors of [10] have developed a semantic geospatial database system, introducing two sub-languages built on top of RDF and SPARQL query language. They have introduced t-SPARQL, an extension that can be directly mapped to standard SPARQL to express temporal queries. While t-SPARQL has not yet managed the temporal features, its potential for future development is promising. The principle of reification in ([6], [7], [13], [33], [37]), which depicts n-ary relations, has a significant problem of data redundancy. The authors in [34] propose knowledge reification as a solution for representing complex relationships and multilevel abstractions using the property graph model. The SWRL and SQWRL [35] rules languages are employed in both approaches [7], [33]. Using inference rules is a fundamental part of knowledge management and a crucial component of the reasoning process. These rules are either written in the SWRL language or incorporate the Horn clause and an OWL- DL. SWRL Temporal Ontology, a significant extension of the SWRL language, allows the annotation, reasoning and querying of temporal knowledge bases. This ontology's proposition, instant, and time interval concepts are crucial for presenting temporal knowledge. It is important to note that the representation knowledge may be complex and better suited for describing temporal entities than the temporal context. Moreover, SWRL raises several limitations, such as the lack of negation. The OWL-Time , a W3C recommendation since October 2017, is a powerful tool that provides a vocabulary for expressing facts about topological (ordering) relations among instants and intervals. OWL-Time does not support dynamic events for representing object properties that change over time. To the best of our knowledge, no reasoning tools allow us to infer new temporal data. Despite these constraints, OWL- Time is still a valuable resource for describing the temporal content of web pages and the temporal properties of web services. The main reasons are: 1) OWL and RDF language are based on binary relations that supply connect two instances, and 2) It cannot be combined with the existing OWL tools [36].

3 Methodology

3.1 Modeling knowledge

HClass is an ontology of concepts. It encompasses more than 2700 concepts. It is identical to the binary OWL ontology. A generalization/specialization structure can be created by using HClass to represent general concepts. The process of naming a concept involves using lowercase symbolic labels and an underscore, like human being, artifact, doctor, sensor and robot . Like OWL, HClass also contains instances (individuals) which are represented in the upper case, including an underscore symbol; For example, BLOOD-SENSOR-PRESSURE-2 SENSOR- ECG-1 are examples of the body sensor concept, and WHEEL-CHAIR-3 is an example of the artefact concept. The nodes in HTemp are hierarchically connected as n-ary structures. This ontology is defined as the formal depiction of elementary events. Our approach distinguishes between an elementary event and a complex event, which describes an entity's behaviour (motions, actions, temporal events, etc.). For example, turning on the coffee machine early in the morning and opening the door are elementary events. However, if the robot moves towards the space where a human is located and interacts with him, it is a complex event. Figure2 depicts the general structure of HTemp ontology divided into seven branches called templates or predicates (MOVE, PRODUCE, RECEIVE, EXPERIENCE, BEHAVE, OWN, EXIST). The BEHAVE predicate, a crucial concept in our understanding of actions and behaviours, represents the actions or behaviours of one or more individuals. On the other hand, EXIST indicates an entity's presence in a given space. EXPERIENCE is typically employed to describe an event that affects an individual, like illness, success, accident, etc. MOVE, a versatile predicate, describes many actions like moving, sending, etc. The OWN predicate can represent the notion of ownership between entities or the state of an entity. The PRODUCE predicate describes the execution of a task, activity, or other action. RECEIVE describes events related to the reception of information.

Table 1: Elementary events (ioe.e85) vs complex events (ioe.m156).

Description	narrative event
The robot gives its assistance by moving itself towards the bathroom where a human is localized and tries to interact with him.	ioe.m156) MOVE SUBJ ROBOT_KOMPAI: (KITCHEN_1) OBJ ROBOT_KOMPAI: (BATHROOM_1) MODAL speech_interaction CONTEXT potential_risq date-1: 2024/11/25/15:25 date-2:
On 2024/11/25, at 14:40, the system observes that a stovetop in the kitchen is turning on in the kitchen denoted respectively by the symbols STOVETOP_1 and KITCHEN_1.	ioe.o145) OWN SUBJ STOVETOP_1:(KITCHEN_1) OBJ property_ TOPIC TURN_ON {obs} date-1: 2024/11/25/14:40 date-2:
On 2024/11/25, at 14:58, the system observes that the temperature on the kitchen stovetop has risen	ioe.e85) EXPERIENCE SUBJ (SPECIF temperature KITCHEN_1) OBJ growth_ {obs} date-1: 2024/11/25/14:58 date-2:

