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Ontology Model for Spatio-Temporal Contexts in Smart Home Environments

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Abstract. Smart home environment supports in simplifying the daily routines of the residents by learning the repetitive tasks and automating the activities. Sensors provide an unobtrusive way of collecting the state change in the environment, residents and the objects. The numbers of sensors are directly proportional to the cost and power consumptions. The sensor to activity mapping can be used for various task in smart home environment like the sensor optimization and sensor placement. Though the data-driven methods are proven to provide accurate results for recognizing activities, it does not provide context information for sensor to activity mapping. This paper deals with identifying sensors used in an activity, based on the spatial and temporal contexts. An ontology model is developed for representing the real-time smart home sensor data. A rule-based reasoner is developed using SWRL and SQWRL to infer spatial and temporal contexts. In SWRL rules, spatial context provides insight on where an activity happens. This becomes vital when more than one activity takes place at two different places. Thereby, the sensors responsible for monitoring an activity during the occurrence of concurrent events are derived. Similarly, with the help of temporal information, the path covered by the user when performing an activity is traced. The results from the developed expert system serve as input for sensor optimization task.

Keywords: Ontology Model, Sensor Optimization, Spatio-Temporal Context, Smart Home.

1 Introduction

With the advancement in engineering and technology, ambient intelligence has become an interesting topic over a decade [1] in smart environments. Smart home environments make the day-to-day surrounding sensitive to people through sensors [2,3]. The activities of the residents can be monitored and captured using ambient sensors, visual sensors, wearable sensors and smartphones [4]. Monitoring user's actions provides

information on the resident's whereabouts and the actions that are carried out at a particular period of time. Such a kind of information becomes essential for applications like, remote health monitoring, support for a senior citizen who lives independently, user's behavior detection, etc.,

The data collected from sensors provides minimal knowledge as the incoming data is a set of raw values. In a multi resident smart home environment, the daily activities captured by the sensors has high volume and velocity. Each activity however is a collection of actions indicated by raw sensor values. Thus, to represent sensor data in a more meaningful manner, this work focuses on developing an Ontology based knowledge representation. The relationship between sensor data and the activities are represented as properties in the ontology model and inferred using SWRL (Semantic Web Rule Language) and SQWRL (Semantic Query-enhanced Web Rule Language) rules. This paper focuses on finding suitable inferences using rule-based reasoning with help of spatial context. The results of inference mechanism will serve as an input for various applications like, sensor optimization, activity recognition, user behavior analysis, sensor selection for efficient power consumption, etc.,

The idea of inferencing based on spatial context is to provide additional information to context-aware applications. For example, to recognize an activity, information about the time and active sensors alone are not sufficient to accomplish the task. The whereabouts of the activity also plays a major role. Similarly, in a multi-resident living, during the occurrence of concurrent activities it becomes tedious to find the sensors responsible for monitoring the activity. This work uses spatial context to derive set of sensors that are responsible for recognizing an activity in a multi-resident smart home. Additionally, temporal context is used to trace the path covered by the user while performing an activity.

This paper is organized as follows: Section 2 provides detailed literature survey of recent advancement in this area of study; Section 3 depicts the working principle of process carried out and the dataset used for this study. Section 4 depicts the dataset used. Section 5 explains the concepts and technologies used for knowledge-based construction and rule-based reasoning. Section 6 provides the experimental results of rules used for inferencing. The proposed method is concluded in Section 7.

2 Literature Survey

Many researchers have explored and developed ontology models to represent context knowledge for a smart home environment. A few such prominent contributions have been discussed here.

To describe real-world data and to build context-aware applications, the ontology model should express hierarchical structure of sensors, user's behavioral information and observational results. Since ontologies help to discover the hidden relationship that are left unrecognized, the relationship between the concepts provides a major contribution to knowledge representation [5]. Numerous ontology-based knowledge representations are used to describe these concepts and relationships. The languages

include Resource Description Framework (RDF), Web Ontology Language (OWL), Ontology Inference Layer (OIL) which allow the semantics understandable to machines.

Surveys are conducted to determine the need and fundamentals of ontologies in the area of context-aware applications [6,7]. In [8], a Smart Home Ontology (SHO) was developed for home automation system, SHO ontology is built on Semantic Sensor Network (SSN) thereby promoting reusability. The main aim of constructing SHO for a home automation system is to cover all the functionalities with minimum number of classes and properties. One main drawback of using SHO is, it does not provide the user's state at a time.

