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ORIGINAL RESEARCH

# Ontology driven human activity recognition in heterogeneous sensor measurements

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**Abstract**
In recent years, sensor-based activity recognition has integrated the field of sensor networks with data mining techniques to model a broad range of human activities and behaviour. Huge amounts of sensor data coming from smart gadgets such as smartphones and smartwatches opens up the possibility of probing and extracting knowledge from the data in the direction of monitoring and health care. Due to the immense popularity and extensive use of smart gadgets equipped with sensors, it is more realistic and effective to utilize them in the activity recognition systems. Sensor-based activity recognition is a challenging task due to the heterogeneous nature and noisy aspect of sensor data. This work presents an ontology-based knowledge model that conceptualizes the task of human activity recognition. The knowledge model is based on two newly developed ontologies: Sensor Measurements Ontology to model the heterogeneous sensor data and Activity Recognition Ontology to conceptualise the activity recognition process by capturing the relationships between the low level acts (simple activities) and high level (inferred activity). Besides activity recognition, the proposed model handles the issue of sensor heterogeneity and provides reusability, interoperability and exchange. The proposed model is validated with a real life dataset containing sensor observations of 60 users with more than 300,000 (three hundred thousand) samples to illustrate the functionalities in the task of human activity recognition.

**Keywords** Ontology · Sensor fusion · Activity recognition · SPARQL · OWL · RDF

## 1 Introduction

With the advent and adoption of the Internet of Things (IoT) technology in different domains like health, transportation, and manufacturing, the IoT devices in the world are expected to rise to a huge number. According to a Cisco report on IoT, the amount of annual global data traffic is expected to touch 10.4 ZB (Zettabytes) by the end of 2019 at the rate of 2.5 quintillion bytes daily coming from approximately 50 billion devices and by 2030 around 500 billion devices will have access to internet (Evans 2011). These IoT devices have sensors embedded within them that interact with the surrounding environment, capture huge amounts of data and establish connection with other devices over the network. Additionally, this enormous data can be heterogeneous and multi-modal in nature consisting of distinct formats like video streams, audio, images, and textual data. The management and analysis of such large-scale sensor data is a key factor in extracting crucial information that needs to be considered while building various smart applications.

Ontologies can model the sensory data in a formalised way and provide a structural format to raise the effectiveness of data storage, search and retrieval and analysis. Ontology based search request on some sensor data is elementary and easy for the user and allows an elaborated perspective of the knowledge retrieved. Additionally, the ontology based semantic inference aims at deriving logical conclusions from the sensory data on the basis of certain rules and axioms. The main purpose behind modelling sensor data through ontology is to develop a knowledge base of the domain and store it electronically. This knowledgebase can be further optimized through a deeper understanding of the subject domain without making many changes to the underlying structure. Thus, developing sensor based ontology and mapping sensory data to domain ontology provides a rock solid

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platform for sharing, reuse and integration of sensor data in a variety of applications (Eid et al. 2007; Khaleghi et al. 2013; Wang et al. 2014).

The large scale multimodal sensory data can play a crucial role in the context of human activity recognition. Human activity recognition is a well understood problem having extreme potential in unearthing patterns in human behaviour to monitor daily human activity for security and health motives. Large amounts of data from various sensors embedded in handheld devices like smartphones and wearable devices like smartwatches and fitness bands can be used in the human activity recognition applications due to escalated dependence and proximity of humans with them. The heterogeneous sensor data can be processed and analysed to gain knowledge of the activities that are being performed by the concerned person in possession of the above said smart devices. The recognition of daily living human activities in case of the elderly can help in independent living and detect abnormal human behaviour in adverse situations.

Smartphones and Smartwatches are new era high-end devices that merge the attributes of small sized communication gadgets with desktop PC like capabilities (Ali et al. 2014). Sensor technology was extended into these devices for making a shift from mere communication gadgets to life-centric sensor platforms for considerable increase in their functionalities supporting research in human activity monitoring and recognition, assisted human living, healthcare, etc. The data collected from sensors within these smart devices is huge and simply raw data, hence providing limited knowledge. In order to extract meaningful information with respect to activity recognition, there is a need to add sense and meaning to the raw sensory measurements.

Additionally, the issue of heterogeneity in sensors generating voluminous data through distinct measuring procedures and in different formats, failing to provide a collective view of data, makes it hard to associate it with the relevant set of activities being performed at the defined instant. Further, the inherent design, features of sensors and absence of adaptability in different conditions restrict the accuracy of the sensed data. The noisy and asynchronous samples collected by heterogeneous sensors result in missing data that restricts efficient analysis for human activity recognition. Further, improper and incomplete sensors specifications and annotations can hinder the human activity inference mechanism on sensor data. All the above problems can be resolved by efficient integration of sensor data. The sensor data integration can enable retrieval of knowledge that is difficult to infer through individual sensors.

So, ontologies can be used to formally specify the sensor data from the wearable sensors in a well defined machine interpretable format and conceptualize the activity recognition process in the form of concepts defined as classes and the relationships between the concepts as properties. Certain axioms or rules can be defined so as to facilitate inference mechanism. The core idea is to map low-level sensor data, information and activity models into ontologies, making inference of high-level activities possible through the usage of domain knowledge and ontological reasoning mechanism. Making use of ontology in the context of human activity recognition comes with several advantages: (i) Ontological activity recognition approaches capture and encode conceptual knowledge in a machine understandable and interpretable format providing the processing and inference tasks a degree of automation. (ii) Ontology can provide the activity recognition process a sense of modularity through a two level abstraction i.e. concepts (classes) and instances (individuals). Hence, it supports coarse grained and fine grain modelling of the activity recognition process. (iii) It effectively builds a gap between the static data (conceptual and domain knowledge) and dynamic data (sensor observational measurements). (iv) The ontology based activity recognition modelling is a unified representation and reasoning approach for recognition which makes it a natural and straightforward approach to support the integration and interoperability between contextual information and recognition of human activity.

In a real world scenario, recognition of daily routine activities of humans can have several applications. For example, it can help in emergency situations demanding attention and instant help. Human activity recognition can play a huge role in daily life monitoring, elderly care, detection of anomalies in behaviour by studying patterns, security and surveillance systems etc.