Each Template can be customized to derive the new templates that could be needed for a particular application. HTemp ontology contains 165 templates. Each branch of template contains seven generic roles (subject(SUBJ), object(OBJ), SOURCE, MODAL, TOPIC, CONTEXT, Beneficiary (BENF)). The space where an event/situation occurs and temporal knowledge are respectively described by location and modulators (described in more detail in the next section). Modulators represent the (start, end, duration) of a given event/context. A role or a variable defined in square brackets ([ ]) are optional elements. In figure 2, the SUBJ, MODAL and TOPIC roles and (var1, var3, var5 and var6) are mandatory, while SOURCE, CONTEXT, roles, and variables (var2, var4, var7) are optional. The variables var1, ..., and var7 represent constraints allowing us to check that the values assigned to each variable when a Cognitive Behaviour Template

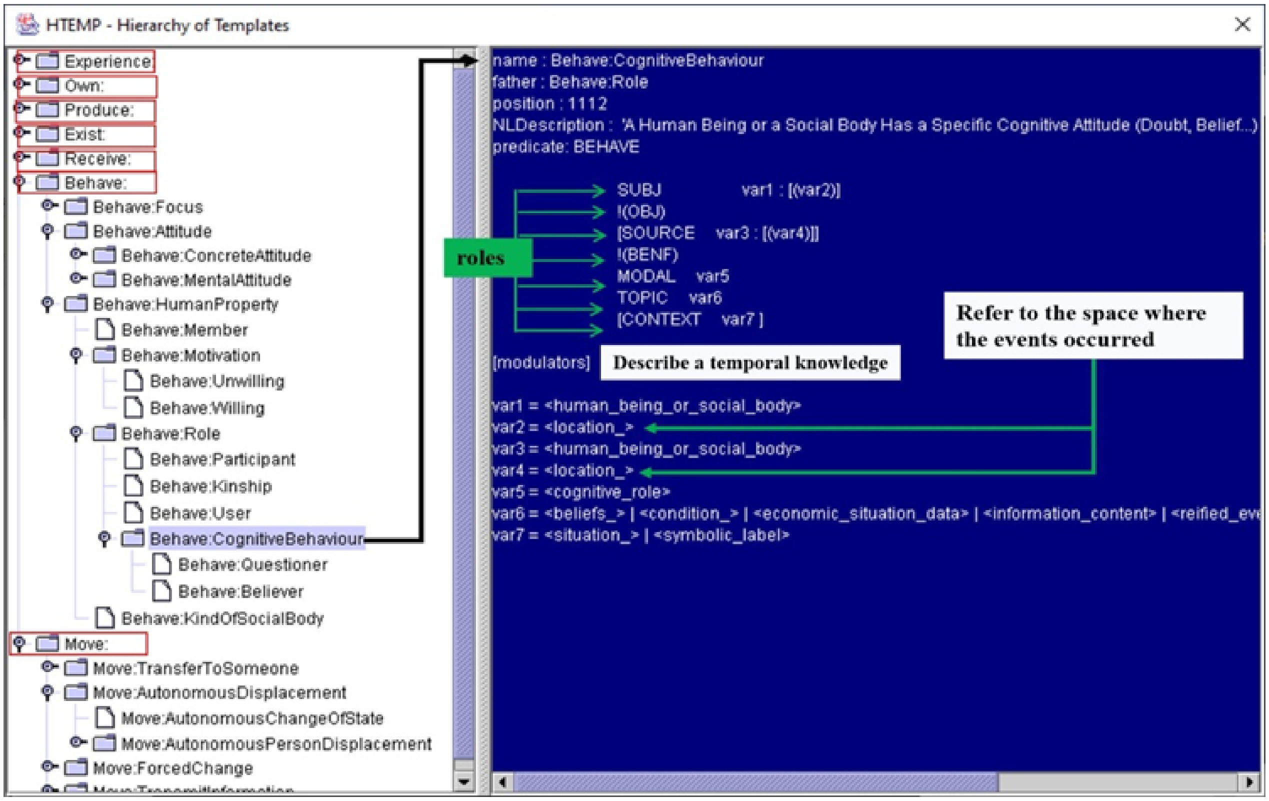


Figure 2: General HTemp ontology structure and Cognitive Behaviour structure.

is instantiated correspond to (concept, sub-concepts) defined in the HClass ontology. Table 1 depicts three examples of elementary events and complex vents. Where each template has a unique symbolic label (SymL) identifying a given template, some examples of SymL : (ioe.m156), (ioe.o145).