The study mentioned in [9] devises an ontology model for deploying software applications on suitable devices with help of context information. To accomplish the task of deploying suitable software applications, it considers user capabilities, device configurations, software needs, and location preferences. In [10], a healthcare ontology using wearable sensors was designed focusing on customized healthcare services. With the help of SSN ontology, residential building monitoring [11] was done to monitor the unhealthy exposure of carbon monoxide. In [12], more contextual information is added to the developed ontology but in the prospects of visual information gathered from visual sensors. These ontologies were domain-specific and application-specific. It also fails to provide knowledge sharing and reusability.

The proposed work focuses on developing an ontology that connects all the aspects of observational values (like sensor data, value, time of occurrence, etc.) along with the user responsible for it. Since the proposed work is based on concepts facilitated by the SOSA (Sensor, Observation, Sample and Actuator) ontology model, it also promotes the idea of reusability. Additional properties are also included to improve the semantic relationship between concepts thereby adhering to the functionality of interoperability.

For context-aware applications, the existence of spatial and temporal context plays a vital role [13-15]. In [16] the authors explain the importance of spatial and temporal concepts in context-aware reasoning. It describes how machine learning and symbolic approaches are used to provide contextual reasoning from the given sensor data. The authors in [17] explain how qualitative reasoning is carried out using spatial and temporal data to monitor elderly activities in a smart home. The research in [18], uses spatial and temporal concepts for recognizing the habit of daily living in a smart home. It uses SWRL rules to generate simple and complex habits exhibited by the user. In [19] a detailed qualitative approach of spatiotemporal reasoning is depicted. This research mentions the use of Allen's temporal relation for tracing the path covered by the resident to accomplish a task. The mentioned work gives only a qualitative study of spatial and temporal reasoning and does not provide suitable insights for multi-resident living. The proposed work focuses on quantitative study of Allen's temporal relations on real-time smart home data. It also depicts how spatial context is used for distinguishing sensors during concurrent activities taking place in a multi-resident smart home.

3 Proposed Architecture

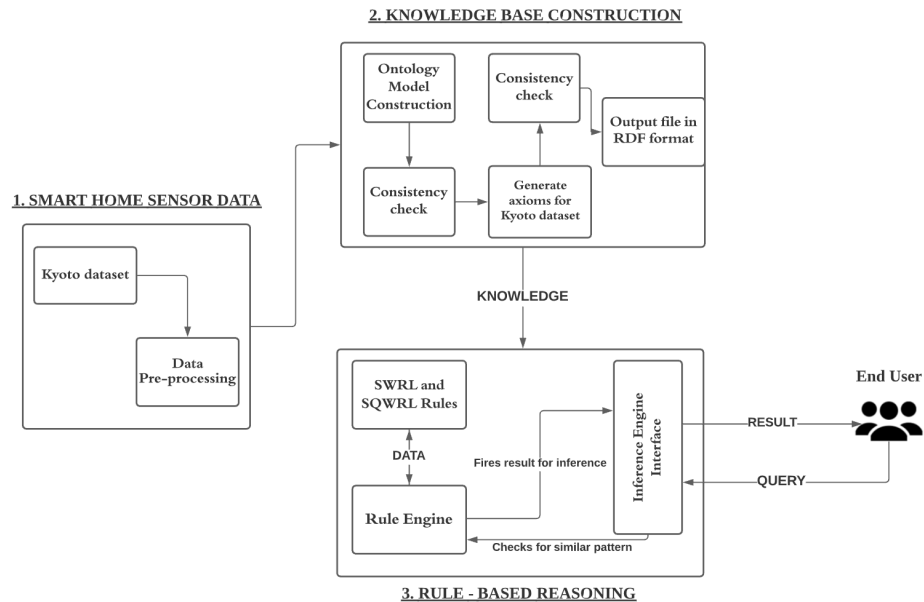


Fig. 1. Architecture Diagram

Fig. 1 shows the architecture in building an expert system; it consists majorly of three modules: pre-processing of smart home data, construction of knowledge base and rule-based reasoning.

3.1 Working Principle

The dataset used in this proposed work, follows Western State University (WSU) housing system [20]. Data pre-processing is applied to real-world smart home data. An Ontology model (using OWL) is constructed which acts as a semantic interoperable layer for representing the sensor data. This is accomplished by converting real-time entities into classes and their characteristics into properties. It is used to create common vocabularies and axioms in a machine-readable format.