### 1.1 Our contribution

i. The proposed ontology based model conceptualises human activity recognition from heterogeneous sensor data.
ii. The developed knowledge base annotates the heterogeneous sensor data as per the designed ontology, thus providing meaning and significance to raw sensor data.
iii. The proposed model also handles structural and syntactic heterogeneity in the data due to different sensor modalities to provide interoperability, exchange and reusability of the processed data across multiple domains.
iv. The knowledge base of the proposed model is implemented using OWL (Ontology Web Language), RDF (Resource Description Framework) and RDFS (RDF Schema) over which SPARQL is deployed as the semantic querying service.

The remainder of the paper is organized as follows: Sect. 2 gives the related work, along with motivation and research gaps. Section 3 presents the ontology based knowledge model for activity recognition. Section 4 describes the experimental evaluation of the proposed model. The paper is concluded in Sect. 5.

## 2 Related work

Sensors can be applied in various application areas such as medical and healthcare, domestic, technology, security etc. A literature review is conducted highlighting applicability of ontologies in the manufacturing applications, home appliances, robot technology, defence, and geographical sciences (Schlenoff et al. 2013). Also, smartwatches and smartphones have a rich set of sensors embedded with them, increasing their capabilities in various ways like opening ground to services such as real-time healthcare, transport and environment monitoring, security applications, gaming and social networking. An energy-efficient framework for sensors embedded in mobiles is proposed for automating human state recognition and status transition detection (Wang et al. 2009). But, large scale sensor data integration in terms of real-time spatial, temporal, and thematic aspects of the smartphone and smartwatch context-aware applications, used to perform decision-making tasks in a rich strategic environment, is critically hard. In this work, an agent-based framework with sensor data fusion and context-aware knowledge exchanges is proposed. However, this framework faces scalability issues indicating the scope of improvement for the design and development of greater applications (Subercaze et al. 2007). Today, most of the context-aware applications make use of the brute force method for collection and analysis of sensory data that leads to wastage of precious energy and resources due to generation of observations and data of limited use.

Various surveys are conducted to examine the purpose and foundations of ontologies in the area of context modelling. This survey is done on context-aware systems (Baldauf et al. 2007; Perera et al. 2014) describing the fundamental design characteristics and different context models of context-aware systems. The focus of these surveys is on the task of analyzing and contrasting distinct approaches used in implementing ontologies. Another survey (Bettini et al. 2010) discusses the needs and requirements for modelling different contexts and describes the abstraction process of high-level contexts. This survey conceptualises and contrasts different context-based ontology models. Also, surveys are conducted to probe the suitability of ontologies to be implemented as knowledge models for semantic annotation and representation of sensors and their networks (Neuhaus and Compton 2009; Compton et al. 2012). So, there arises a need for a universally accepted and identified standard for the representation of sensors, their definitions, attributes, taxonomies to achieve integration and interoperability in sensor data (Russomanno et al. 2005a).

Smartphone sensors have similar sensing functionalities and capabilities compared to any sensor but with more extensive usage. This is because along with sensing capabilities, the smartphone sensors are supported by substantial processing, storage, and transmission techniques fused into a single handheld unit turning smartphones into smart sensor-based devices. However, the existing ontologies for sensors and sensor-based networks (Kim et al. 2008) do not apply directly to smartphone sensors supporting context-aware applications.

Several ontologies are modelled for recognizing human behaviour and context. So, most well-known ontologies that model contexts in context recognition applications are SOUPA (Standard Ontologies for Ubiquitous and Pervasive Applications) and CONON (CONtext ONtology) (Chen et al. 2005; Wang et al. 2004). Both these ontologies are generic and are extensible to model behaviour in the application-specific frameworks and areas. For example, the Context Broker Architecture (CoBrA) (Chen et al. 2003) is built upon the SOUPA ontology and the SOCAM (Service-oriented Context-Aware Middleware) (Gu et al. 2004) is extended upon the CONON ontology. In (Khattak et al. 2011), an ontology-based context detection system by using accelerometer, gyroscope, vision and ambient sensors is proposed. However, object context is not specified in the ontology for activity inference. In this work (Wongpatikaseree et al. 2012) an ontology-based activity recognition system in which the activity model specifies human posture, location and object contexts is presented. Some other works highlight the detection of context, mainly in the form of activities such as locations. ActivO (Riboni and Bettini 2011) is an ontological approach based on statistical and ontological inference mechanism for activity detection.

In this work (Helaoui et al. 2013), an ontology-based system to achieve context recognition in a multilevel approach is proposed. The ontology proposed conceptualises different types of activities or gestures: primitive or atomic gestures (basic actions that can not be divided further), manipulative or complex gestures (carrying out a set of basic actions), simple actions (various manipulative activities associated with timestamp) and complex activities (execution of simple actions in a parallel fashion).

In the presented work (Rodriguez et al. 2014), ontology based on fuzzy approach for the representation of human activities and reasoning and inference on uncertain and unknown data is proposed. The ontology developed here covers three domains: users, their behaviour and locations and actions which constitute the user environment. Table 1

**Table 1** Summary of existing ontology based knowledge systems

| Author(s) | Proposed technique | Goal(s) | Research gaps |
|---|---|---|---|
| Chen et al. (2005) | Shared ontologies are defined in OWL language for modelling context and for supporting reasoning | Proposed SOUPA ontology is described to support ubiquitous and pervasive computing applications | Deductive and abductive reasoning together is not considered |
| Wang et al. (2004) | OWL encoded context ontology for modelling context in pervasive computing environments, and for supporting logic based reasoning | Proposed conon ontology to provide open, reusable framework for context aware applications | Model scalability can be incorporated |
| Chen et al. (2003) | Proposed broker-centric agent architecture that provides knowledge sharing, context reasoning and privacy protection | Proposed COBRA-ONT ontology expressed in the Web Ontology Language(OWL) for supporting pervasive context-aware systems | Scope for reusability of other ontologies and interoperability |
| Gu et al. (2004) | Presented a service-oriented context-aware middleware (SOCAM) architecture for the building and rapid prototyping of context-aware mobile services | Proposed SOCAM architecture to achieve reasonable performance in context reasoning and searching | Integration of service adaption with regards to varying contexts |
| Riboni et al. (2011) | Proposed a solution based on the use of ontologies and ontological reasoning combined with statistical inference | Ontological reasoning to recognize complex activities | Inclusion of a wider class of context data (only location is considered) |
| Helaoui et al. (2013) | Proposed a tightly-coupled hybrid system for human activity recognition uniting both symbolic and probabilistic reasoning through highly expressive log-linear DLs | To support the inherent uncertain nature of human activities without sacrificing the advantages of ontological modelling and reasoning | Proper handling of intra-temporal relationships and fine grained activities or contexts |
| Rodriguez et al. (2014) | Developed a fuzzy ontology to deal with uncertain or vague knowledge representation | To demonstrate that fuzzy ontological reasoning improves accuracy and it is scalable | Modelling of rules in fuzzyDL for reasoning and inferencing |

demonstrates existing ontology based knowledge systems, the proposed techniques and goals.