3.2 Spatio-temporal representation

According to [37] narrative events are those that take place in reality. As for [38], a narrative event provides the classical theory of narratology. A logical and chronological sequence of events makes up the fabula entity. The story entity is a fragment of fabula arranged into a new sequence. Finally, the narrative describes how events are narrated in a given language, media, signal, etc. In our approach, the Allen interval's logic can be recreated relying on two properties (date 1) and (module):

1. 1. The property (date 1) represents the event that begins at timestamp t1;
2. Date 2 is the property that signifies the maximum time limit for the event at timestamp t2;
3. Temporal attributes can be associated with temporal modulators like begin, end, and observe (obs) to mark the start or end of an event;
4. Point time is a time stamp that indicates that the date associated with date-1 is solely a specific point in the temporal interval associated with the event. The second property, date-2, is empty;

Table 2 shows two examples, the narrative event denoted by (ioe.b148) expresses that the symbol DAVID-1, which is used as filler of the SUBJ(ect) role, represents a human who is localized at the bathroom denoted with the symbol BATH-ROOM-1, the user filler of the Modal role describes that INDIVIDUAL-PERSON-1 is performing the activity (using the bathroom's shower tap) described in the TOPIC role as SHOWER-TAP-1. The property (date 1) depicts a specific time-point within the temporal interval corresponding to an event. As for (ioe.o25), throughout the scenario, DAVID-1 is the house owner denoted with HOUSE-1.

3.3 Chronological Knowledge representation

Binding narrative, a structure used to link together several events/contexts, taking into account semantic linking, are formalized by the binding operators. These operators, such as GOAL, COORD(ination), and CAUSE, play a crucial role in formalizing the logical semantic link between the narrative events using their symbolic labels (SymL). Furthermore, they allow describing complex IoE scenarios. The binding narrative can be expressed as follows:

$$(bind.operator\ [\ SymL_1\ o\ SymL_2\ o\ SemL_3 \dots\ SemL_i]) \qquad (1)$$

Table 2: The location where the scenario takes place is depicted in this narrative event. The house referred to as HOUSE 1 here belongs to INDIVIDUAL PERSON 1

narrative event
ioe.b148) BEHAVE SUBJ DAVID_1: (BATH_ROOM_1) MODAL user_ TOPIC SHOWER_TAP_1 date-1: 2024/11/25/15:03 date-2:
Behave:CognitiveBehaviour
ioe.o25) OWN SUBJ INDIVIDUAL_PERSON_1 OBJ HOUSE_1 date-1: 2024/05/25/10:00 date-2: Own:ConcreteResource

Formul 1 denoted a binary structure under the list of arguments SemL. The SymL corresponds to a symbolic label or recursively to sets of labelled lists in (Equation1). For instance, the narrative event ioe.b148 allows the robot to determine David's presence in the bathroom. Simultaneously, the narrative ioe.e85 indicates that the oven is in use, Table 1. In response, the robot sends a proposal to turn off the stovetop, a crucial action to prevent a potentially hazardous issue. This decision depicts a complex event that should be separated into three formal elementary events (derived from three different templates of the HTemp ontology):

- The temperature on the kitchen stovetop has risen (ioe.e85, Table 1);
- The robot takes note that David is not in the kitchen since he is in the bathroom (ioe.b148, Table 2);
- Provide an early warning, the robot moves towards BATHROOM_1 where the person is localized (ioe.m156 depicted in Table 1);

Using the COORD operator, the narrative events (ioe.m148) and (ioe.e85) can be linked to represent the entire narrative described by (ioe.c1), Table 3. So, the full description of these events is represented by the unique narrative event (ioe.s2).

4 Experiment and results

This section provides a detailed explanation of how the inference process is implemented. We, therefore, exclude aspects such as modelling and rule editing tools that are not necessary for the system to run, as they are mostly used during the design phase. We explain thorough knowledge acquisition methods, the process of integrating perceptual information into the knowledge base, and general query processing. Context recognition requires the fundamental knowledge provided by HClass and HTemp ontologies. The HClass ontology comprises 2700 concepts, while the HTemp ontology features 165 templates.

4.1 A use case scenario

The following will describe a scenario demonstrating the proposed approach in a practical, real-world context. Identifying situations and providing customized assistive and monitoring services in elderly healthcare can be challenging for any system if it cannot capture and comprehend chronologically related events. In our scenario, the robot not only gathers real-time information about the senior citizen's actions but relies on narrative querying-processing, demonstrating the effectiveness of a high level of understanding of the activities. The system is responsible for identifying the activity the person is engaged in and interpreting the associated risks. Let us now assume that David, a senior citizen living alone, wishes to prepare a meal which involves using appliances such as a stovetop and various kitchen utensils like pots and baking dishes. After 20 minutes, David heads to the bathroom and opens the shower tap. A sensor installed on the shower tap confirms when it's open, which allows the robot to determine David's presence in the bathroom. At the same time, the oven's temperature sensor detects an increase in temperature, which indicates that the oven is in use and there is no one around. The robot concludes that David cannot be in two different locations simultaneously since David is taking a shower in the bathroom and the stovetop is turning on. The robot, acting as a vigilant companion, moves towards where David is localized and tries interacting with David by sending an audio notification to suggest turning the stovetop off. David did not respond immediately. Two minutes later, the robot tries to ensure everything is okay and tries to confirm David's health condition. Establishing dialogue-based interaction with David will help collect information about his health. If David does not interact with the robot, he is considered unconscious, and consequently, the current context corresponds to an emergency. Let us clarify why these analyses are crucial.