After the successful creation of the ontology model, the consistency of the model is checked using reasoners. The reasoner helps to infer a set of logical relations from a set of facts. It also checks the compatibility of the axioms generated with the annotations defined. These sets of facts represent the semantics about the smart home data. The facts and axioms are stored in Resource Description Framework (RDF) format and act as a Knowledge base for inferencing.

With the knowledge created, SWRL and SQWRL rules are developed to identify the sensors during the occurrence of concurrent events. To do so, the rules make use of

spatial context; temporal context is also used for order of activity carried out by a user and for tracing a user's activity.

4 Dataset Description

A smart home is precise in its functionality and conforms that monitoring any activities does not affect the lifestyle of residents. Many residents might feel using vision-based sensors would invade their privacy. So, this research focuses on non-visual sensors monitoring the activities of the residents.

The dataset used for this research comes from a real-world smart environment deployed by the CASAS (Centre of Advanced Studies in Adaptive Systems) facility. The Kyoto dataset represent sensor values in a three-bedroom apartment and based on WSU (Washington State University) Housing System. Many machine learning algorithms [21] have been used on the CASAS dataset and proved to be effective for monitoring Activities of Daily Living (ADL) tasks.

The residents in the apartment are two undergraduate students performing their daily activities. In the smart home environment, sensors are deployed in living room, kitchen, closets, bedroom and bathroom. The sensors that are deployed in this smart apartment are motion sensors (M0##), light sensors (L0##), temperature sensors (T0##), door sensors (D0##), certain object sensors are also deployed on particular objects (I0##) and electrical usage (P001).

Kyoto dataset consists of 13 activities carried out by two residents (R1 and R2) in the year 2009-2010 where each sample in the dataset consists of the date and time of each event, sensor ID, and sensor status (numeric and binary) activated during an event. The dataset records concurrent activities happening in the household.

5 Construction of Expert System

5.1 Development of Ontology Model

Out of many sensor ontologies developed, W3C Semantic Incubator Group developed an OWL 2 ontology called as Semantic Sensor Network (SSN) Ontology that describes the capabilities of sensors, observed property, a feature of interest that is to monitor, and actuator properties, and much more. Michael Compton et.al [22] explains about Semantic Sensor Network (SSN) Ontology along with concepts and relationship established between the concepts.

SSN follows on two types of architecture namely, horizontal and vertical modularization by including lightweight Sensor, Observation, Sample, Actuator (SOSA) ontology as self-contained core ontology. The ontology model is built based on SOSA architecture thereby promoting reusability of existing concepts. The ontology model was developed based on the incoming sensor data from the Kyoto testbed and according to guidelines specified by Thomas R. Gruber [23]: explicit specification of concepts, usage of ontological commitments to communicate knowledge of an agent

involved, consistency between concepts and relationship, and ability to share vocabulary.

Fig. 2 demonstrates the set of classes and properties used for representing sensor data from smart environment.

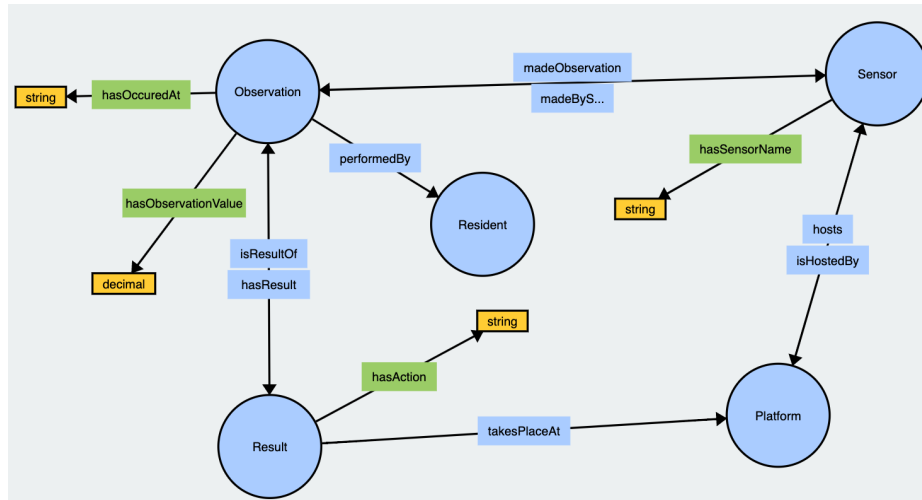


Fig. 2. Ontology Model for representing sensor data

The classes described in Fig. 2 exhibit similar vocabularies of Sensor, Observation, Sample, and Actuator (SOSA) Ontology model [24]. The class `sosa:Resident` is equivalent to `sosa:FeatureOfInterest` class of SOSA model.