### 2.1 Motivation and Research gaps

The potential residing in the booming sensor technology can be best exploited when there is availability of a well-developed common platform for expressing various aspects of sensors and sensing procedure (Russomanno et al. 2005b). Some standards have already been established for sensor devices and measurements for providing a common format for heterogeneity in sensor data repositories and applications (Henson et al. 2009). However, these types of standards lack the aspect of semantic description to perform logical and reasoning tasks. Semantic technologies (OWL, RDF, SPARQL) can be used to add an additional semantic layer to achieve semantic compatibility and interoperability in terms of sensor devices and the observation data. In this respect, ontologies provide semantic annotations to sensory data through temporal, spatial, and thematic metadata and thus, boost semantic interoperability, understanding, and mapping of relationships and associations among different mismatching terms through defining axioms and rules over the data. Semantic Annotation of sensory data paves way for the effective inference mechanisms to be applied for activity analysis. Even the concept of Open World Assumption (Russell et al. 2010) holds true for semantically processed data. While performing semantic inference, some unknown information in not considered absent, rather it may be inferred through semantic mechanisms using ontologies. Additionally, using ontologies enhances integration and interoperability of heterogeneous sensory data which can be reused as contextual information for achieving situational awareness in case of human activity recognition systems. The ontology creation can revolutionize smartphone and smartwatch context-aware applications through a broader data representation model with the potential to add fresh content as newly inferred properties and identifying relationships that already exist but lay dormant and unrecognised within the data. The ontology can segregate the application part of the knowledge from the operational part, hence, enabling applications to achieve easier knowledge management (Noy and McGuinness 2001).

The available context-aware applications based on smart-devices, aiming to achieve human activity recognition, are not well equipped to manage raw sensor data and measurements. Even minor changes in conditions become difficult to accommodate and lead to entire application redesign. Further, to develop realistic functional applications, developers need actionable knowledge and information, which cannot be extracted from raw sensor observations (Korpipää and Mäntyjärvi 2003). Thus, management, representation, processing and analysis of sensory data collected from sensor based systems such as smartphones and smartwatches pose a big challenge. Therefore, exploiting state-of-the-art semantic technologies for meaningful representation and interpretation of sensors and observational data can be very helpful in context-aware and human activity recognition applications.

The Table 2 demonstrates feature based comparison of existing approaches with the proposed approach for activity recognition.

In this paper, an ontology driven knowledge model for recognition of human activity is proposed to address issues of heterogeneous sensor data representation, integration and inference tasks.

## 3 Proposed ontology based knowledge model for activity recognition

In this research, an ontology based model for activity recognition is proposed which consists of three main components: heterogeneous sensor observational data, knowledge base development and data querying and inference for analysis

**Table 2** Feature based comparison of existing approaches with the proposed approach for human activity recognition

| Approach | Pre-processing done | Heterogeneous sensor measurements | Temporal aspect addressed | Spatial aspect addressed | Semantic repository support | Scalability and adaptation |
|---|---|---|---|---|---|---|
| Chen et al. (2005) | ✗ | ✗ | ✓ | ✓ | ✗ | ✓ |
| Wang et al. (2004) | ✗ | ✗ | ✓ | ✓ | ✗ | ✗ |
| Chen et al. (2003) | ✗ | ✗ | ✓ | ✓ | ✗ | ✗ |
| Gu et al. (2004) | ✗ | ✗ | ✗ | ✓ | ✗ | ✓ |
| Riboni et al. (2011) | ✗ | ✗ | ✗ | ✓ | ✗ | ✓ |
| Helaoui et al. (2013) | ✗ | ✗ | ✗ | ✗ | ✗ | ✓ |
| Proposed | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

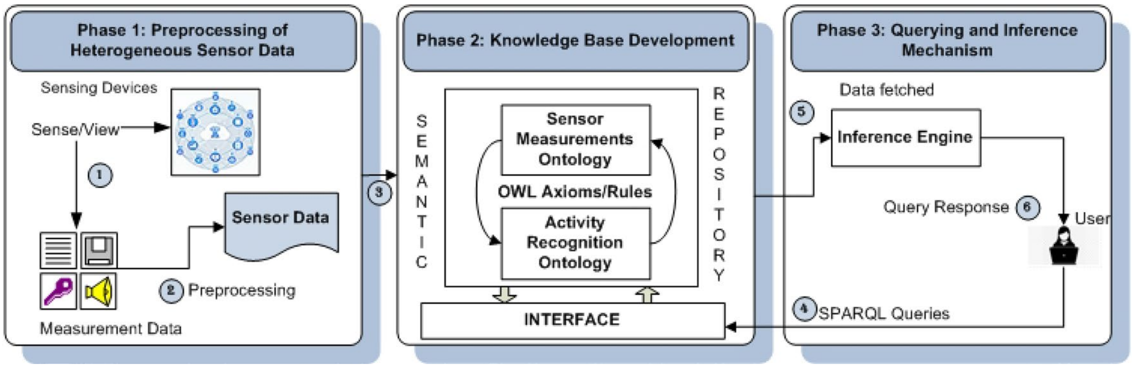



**Fig. 1** Architecture of the proposed model

and knowledge gathering. Figure 1 shows the architecture of the proposed model. The proposed model takes in processed sensor data as input, stores it and performs ontology based analysis whenever a query is fired. It returns the required knowledge to the client or user (whoever fires the query) based upon the inference mechanism carried out. The result of the query is the type of activity that is being performed during a particular time interval or at that instant by the person under consideration. The three phases that constitute the activities performed in the proposed ontology based recognition model are:

### 3.1 Phase 1: Preprocessing of heterogeneous sensor observational data

During this phase, preprocessing of the heterogeneous sensor data is performed. The main issue addressed here is the problem of missing values in the data, which is dealt in two ways:

a. **Record removal**: The set of continuously captured sensor observations which contained missing values due to some sensor fault are removed so as to prevent the issue of memory overhead and unnecessary triples in the triple store which increases the data fetch time during inference tasks.
b. **Substitution**: The observations which have missing values are replaced with values of the same sensor from the previous epoch or interval, based on the assumption that not much has changed in the next epoch, since the interval length is fixed and same for all the sensors.