1. Chronological analysis involves understanding the sequence of events, such as moving from the kitchen to the bathroom and the time spent there;
2. If the person stops moving, the system will recognize a potential issue and react accordingly;
3. Consider suggesting or taking action, like turning off the stovetop, based on a time interval (e.g., after a long cooking session or be a while in the bathroom);
4. The chronological analysis significantly enhances safety by proactively preventing forgotten cooking sessions, thereby ensuring a secure environment free from potential fires or accidents;

4.2 General Querying-processing mechanism

The following equation governs the handling of all inference rules:

$$S \ iff \ Y1 \ and \ Y2 \ :: \ Yn \tag{2}$$

Where S is the event/context to infer and Y1,..., Yn represent the reasoning steps. X, Y1,..., and Yn are modeled as instances of the template (narrative event). Y1 is called condition in

Table 3: Binding narrative events.

It is clear that there is a logical connection between ioe.e85 and ioe.b148.	ioe.c1) (COORD ioe.b148 ioe.e85)
ioe.c1 triggers the narrative event that is described in ioe.m156	ioe.s2) (CAUSE ioe.c1 ioe.a156

hypothesis rules and called antecedent in transformation rules. A transformation rule contains an antecedent (i.e., a left-hand side) representing the search query to transform and one or more consequents (i.e., right-hand sides) representing search patterns for which a QPM will substitute the query.The reasoning step Yi is started once the reasoning step Yi-1 has succeeded. The Yn (Equation 2) denotes the leaf in the tree structure, which symbolizes the success of the reasoning process. A QPM (figure1) component converts during a reasoning steps a search pattern derived from the variables and their values into search patterns Si that attempt to match and unify these queries with the knowledge stored in the knowledge base. The ontology HClass which represents a higher-level abstraction within the system allow adapting each concept/individual that occurs in the query to all subsumed concepts/indivduals.

Query Formulation: In this context, the antecedent refers to the condition or situation that prompting the system to create a query to understand the situation better. For example, the senior person has not moved from the bathroom for an unusually long time. This would involve applying semantic and chronological analysis, as well as correlating other factors, such as health status, time, and location.

4.3 Chronological and Semantic Analysis of Events

David's failure to hear the audio notification message results in his unawareness of the robot's interaction. This breakdown in communication disrupts the robot's on David's interaction, leading it to assume that David is in danger and the situation is an emergency. This scenario underscores the need for deep reasoning about spatiotemporal events, semantic analysis, and past and ongoing events. It also reiterates the importance of human-robot communication in the robot's decision-making process, as it is a key take away from the scenario.

4.4 Extraction of implicit observations

The hypotheses rules and transformation rules explain the causal reasoning by extracting and transforming relevant information from the knowledge base. The first query is adjusted to obtain relevant information or infer new causal relationships from existing data, enabling the creation of a narrative that explains the triggering alarm.

X1) Initial request (search pattern)
PRODUCE
SUBJ(ect): robot_
OBJ(ect): triggering_
TOPIC: alarm/control_tool

Table 4: Since David did not respond, the robot triggered an alarm

Description	Narrative event
Narrative event representing the initiator (agent) who triggers the alarm	ioe.p158)PRODUCE SUBJ ROBOT_KOMPAI OBJ triggering_ TOPIC emergency_alarm CONTEXT EMERGENCY_SITUATION_1 date-1: 2024/11/25/15:28 date-2: is instance of Produce:PerformTask/Activity

The NKRL search patterns operate like database queries in conventional systems, such as those used in information retrieval (IR). Similar to database query (e.g., in SQL), a pattern in NKRL enables systems to query and obtain answers directly from the knowledge base. Nevertheless, in our approach, a pattern is a formalized representation of a query that may involve logical relationships, constraints, and conditions expressed in a knowledge representation language as instances of HTemp ontology. The pattern is used to search for information, facts, or relationships within a semantic or knowledge-based system. Therefore, when the reasoning process is performed, the explicit variables in the template are replaced with concepts (abstract categories like "person," "robot," or "location") or individuals (specific entities like "DAVID_" "BATH_ROOM_1," or "STOVETOP_1"). The constraints imposed on these variables ensure that the substitute is consistent with the knowledge base. For instance, if a template has a variable "vari" that represents a "location," only concepts or individuals classified as a location in the knowledge base would be valid replacements for this variable. In a narrative-based knowledge base, all events might be represented as structured statements or facts, often involving temporal or causal relationships (e.g., David be present in the bathroom since 15h03, The temperature increase, David heads to the bathroom and opens the shower tap). For example, if the search pattern asks for events involving David, the system will also check if the symbol "DAVID_" is a valid instance of the person_ concept or any of its subclasses (like human_being, owner_, etc.).