The data property, `owl:hasObservationValue` represents the sensor value made for `sosa:Observation`, whereas `owl:hasAction` indicates the type of activity, and `owl:hasOccuredAt` denotes the timestamp of when `sosa:Observation` occurred. Other object properties have similar definitions of SOSA Ontology Model.

5.2 Importing Sensor data as Individuals

With classes and relationships specified, the ontology model is created with help of Protégé tool. The developed ontology model is checked for consistency with help of HermiT reasoner. Only when a model is consistent, any logical relationship derived with instances of the ontology model will be stated to be true or valid.

Protégé comes within an inbuilt plugin called as Cellfie. The functionality of the Cellfie plugin is to convert instances in Kyoto dataset from an excel sheet into individuals of the ontology model. After loading the instances, to convert the samples into axioms of classes and properties, transformation rules are used. The role of transformation rules is to convert raw sensory data into individuals (i.e.,) converts the instances into Description Logic

The mappings of data samples from excel sheet into OWL ontologies are done by MappingMaster which uses Domain Specific Language (DSL). With the help of DSL,

any clause that is represented in Manchester Syntax indicating OWL class, OWL property, OWL individual can be replaced with a reference clause. The references in MappingMaster DSL are prefixed by '@' symbol, which is generally followed by an Excel-style cell.

An example of transformation rule:

Individual: @A*

Types: Observation

Facts: madeBySensor @C*, isPerformedBy @F*, hasResult @G*,

hasOccuredAt @B*(xsd:dateTime), hasObservationValue @D*

Here, "Individual" represents the instances that are in the dataset. '@A*' denotes an Excel sheet reference cell and '*' specifies all the instances in the specified column. The above transformation rule states that all instances from column-A are of type Observation class. The corresponding properties associated with `sosa:Observation` class are defined in the Facts section. After loading the Transformation rules, a set of individuals and corresponding axioms are generated according to rules specified.

Fig. 3 depicts the set of axioms generated successfully for the individuals mentioned in the transformation rules.

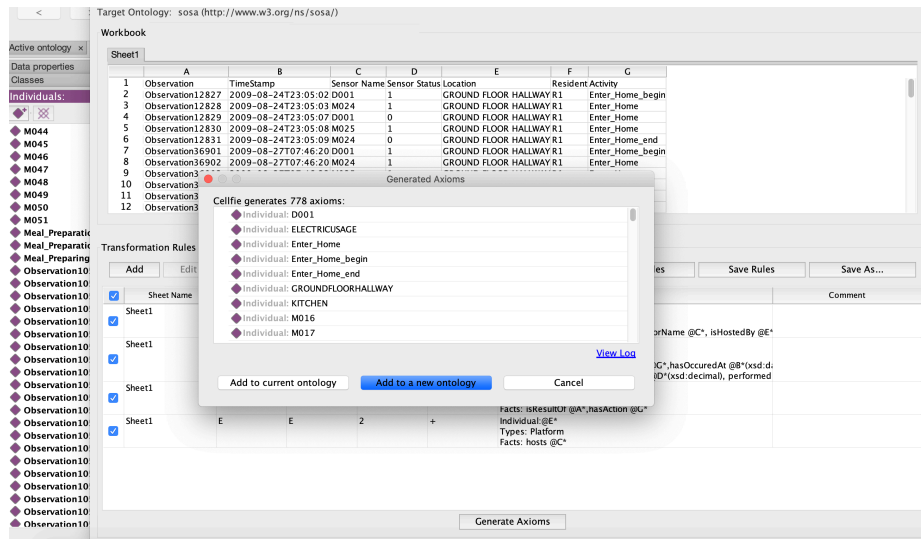


Fig. 3. Axioms generated for Individuals using Cellfie plugin

After successful creation of axioms, the ontology is stored in RDF format because the data becomes semantic which is excellent for data integration and interoperability. With the Knowledge Base constructed, rules are used to derive the desired results.

6 Results and Discussion

In the following sections, the notations described in Section 5 are used for creating SWRL and SQWRL rules.