### 3.2 Phase 2: Knowledge base development

The knowledge base development phase is subdivided into two main steps. The first step of this phase consists of ontology modelling of the sensor data obtained from the previous phase. It consists of development of two ontologies which form the knowledge base for our model: sensor measurements ontology and activity recognition ontology. The second step deals with the storage of developed ontologies in a triple store.

#### 3.2.1 Ontology construction

In the proposed model, ontology development is performed on the basis of the design criteria defined by Gruber (1995): clarity in conceptualisation of defined terms, coherence in the axioms over the defined conceptualisation, extendibility in terms of anticipating the shared usage of the developed vocabulary, minimal bias in encoding to ensure independency on any particular symbol-level encoding and minimal ontological commitment to support knowledge sharing. The knowledge base is developed with the timestamped heterogeneous sensor data in the sensor measurements ontology. The activity recognition ontology consists of semantically annotated domain knowledge along with a well defined set of axioms over the entities and their relationships.

The Step 1 is accomplished as follows:

a. **Development of sensor measurements ontology**

Sensor measurements ontology is a temporal ontology consisting of statistically processed heterogeneous sensor observational data. It adds semantic enrichment and significance to the data by including metadata of the sensor data.

The RDF4j framework is used for the implementation of this ontology.

The sensor measurements ontology constitute of a set of concepts represented as classes and relationships between them through links in the form of two types of properties:

owl: ObjectProperty and owl: DatatypeProperty. It contains 6 core classes namely:

- ex:Observation,
- ex:Sample,
- ex:Sensor,
- ex:SensorOutput,
- ex:Property and,
- ex:UserID.

Figure 2 shows the graphical representation of sensor measurements ontology.

The Fig. 3 represents the underlying skeleton of the above described sensor measurements ontology. The red colored nodes represent the core OWL classes or entities and the blue ones are the subclasses of the core entities.

The algorithm 1 depicts the process of creating a basic skeleton and structure of sensor measurements ontology.

**Fig. 2** Sensor measurements ontology

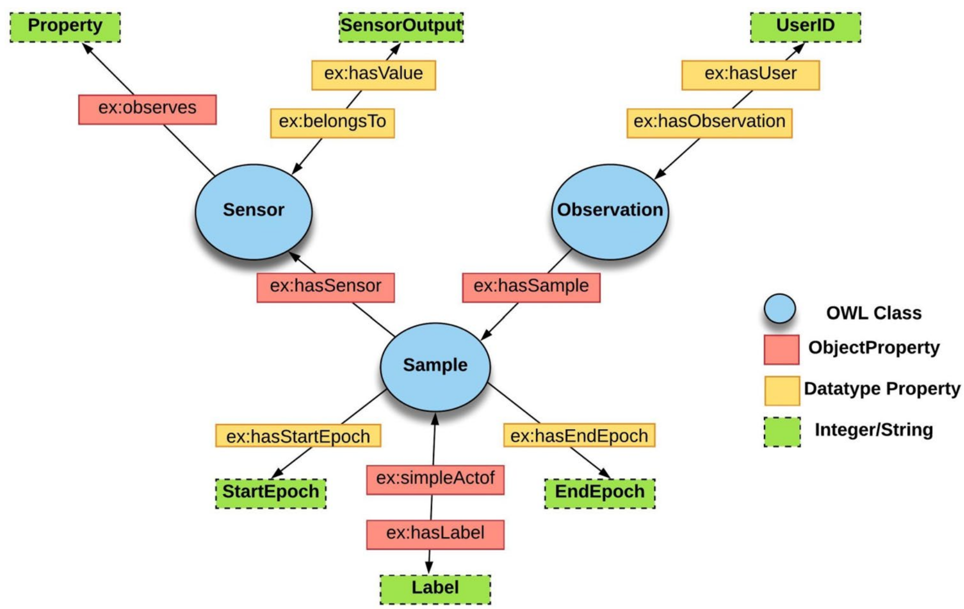
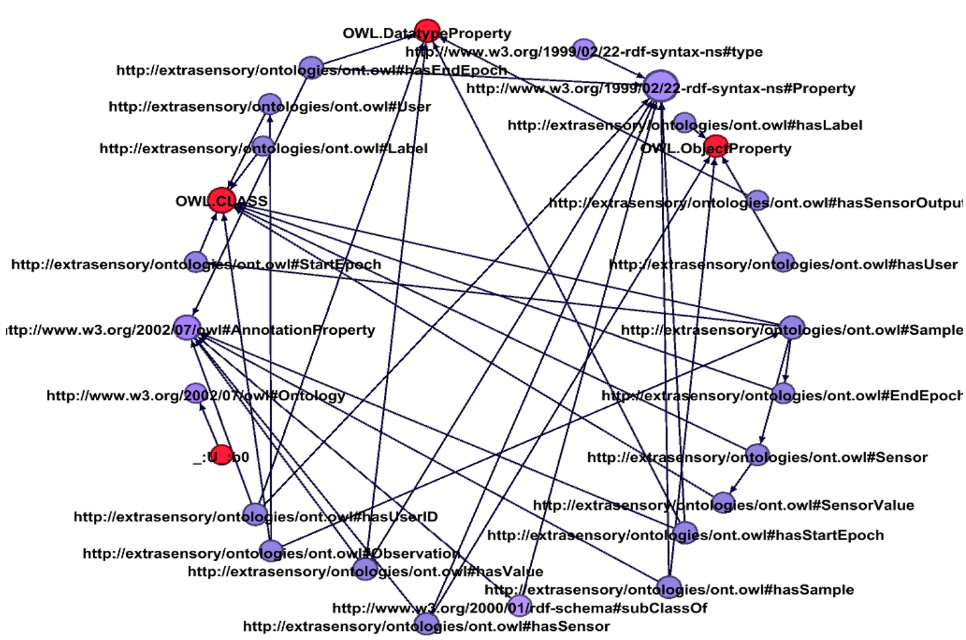