The query (X1) plays a crucial role in defining the event. The search pattern defined by the conceptual predicates (PRODUCE with the roles of SUBJ and TOPIC) will result in a set of narrative events that match with the specified concepts (i.e., the output of the query will consist of all instances where the robot_ is associated with the production of an alarm/control_tool).

The system symbolised by (ioe.p158, Table 4) depicts that ROBOT_KOMPAI is the agent responsible for triggering the alarm. The consistency-checking mechanisms validate the symbol robot_ in Table 4 by relying on the HClass ontology and the constraint associated with variable var1 in the hypothesis rule. This component checks that the robot_ symbol is an instance of the alarm/control_tool concept and establishes a hierarchy of concepts from the generalisation/specialisation relationship between the emergency_ alarm concept and the alarm/control_tool concept. The inference process continues its reasoning by attempting to verify the step indicated by Y1, which corresponds to condition 1 of the hypothesis rule. The new pattern is produced (see pattern (Y1)) by utilising the value var2 = human_being and the var1 = robot_ symbol. Condition 1 is used to check that the filler represented by ROBOT_KOMPAI is an agent (i.e., subconcept of control_tool) and monitoring system.

Y1: condition 1) PREDICAT: OWN
SUBJ(ect): ROBOT_1
OBJ(ect): control_
BENF: human_being

4.5 Using a transformation rule

Based on an ontology-based system, the query (Y1), the robot tries to find direct matches or relevant data. Since the direct search might not yield a valid or concrete result, the robot employs a transformation rule. This rule infers implicit knowledge not directly available in the knowledge base but can be derived logically. Applying the transformation rule, the system finds a form of knowledge not directly queried as implicit knowledge. The narrative event (ioe:p159), Table 5 denotes a specific event where someone is in the bathroom. The property detection is a role that holds the "object" of the event as a filler of the OBJ(ject) role. DAVID represents an individual human being. So, DAVID is the filler of the Topic. Thus, the querying processing infers that DAVID (a human being) is in the bathroom. The latter knowledge is not directly found through the query but is derived through implicit knowledge inferred from the system's transformation rule. The first condition of the hypothesis rule has been satisfied, and the reasoning process can now proceed with the processing of condition 2. In this step, the inference engine tries to find within the knowledge base any information indicating that the robot has attempted to establish a dialogue with DAVID (i.e., David as a person), thereby creating the search pattern (Y2).

Table 5: Results for transformation rule 1

Description	Narrative event
Narrative event specifying that DAVID is located in the bathroom.	ioe.p159) PRODUCE SUBJ ROBOT_KOMPAI OBJ detection_: BATH_ROOM_1 TOPIC DAVID_ date-1: 2024/11/25/15:03 date-2: is instance of Produce:Assessment/Trial

The first condition of the hypothesis rule has been satisfied, and the reasoning process can now proceed with the processing of condition 2. In this step, the inference engine tries to find within the knowledge base any information indicating that the robot has attempted to establish a dialogue with DAVID_ (i.e., David as a person), thereby creating the search pattern (Y2).

Y2) PREDICATE BEHAVE
SUBJ(ect) :ROBOT_KOMPAI :
MODAL(ity) : user_
TOPIC : robot_
CONTEXT : (SPECIF control_ DAVID_)

Actions/Relations: Semantic Representation

- **Communication (Robot, David**: The robot plays a crucial role in the communication process, being the entity responsible for interacting with David;
- **Modality (Robot, Touch Screen, David)**: The robot's touch screen serves as a powerful tool, enabling DAVID to communicate effectively;
- **Notification (David, Touch Screen, Help)**: A message was sent to David to inform him that he can request assistance using the robot's touch screen.

Transformation Rule 2

The following formal representation provides a clear and concise explanation of how the message is transmitted, who receives it, and the communication mode.