6.1 Rule for Activity Based Sensor Identification – Without Spatial Context

```
sosa:Observation(?obs) ^ sosa:madeBySensor(?obs, ?sensor) ^
sosa:isHostedBy(?sensor, ?platform) ^ sosa:hasResult(?obs, sosa:Eating) ^
sosa:performedBy(?obs, ?res) ^ sosa:hasOccuredAt(?obs, ?time) ->
sqwrl:selectDistinct(?sensor, ?platform, ?res, ?time, sosa:Eating) ^
sqwrl:orderBy(?time)
```

This rule retrieves all sensors that are activated when a resident is eating (i.e.,) sensors that are activated in the specified time window. The query produces the following result,

Table 1. Results produced for sensor identification – without spatial context

sensor	platform	res	Time	c4
sosa:M005	sosa:LIVINGROOM	sosa:R1	2009-08-30T23:24:03	sosa: Eating
sosa:M034	sosa:RIGHTBEDROOM	sosa:R1	2009-08-30T23:24:04	sosa: Eating
sosa:M034	sosa:RIGHTBEDROOM	sosa:R1	2009-08-30T23:24:05	sosa: Eating
sosa:M034	sosa:RIGHTBEDROOM	sosa:R1	2009-08-30T23:24:06	sosa: Eating
sosa:M005	sosa:LIVINGROOM	sosa:R1	2009-08-30T23:24:07	sosa: Eating

From Table 1, it is clear that when R1 is eating some sensors are activated in the LIVINGROOM and RIGHTBEDROOM at the same time, this makes the above result inconsistent. The inconsistency is because, in a multi-resident living there are possibilities of more than one activity occurring at the same period. The sensor readings from RIGHTBEDROOM are activated when another person (say R2) is doing a different activity when R1 is eating. Thus, for consistent results, to find the sensors that are utilized when a particular activity is carried out, spatial context information plays a vital role.

6.2 Rule for Activity Based Sensor Identification – With Spatial Context

```
Step 1: sosa:Observation(?obs) ^ sosa:madeBySensor(?obs, ?sensor) ^
sosa:isHostedBy(?sensor, ?platform) ^ sosa:hasResult(?obs, sosa:Eating_begin) ->
sosa:takesPlaceAt(sosa:Eating, ?platform)
```

The rule specified in Step 1 retrieves the spatial context of where an activity begins and stores it to the existing ontology. So even when a user performs the same activity in different locations, the SWRL rules fetches the information from a set of facts and assigns the spatial context information to ontology's object property "takesPlaceAt".

Step 2: $\text{sosa:Result}(\text{sosa:Eating}) \wedge \text{sosa:takesPlaceAt}(\text{sosa:Eating}, ?\text{platform}) \wedge \text{sosa:isResultOf}(\text{sosa:Eating}, ?\text{obs}) \wedge \text{sosa:madeBySensor}(?\text{obs}, ?\text{sensor}) \wedge \text{sosa:isHostedBy}(?\text{sensor}, ?\text{platform}) \wedge \text{sosa:performedBy}(?\text{obs}, ?\text{res}) \wedge \text{sosa:hasOccuredAt}(?\text{obs}, ?\text{time}) \rightarrow \text{sqwrl:select}(?\text{sensor}, ?\text{platform}, ?\text{time}, ?\text{res}, \text{sosa:Eating}) \wedge \text{sqwrl:orderBy}(?\text{time})$

It becomes a laborious process to distinguish between the sensors responsible for monitoring a set of activities in a multi-resident living, especially when more than one user performs different activities at the same timestamp. However, this rule associates a sensor reading to a specific user performing a specific activity. Table 2 depicts the result of successful execution of rules specified in Step 1 and 2, fetching only the sensor activated when the resident is eating.

Table 2. Results produced on execution of Step 1 and Step 2

sensor	platform	time	Res	c4
sosa:M006	sosa:LIVINGROOM	2009-08-31T00:14:44	sosa:R1	sosa:Eating
sosa:M007	sosa:LIVINGROOM	2009-08-31T00:14:47	sosa:R1	sosa:Eating
sosa:M006	sosa:LIVINGROOM	2009-08-31T00:14:48	sosa:R1	sosa:Eating
sosa:M007	sosa:LIVINGROOM	2009-08-31T00:14:49	sosa:R1	sosa:Eating
sosa:M007	sosa:LIVINGROOM	2009-09-01T07:27:45	sosa:R2	sosa:Eating
sosa:M009	sosa:LIVINGROOM	2009-09-01T07:27:46	sosa:R2	sosa:Eating
sosa:M015	sosa:LIVINGROOM	2009-09-01T07:27:47	sosa:R2	sosa:Eating

When temporal value is sorted in ascending order, the path covered by user while performing an activity is traced. On finding the sensors utilized, these results have the potential to act as input for sensor optimization applications, activity recognition tasks, and for sensor selection scenarios to minimize power consumption.