**Fig. 3** Structure of sensor measurements ontology



**Algorithm 1**: Creating skeleton of Sensor Measurements Ontology

```
Input: Set of m entities (E), n properties (P) and r relationship triples (R).
Output: Sensor measurements ontology file in turtle format.
Give format of output file with filename i.e. sensorMO.ttl
Instantiate ModelBuilder class
Give namespace for the ontology
for i= 1 to m   // Add entities to the ontology
    Add triple (E[i], rdfs.subclass, owl.class)
End
for j = 1 to n
    if (object property) then
        Add triple ( P[j], rdfs.subclass, owl.objectproperty)
    else if (datatype property) then
        Add triple ( P[j], rdfs.subclass, owl.datatypeproperty)
End
for k=1 to r
    Add a triple for each relationship b/w classes
End
```

The Table 3 describes different entities or classes of sensor measurements ontology. The Table 4 depicts relationships between the entities or classes of sensor measurements ontology.

The algorithm 2 depicts the instantiation process of the sensor measurements ontology.

**Algorithm 2**: Instantiation of Sensor Measurements Ontology

```
Input: Set of 'f' heterogeneous sensor data files (F).
Output: Instantiated Sensor measurements ontology file with turtle format.
Create a structure of Sensor Measurements ontology      // using Algorithm (1)
Enter path to sensor data files
Instantiate BufferedReader class with path+file name
for i= 1 to f   // Read all files one by one
    Add triple (F[i], rdf.type, Observation)
    Add triple (F[i], ex:hasUser, UserID)
    for j = 1 to total samples
            // each observation/file has different set 'Tj'of samples
        Add triple ( Tj, rdf.type, Sample)
        for k= 1 to total sensors
                // each sample has different set 'Sk'of samples
            Add triple ( S[k], rdf.type, Sensor)
            for l=1 to all observed outputs  // each sensor has different observed o/p 'O'
                Add triple ( S[k], ex:observes, Ol)
                Add triple (Ol, ex:hasValue, V)
                        // V is literal value of sensor output
            End
        End
    End
End
```

**Table 3** Classes of sensor measurements ontology

| Entities | |
|---|---|
| **Classes** | **Description** |
| ex:Observation | The class ex:Observation represents the sensor observations with respect to each person. This class can contain thousands of samples taken in pre defined intervals by different sensors |
| ex:Sample | The entity ex:Sample models the class which has instances uniquely associated with a timestamp and have values captured by heterogeneous sensors. Each instance of ex:Sample has values captured by different sensors |
| ex:Sensor | The entity ex:Sensor models a concept that senses a change in stimuli and provides observational values and data |
| ex:SensorOutput | The entity ex:SensorOutput models the processed sensor outputs with respect to a particular instance of ex:Sensor class |
| ex:Property | The entity ex:Property models the properties targeted by the class ex:Sensor. For example, Accelerometer can be a member of class ex:Sensor which observes property Acceleration. So, Acceleration is member of the class ex:Property |
| ex:UserID | The entity ex:UserId denotes the class of persons or subjects associated with his/her ex:Observation, uniquely identified by an ID |

**Table 4** Properties in the sensor measurements ontology

| Relationships | |
|---|---|
| **Properties** | **Description** |
| ex:hasSample | Links members of class ex:Observation to members of class ex:Sample |
| ex:hasUser | Links members of class ex:Observation to members of class:UserID |
| Ex:hasObservation | Links Observations to the class ex:UserID |
| ex:hasSensor | Links members of ex:Sample to members of class ex:Sensor |
| ex:observes | Links members of class ex:Sensor to members of class ex:Property |
| ex:hasStartEpoch | Relationship between a literal timestamp value and class ex:Sample |
| ex:hasEndEpoch | Relationship between a literal timestamp value and class ex:Sample |
| ex:hasValue | Links the sensor with the sensor output value |
| ex:belongsTo | It is the reverse relationship of ex:hasValue |
| Ex:simpleActof | Links the labels associated to ex:Sample |
| Ex:hasLabel | Relationship between Labels or Simple acts and ex:Sample |

The W3C incubator group developed SSN (Semantic Sensor Network Ontology) which can subsume the concepts and properties of the developed Sensor Measurements Ontology. The ontology alignment can be defined using the description logics in the following manner:

- ex:Sensor ≡ ssn:Sensor,
- ex:SensorOutput ≡ ssn:SensorOutput,
- ex:Property ≡ ssn:observedProperty,
- ex:User ≡ ssn:FeatureOfInterest,
- ex:observes ≡ ssn:hasObservableProperty.

The symbol ≡ denotes equivalence relation between the two entities and ⊑ symbol represents concept inclusion concept. If class A⊑B, then the concept A is included in the concept B.

b. **Development of activity recognition ontology**

The aim of the activity recognition ontology is to model the domain concepts and perform the reasoning mechanism. This ontology describes the concept of "Action". Action is associated with a person and the restriction that is imposed on the concept "Action" is that it must have a start time while finalization of the Action is not necessary. This is because an Action that is being performed started at a particular instant and is being performed at the current time. The ontology defines the concept Action to be of 2 types (subclasses):

- Simple Act and,
- Inferred Act.

The class "simple act" comprises of simple activities which can imply occurrence of an inferred act during a particular interval. The class "inferred act" is defined to have 6 subclasses: activity, inactivity, exercising, home activity, outside home and indoor activities. It can be comprised of more than these subclasses. The Fig. 4 represents the structure of activity recognition ontology.

Situations in the form of labels like lying down, sitting, running, cleaning, computer work etc. are members of the class simple act. An inferred act can be determined from the presence of one or more simple acts. In some cases, even a single simple act is enough to infer the type of inferred activity. For example, sitting, a type of simple activity, classifies the action to be a member of the class Inactivity, a type of inferred act. Such axioms are defined in the ontology to classify simple actions (associated with sensor measurements) into high level acts or Inferred Act.