- MOVE(ROBOT_KOMPAI, DAVID_, "You can use the touch screen to request help"): DAVID_ is being notified by the robot that he can use the robot's touch screen to request help;
- BENF(ROBOT_KOMPAI) : It is evident that ROBOT_KOMPAI is the intended recipient of the message if DAVID_ responds;
- MODALITY(touch_screen) : states that the robot's touch screen is the communication mode;

Table 6: Results for transformation rule 2

Description	Narrative event
David can use the touch screen to interact with the robot	ioe.m145) MOVE SUBJ DAVID_:BATH_ROOM OBJ confirmation_statement BENF ROBOT_KOMPAI TOPIC (SPECIF assistance_ ROBOT_KOMPAI) date-1: 2024/11/25/15:25 date-2: Produce:Assessment/Trial

var4 = emergency button in (Y3). The search pattern (Y3) is designed to explore past events (according to their temporal interval) and find narrative events that indicate DAVID should press the emergency button. The search pattern (Y4) aims to retrieve explicit knowledge indicating that the emergency button is an actuator embedded in the robot.

Y3) PREDICATE PRODUCE
SUBJ(ect) : DAVID_

OBJ(ect): button_pushing
TOPIC: emergency_alarm

Y4) PREDICATE OWN
SUBJ(ect): SOS_BUTTON_1
OBJ(ect): property_
TOPIC:(SPECIF part_of (SPECIF alarm/control_tool ROBOT_KOMPAI)

The search pattern (Y3) derives the answer depicted in Table 7. The oblig(action) modulator expresses obligations, permissions, and prohibitions in formal logic to validate an emergency situation. The narrative event (i.e., ioe.o24) indicates that the SOS BUTTON 1 button is part of the robot's touch screen, and this relationship is established using a "part of" property. After treating condition 5 of the hypothesis rule, the inference engine will verify that David did not press the emergency button to explain why the alarm was triggered. The (Y5) search pattern below is used to infer this knowledge.

Y5) PREDICATE PRODUCE
SUBJ(ect) : DAVID_
OBJ(ect): button_pushing
TOPIC: SOS_BUTTON_1
{negv}

A crucial aspect of our work is the reasoning process, which is significantly driven by a formal narrative representation. Modulator negv is a formal narrative mark of negative events in our querying-processing system. It represents negation denoting an event's negation (in this case, not pushing the emergency button). The rule processing hypothesis, derived from the (X1) initial request, plays a pivotal role in recognizing the emergency context situation. The successive reasoning process, crucially involving the consideration of missed actions and the overall chronological of events, is instrumental in understanding the sequence of events that led to the triggering an emergency situation. According to the knowledge base's ioe.m160, Table 6 event, the robot offered David assistance, but he didn't respond, as evidenced by the ioe.p161 event, Tables 7.

Table 7: Formal narrative mark of negative events in our querying-processing system

Description	Narrative event
Narrative event specifying that the emergency state has been triggered because David did not push the emergency button after the fall has been observed.	ioe.p161)PRODUCE SUBJ DAVID_ OBJ button_pushing TOPIC DAVID_ CONTEXT LIVE_SAVING_BUTTON_1 {negv} date-1: 2024/11/25/15:05 date-2: is instance of Produce:PerformTask:Activity

5 Evaluation and scalability

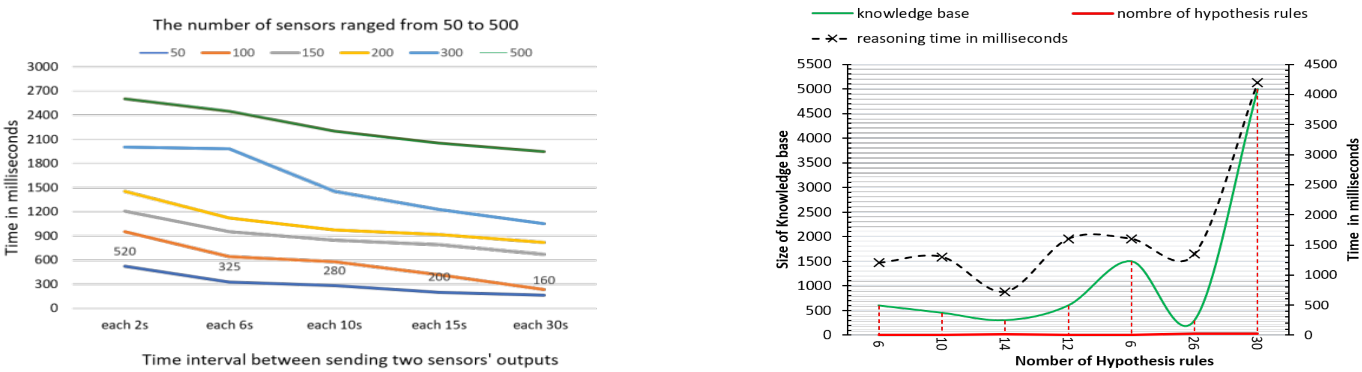
The purpose of the use case is to assess the proposed framework's performance in real-time, with a focus on response time and emergency context processing as follows:

- **Detecting Inactivity**
  1. **Goal**: Determine if the system can recognize when someone has left an activity, interrupted it, or been inactive for a specified period, and categorize it as a potential emergency;
  2. **Expected Action 1**: In order to respond, the system should activate an emergency protocol;
  3. **Expected Action 2**: To ensure user safety and prevent accidents, the system should recommend preventative safety measures (such as turning off the stovetop;

- **The Framework's evaluation criteria**
  1. **Real-Time Responsiveness**: What is the system's response time to recognizing inactivity or dangerous contexts and taking action?
  2. **User Trust and Intervention**: User Trust and Intervention : The system's ability to suggest or take preventive actions without constant user intervention is dependent;

Through our narrative querying-processing approach, the system can be both responsive and able to prevent accidents in real time, while also taking into account the safety of the user. The narrative model balances a trade-off between reasoning time and the amount of context knowledge inferred. The model can infer a broader and deeper understanding of implicit knowledge while taking more time to combine hypothesis rules with transformation rules. Recognizing complex situations or removing doubts is crucial in emergency management. The effectiveness of this approach lies in its ability to recognize complex and specific contexts, particularly in scenarios that do not require immediate response times but require deep contextual understanding. Emergency management and doubt removal require a response time of 3.8 seconds to recognize context figure 4, part (b). The querying-processing approach operates efficiently for real-time applications because it falls within an acceptable range. The response covers the time it takes an Abstraction Layer to process sensor outputs, encode them, and add facts to a knowledge base.

Our evaluation of scalability regarding sensor outputs was comprehensive. We developed a set of synthetic scenarios that incorporate HClass concepts and up to 30 hypothesis rules. We also included 24 transformation rules. The number of sensors ranged from 50 to 500. We conducted rigorous testing of the platform multiple times for each scenario and measured the average execution time across various parts of the architecture. The effectiveness of the proposed representations is measured by relying on both time intervals and points to recognize an activity effectively. Therefore, elementary events containing points and intervals were exploited to measure the response times of the reasoning process. First, we sought to infer contexts based solely on hypothesis rules. Subsequently, the semantic relationships extracted from the hypothesis rules were combined with transformation rules. The experiments were conducted on



(a) Real time Semantic Annotation

(b) Average reasoning time with hypothesis rules.

Figure 3: Evaluate the scalability of a system concerning sensor outputs while considering only hypothesis rules.

a PC with the Intel Core i5 processor, Dell Latitude 5550 15p, 16GB of RAM, and a 500GB SSD. It is crucial to point out that all the executions were done in a single-threaded way. Each test run was designed to contain 6-30 hypothesis rules and 12-24 hypothesis and transformation rules.

Our approach is versatile and can be applied across domains where sensor data plays a pivotal role in decision-making. For instance, a system with around 250 sensors dispersed in a home automation environment can maintain adequate context awareness without causing a bottleneck, thanks to the short time interval between sending two sensors' outputs, figure3. The figure also illustrates how data annotations in semantic representation enable actions to be executed in near real-time, ensuring the system's responsiveness. The annotation process is significantly influenced by each sensor's signal transmission time differences; the time annotations decrease when there is a longer gap between two sendings. For example, a door/window sensor may not need to transmit a signal every second, as it only matters when the state changes (open/closed). Similarly, for human health monitoring, wearable sensors can transmit updates every 180-300 seconds, providing sufficient data for the application without overburdening the system.