6.3 Rule for Identifying Order of Activity: With Temporal Context

With the developed ontology model and with help of SWRL rules, user's behaviour can also be inferred using spatial and temporal context. On making use of Allen's temporal relations [25] with SWRL rules, different combination of results can be inferred. An example of deriving the amount of time taken by the user to wander after sleep is obtained using the following SWRL rule with Allen's temporal relation `temporal:after()`,

```

sosa:Observation(?obs) ^ sosa:hasOccuredAt(?obs, ?sleep_end) ^
sosa:hasResult(?obs, sosa:Sleep_end) ^
sosa:takesPlaceAt(Sleeping,?platform)^sosa:performedBy(?obs,R1)
^sosa:Observation(?obs1)^sosa:hasOccuredAt(?obs1,?wander_begin)^sosa:hasResult
(?obs1,sosa:Wandering_in_room_begin)^sosa:takesPlaceAt(Wandering_in_room,
?platform1)^sosa:performedBy(?obs1,R1)^temporal:after(?wander_begin,?sleep_end)
^temporal:duration(?d,?sleep_end,?wander_begin,"Minutes")->
sqwrl:select(?sleep_end, ?wander_begin, ?d) ^ sqwrl:orderBy(?sleep_end)

```

The results of successful execution of the rule created for finding the order of activity are depicted in Table. 3. The time difference between two events is described in minutes.

Table 3. Results produced for Identifying order of Activity

sleep_end	wander_begin	d
2009-08-24T00:05:21	2009-08-24T00:16:29	“11”xsd:long
2009-08-24T00:10:14	2009-08-24T00:16:29	“6”^^xsd:long
2009-08-24T00:16:27	2009-08-24T00:16:29	“6”^^xsd:long
2009-08-26T06:18:22	2009-08-26T07:07:09	“49”^^xsd:long
2009-08-28T06:29:13	2009-08-28T07:01:00	“32”^^xsd:long

Qualitative analysis of spatiotemporal reasoning in the literature does not provide suitable insights on how the rule behaves in a multi-resident living space. To overcome those constraints the SWRL and SQWRL rules are created based on spatial and temporal context on real-time smart environment and provide the following inferences that also gives suitable insights for many Ambient Intelligence applications,

- With spatial context, differentiating concurrent activity occurrence by different users in same timestamp is established.
- Using spatial and temporal context, the pattern of user performing an activity and the order of the activity (i.e., a MEAL PREPARATION is generally followed by an EATING activity) can be interpreted (using Allen’s temporal relations).

With statistical analysis, the mapping of sensors activation when an activity being performed is probabilistic due to lack of contextual information. To enhance the activity-sensor mapping, the spatial and temporal information are embedded in the ontology model. This contextual information helps in identification of sensors being triggered for every action undergone by the user to complete an activity. With spatial and temporal context used in the ontology model, the results say that, sensor *S* is activated when an activity *A* is performed by the resident *R* for every timestamp between begin and end of an activity. Thus, the results produced eventually leads to higher precision and recall scores.

7 Conclusion and Future Work

In this article, we have discussed an ontology-based knowledge representation for smart home sensor data that was built for performing logical inferences with the help of spatio-temporal context. Smart home sensor data are semantically annotated with the help of SOSA ontology. The instances from Kyoto's smart environment are converted into individuals and axioms of the ontology. The rule-based reasoner allows to perform logical inferences from existing facts. SWRL and SQWRL rules were developed to infer logical relationships that exist but remained unrecognized with help of spatial and temporal contexts from ontology. The developed rules are validated with the data derived from the Kyoto smart home environment. The rules make use of spatial and temporal data from smart home environment to provide consistent results on sensor identification, order of activity identification and tracking user's activities. As ontology models are reusable and extendible, new domain concepts can also be added to enrich the knowledge base of an expert system. The spatial and temporal contexts obtained from the reasoner could be further used in sensor optimization task.

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