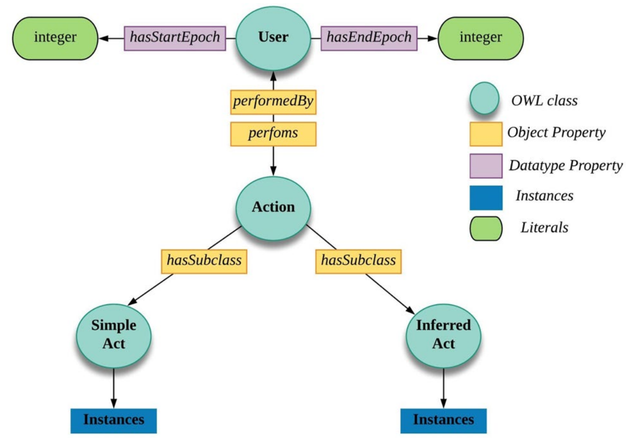



**Fig. 4** Activity recognition ontology

### 3.2.2 Ontology storage

In this step, the constructed ontologies are stored in Triple Store for efficient storage and retrieval of data with maintaining data consistency and no loss. Triple Store is a database for persistence storage of the Sensor Measurements Ontology and Activity Recognition Ontology. The ontologies are stored as concepts, the properties and their instances in the form of triplets in Ontotext GraphDB. GraphDB fulfils the requirement of the database to be devised in the form of a triple store. The triple store database allows the reading and editing of the stored ontologies. Further, it facilitates storage of class instances of the ontology. It allows for adding of new instances and retrieving of old instances from the triple store repository.

## 3.3 Phase 3: Designing of querying and inference mechanism

Once the ontologies are stored in the GraphDB, SPARQL (Pérez et al. 2009) queries can be launched on the triple store to fetch results for further inference tasks. In order to connect to the repository, a connection needs to be established through the RDF4j framework. Multiple queries can be generated depending upon the input triples required by the inference engine to get the desired results in a particular use case scenario. The Fig. 5 illustrates the flowchart of querying and inference mechanism.

The query fired fetches the triples that match a pattern specified in the query. The result of the query acts as input data to the hermiT reasoned to perform inference. For example, a query is fired to the repository in the triple store, to get the startEpoch and endEpoch times of

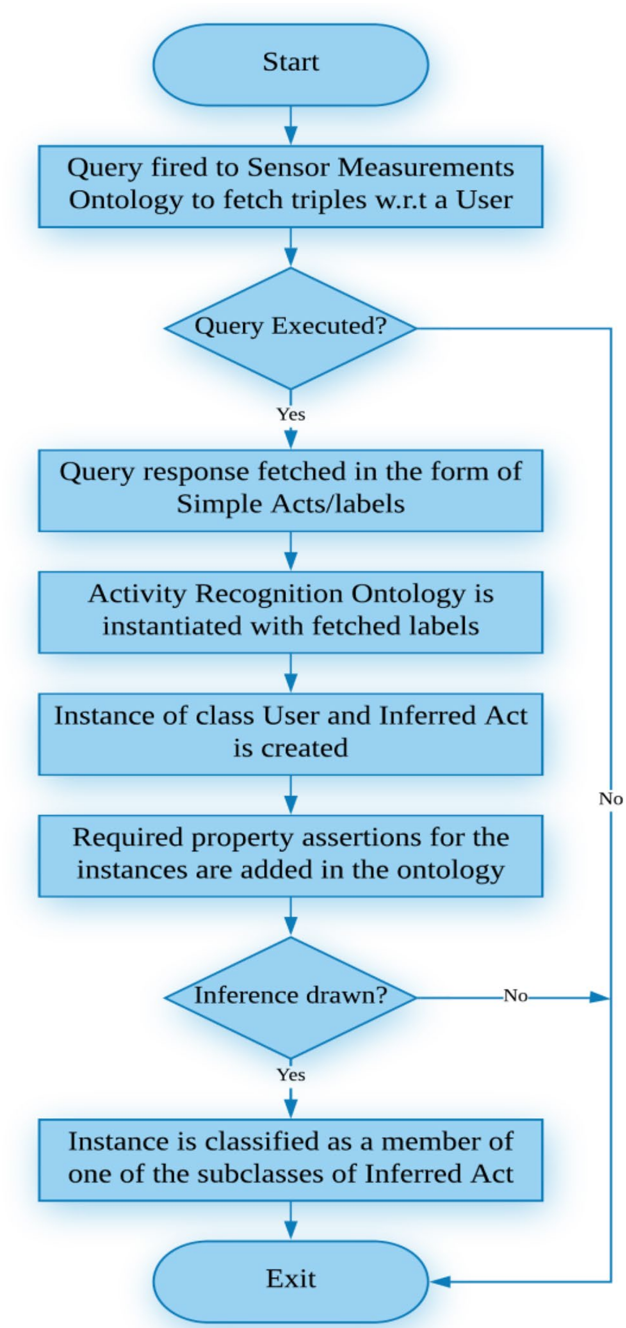



**Fig. 5** Flowchart of querying and inference mechanism

the user that performs an activity, in order to classify it into one of the subclasses of the class "inferred act". The query also fetches all the simple activities that are being performed at that time interval. The aim is to assign the unclassified instance to a high level or inferred activity. This is achieved by activating the reasoner to act upon the defined axioms and rules over the classes and the relationships. The query can also be customised to check if a particular unclassified instance is being continued in the next epoch with the same set of simple acts.

## 4 Experimental analysis

### 4.1 Dataset used

The extrasensory dataset contains observations of multimodal sensors embedded in smartphones and smartwatches (Vaizman 2017, 2018). The extrasensory dataset contains sensory data extracted from 60 users who were engaged in their day to day activities and exhibiting their natural behaviour. Each user is uniquely identified with an identifier value called as UUID (Universally Unique Identifier). Each user has large number of measurements taken by each sensor and extracted every 20 s. Each sensor measurement contains low level labels self reported by the user, except some missing values. The age range of the user under consideration is 18–42 with approximately 24 years as the mean age with 36 females and 24 males.

The Table 5 shows few contextual labels and the corresponding users involved in those contexts. Also, it shows the number of examples or observations associated with a particular contextual label.