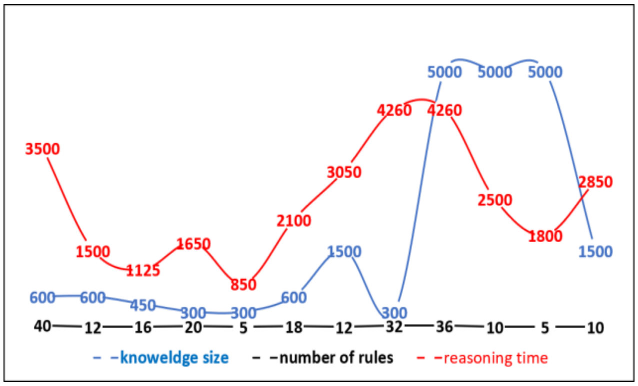
6 Discussion and Conclusion

6.1 Discussion

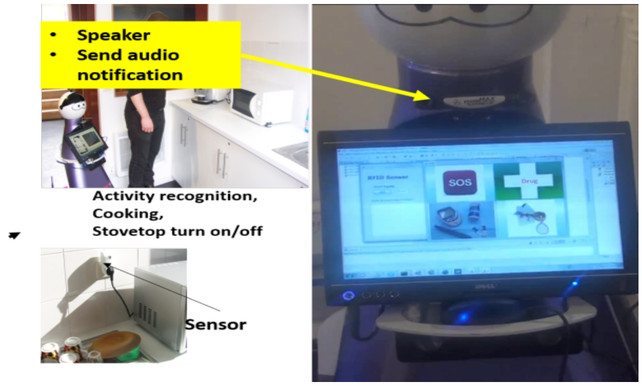
OWL, the de facto ontological language for defining concepts and reasoning about static relationships, is currently limited in its potential for building advanced inference engines due to its lack of variables. This is a significant limitation that needs to be addressed. OWL's strengths lie in classification and subclass reasoning, but its static nature hinders its ability to fully capture the complexity of real world phenomena, particularly those that change over time or depend on specific temporal conditions. Our approach is focused on managing, analysing, and understanding interconnected devices, sensors, and people in the Internet of Everything (IoE) ecosystem. We believe that narrative models are essential for understanding and processing the semantic, spatio-temporal context, enabling us to provide early warnings for potential risks, such as health deterioration or unsafe behaviors. Introducing temporal reasoning and event modeling in OWL often leads to redundancy in the ontology, making it more challenging to maintain, error-prone, and inefficient, as both the static and dynamic aspects must be kept. Modifying existing static ontologies to incorporate dynamic reasoning necessitates significant changes to the ontology structure. We underline that one of the key drawbacks of the approaches discussed earlier is the challenge of defining predicates of any arity to represent the temporal dimension of properties. This challenge underscores the need for further research in the field, as temporal reasoning often requires the representation of time-dependent relationships between entities, a task that is complex and difficult to achieve within the structure of a typical ontology or logic system. Combining OWL with SWRL never tackles the issues below. Indeed, SWRL raises several limitations. First, SWRL does not natively support negation and does not have built-in support for negation as a primitive feature. Therefore, we can not say David did not push the emergency button or express any negation statement. As an alternative approach, SWRL uses the DL safe rule, where negation is allowed on the variables in the head of the rule, which restricts negation when an application must exclude any fact. Moreover, in OWL 2 DL, The owl:NegativePropertyAssertion is used to represent a negative property assertion (i.e., state that there is no relation between two individuals), such as Robot Kompai does not assist David. Formerly, the owl:NegativePropertyAssertion relies on three RDF components: Subject, Predicate and Object. The subject concerned the individual involved in the relation; the predicate represents the negative relation, and the object represents the relation's target.

6.2 Limitations

While the proposed spatio-temporal ontology-based querying approach enhances context-aware reasoning and adaptive activity recognition, several limitations remain. First, the



(a) Average reasoning time combining hypothesis and transformation rules



(b) Robot and push button are used to detect and confirm early warning contexts

Figure 4: Assess the proposed framework's performance in real-time. Response time to recognizing inactivity or dangerous contexts and taking action.

current system has been evaluated in controlled or small-scale IoE environments; scalability to large, heterogeneous, and noisy deployments has not yet been demonstrated. Second, the ontology's conceptual scope is limited to predefined spatio-temporal and contextual dimensions, which may restrict adaptability to new domains or unforeseen events. Third, the reasoning process relies on deterministic temporal logic, which may be less effective in handling uncertainty, incomplete data, or contradictory sensor readings.

6.3 Future work

Scalability and real-time deployment – Evaluate the system's performance when deployed at large scale in heterogeneous IoE environments with high-frequency data streams, ensuring low-latency reasoning and response.

Integration of richer contextual dimensions – Extend the ontology to incorporate psychological, social, and environmental factors, allowing more nuanced activity recognition and risk prediction.

6.4 Conclusion

We present an ontological querying-processing approach that leverages narrative querying and event correlation analysis to monitor and ensure senior person safety in a smart environment. Ontology querying-processing allows gathering information from sensors (e.g., cameras, directly through voice interaction or robot's embedded tools) and a dynamic understanding of the environment. Relying on context-based questions ("Was there an unusual change in the human behaviour?"), the system can evaluate real-time actions or interruptions. Moreover, using a temporal ontology (HTemp) to perform a chronological and semantic analysis of events might track a sequence like cooking, taking a shower, moving to the bathroom, and an unexpected behaviour change. The system can then determine if an activity interruption (e.g., doesn't finish cooking) is abnormal and needs preventive actions. Lastly, contextual awareness has different safety implications according to location and activity in the person's environment (e.g., bathroom, kitchen). The system must know about the expected activities in each area (such as cooking in the kitchen); thanks to the hypothesis rules and transformation rules, the system should be able to determine if the activity is interrupted or if the person is not performing as expected.

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