### 4.2 Ontology instantiation

The ontology based analysis and inference classifies the sensor measurements into Activities like Home Activities, Exercising, Outside Home, Indoor activities with respect to the labels or simple acts assigned to a particular sensor measurement. The implementation required construction of two ontology: one for observational data and another for conceptual knowledge. We implemented the ontology through OWL (Ontology Web Language), RDF, RDFS and RDF4j framework and used Protege 5.2 (Noy 2001) as the ontology editor along with the required plugins activated.

**Table 5** Contextual labels and samples in the dataset

| Simple acts/labels | No. of samples |
|---|---|
| OR_indoors | 184692 |
| LOC_home | 152892 |
| SITTING | 136356 |
| PHONE_ON_TABLE | 115037 |
| LYING_DOWN | 104210 |
| SLEEPING | 83055 |
| AT_SCHOOL | 42331 |

**Table 6** Tools/technologies used

| Proposed model component | Tools/Technologies used |
|---|---|
| Knowledge base | RDF4j, OWL, RDF, RDFS, protege |
| Ontology storage | GraphDB |
| Inference mechanism | HermiT reasoner |
| Querying | SPARQL |

```
PREFIX ex: <http://extrasensory/ontologies/ont.owl#>
SELECT ?simpleAct
WHERE {
    ?a ex:haslabel ?simpleAct .
    ?a ex:hasStartEpoch "1444146916" .
    ?a ex:hasUser "00EABED2-271D-49D8-B599-1D4A09240601" .
} LIMIT 100
```

**Fig. 6** SPARQL query

The hermiT reasoner is used for the inference mechanism and Ontotext GraphDB for storage of constructed ontology in the form of triples. A local repository in the GraphDB is dedicated to storage of the constructed ontology. The Table 6 shows the tools and technologies used to implement the proposed model.

Lets's say, we wish to find out the inferred activity with respect to a certain set of simple activities performed by a particular user uniquely identified by the UIID "00EABED2-271D-49D8-B599-1D4A09240601" at a particular instant or epoch with value "1444146916". The following is the sequence of steps involved to draw the required inferences from the knowledge base:

a. **Querying and fetching data from the triple store:** The SPARQL query needs to match the required simple activities in the form of labels with the given timestamp/epoch and the user performing the activities. The SPARQL query to fetch this information is given in Fig. 6.

The specified SPARQL query requests the local repository created in the triple store to open a connection and fire the query to retrieve results corresponding to User ID 00EABED2-271D-49D8-B599-1D4A09240601 and timestamp 1444146916. The query performs pattern search in the set of triples and fetches results in the form of labels or simple activities. The result of the query depicts that the person is labelled with Sitting, IN_CLASS, PHONE_ON_TABLE at that specific epoch. So, the obtained result of the query represents the simple acts carried out by the user. After result of the query is obtained, the connection to the repository is closed to assure no data leakage or loss.

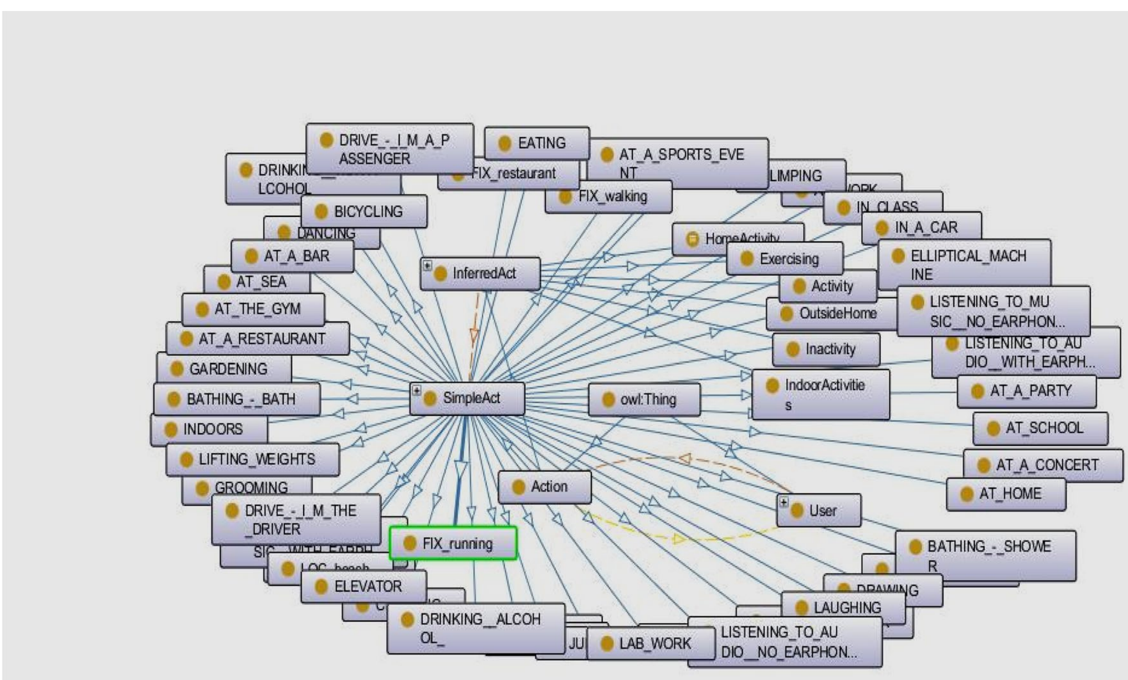



**Fig. 7** Activity recognition ontology instantiation

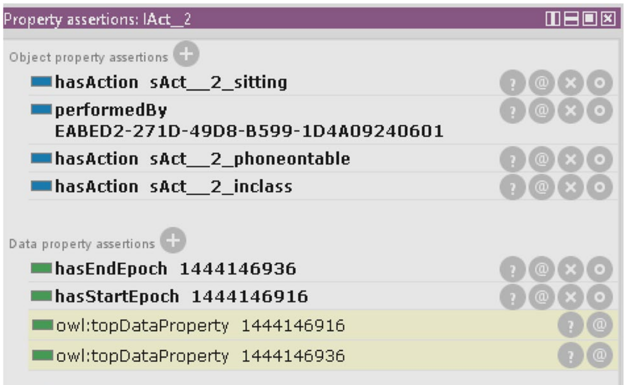



**Fig. 8** Property assertions on the inferred act instance

b. **Instantiate the ontology:** After, we have obtained the query results from the Sensor Measurements Ontology and instantiation of the Activity Recognition Ontology is performed as shown in Fig. 7.

Firstly, the class simple act is instantiated corresponding to the labels returned from the SPAQRL query. The instances created are: sAct__2_sitting, sAct__2_inclass, sAct__2_phoneontable. The instance of the class User is created as 00EABED2-271D-49D8-B599-1D4A09240601. Also, inferred act is instantiated with its member IAct__2.

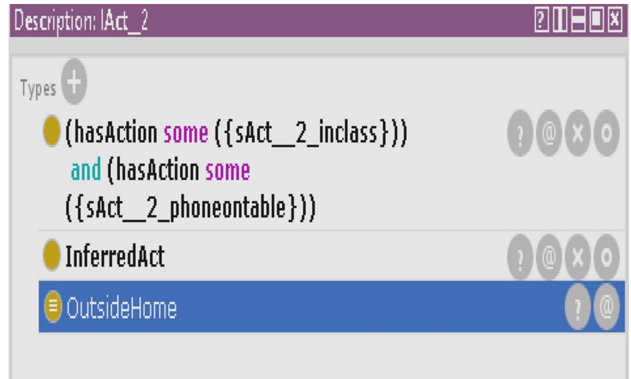



**Fig. 10** Classification of IAct__2 as outside home

The assertions that we made are:
performedBy(00EABED2-271D-49D8-B599-1D4A09240601,IAct__2),
hasAction(IAct__2, sAct__2_sitting),
hasAction(IAct__2, sAct__2_ inclass),
hasAction(IAct__2, sAct__2_ phoneontable),
hasStartEpoch(IAct__2,1444146916) and
hasEndEpoch(IAct__2, 1444146936).

The Fig. 8 shows the property assertions made in protégé tool.

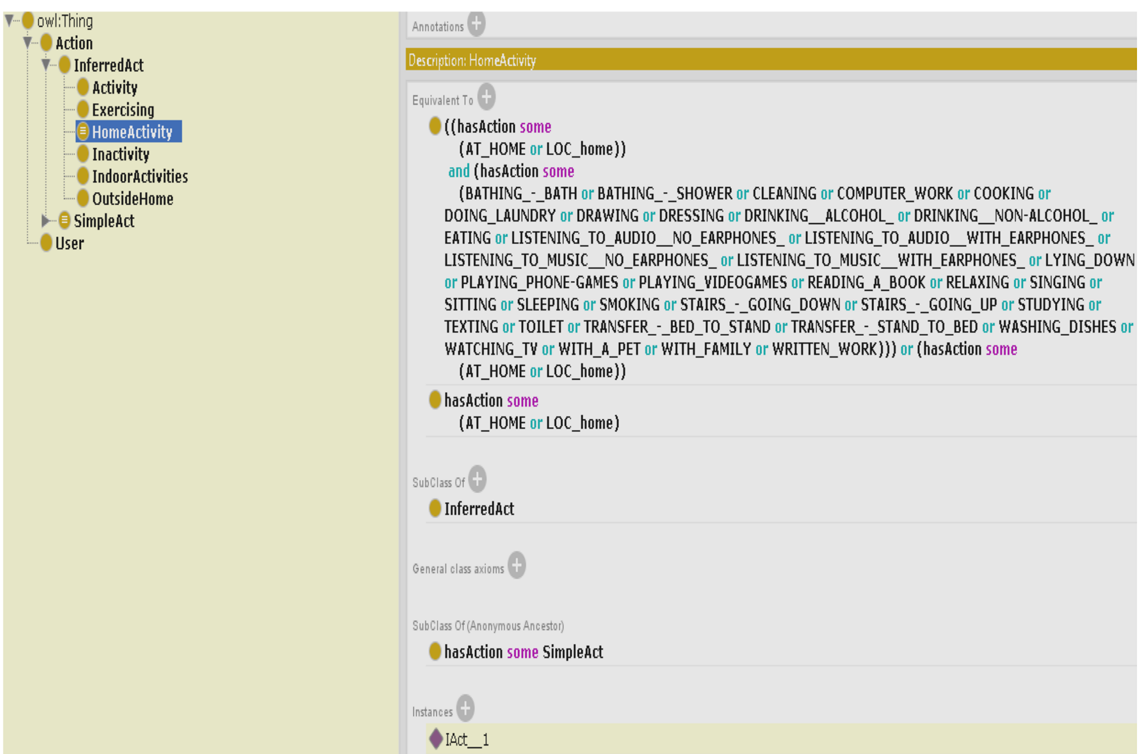



**Fig. 9** Inference mechanism

c. **Inference mechanism:** After the ontology is instantiated and the required property assertions are made as per the universal and existential restrictions defined on the ontology, inference engine is activated to draw useful inferences. The reasoner is activated giving the set of assertions as input to generate the inference as shown in Fig. 9. The reasoned upon performing the reasoning task classifies the instance IAct__2 as the member of the class Outside Home. The Fig. 10 shows the inference result of the reasoner.

## 5 Conclusion

In this paper, an ontology based knowledge system for human activity recognition is proposed. The proposed model exploits semantic technologies to conceptualise the activity recognition process. The heterogeneous sensor data is semantically annotated in the Sensor Measurements Ontology. The query fired fetches data and the reasoning tasks are performed for knowledge gain. The inference tasks are carried out over the Activity Recognition Ontology through dependencies between a complex activity (inferred act) and a combination of simple acts. The proposed knowledge model provides activity awareness of the user under consideration in the form of inferred activity that is being performed at a specific interval or instant of time. It also facilitates easy reuse and exchange of knowledge across multiple domains. It provides interoperability through fusion of heterogeneous sensor data in a common standardized format. Additionally, due to the modular design of the developed ontologies, it is easier to integrate new information into the knowledge base without changing the underlying structure. The ontology based knowledge system is validated with extrasensory dataset consisting of various sensor samples of 60 users from sensors in their smartphones and smartwatches. The results classify the sensor measurements at a particular instant with respect to a particular user/subject into a high level activity. The resultant knowledge model provides effective analysis and promising results.

The future work in this direction would be to enhance the performance of the proposed model by better and efficient query results.

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