

## Chapter 3

### Activity Recognition: Approaches, Practices and Trends

Liming Chen<sup>a</sup>, Ismail Khalil<sup>b</sup>

*<sup>a</sup>School of Computing and Mathematics, University of Ulster,  
BT37 0QB, Northern Ireland, UK*

*<sup>b</sup>Institute of Telecooperation, Johannes Kepler University Linz,  
Altenberger Strasse 69, A-4040 Linz, Austria  
l.chen@ulster.ac.uk, ismail@iiwas.org*

Activity recognition has attracted increasing attention as a number of related research areas such as pervasive computing, intelligent environments and robotics converge on this critical issue. It is also driven by growing real-world application needs in such areas as ambient assisted living and security surveillance. This chapter aims to provide an overview on existing approaches, current practices and future trends on activity recognition. It is intended to provide the necessary material to inform relevant research communities of the latest developments in this field in addition to providing a reference for researchers and system developers who are working towards the design and development of activity-based context aware applications. The chapter first reviews the existing approaches and algorithms that have been used for activity recognition in a number of related areas. It then describes the practice and lifecycle of the ontology-based approach to activity recognition that has recently been under vigorous investigation. Finally the chapter presents emerging research on activity recognition by outlining various issues and directions the field will take.

#### 3.1. Introduction

With the advance and prevalence of low-cost low-power sensors, computing devices and wireless communication networks, pervasive computing has evolved from a vision [1] to an achievable and deployable computing paradigm. As a result, research is now being conducted in all areas related to pervasive computing, ranging from low-level data collection, to intermediate-level information processing, to high-level applications and service delivery. It is becoming increasingly evident that intelligent environments which can support both living and work places through flexible multimodal interactions, proactive service provision, and context aware personalized activity assistance will be commonplace in the very near future. For example, Smart Homes (SH) - augmented real or simulated home settings equipped with sensors, actuators and information processing systems, have been extensively studied. Work in this area has produced a number of lab-based or real-world SH prototypes [2]. Within a SH the Activities of Daily Living (ADL) of its inhabitants, usually

the elderly or disabled, can be monitored and analysed so that personalized context-aware assistive living can be provided.

Activity recognition has emerged as a decisive research issue related to the successful realisation of intelligent pervasive environments. This relates to the fact that activities in a pervasive environment provide important contextual information and any intelligent behaviour of such an environment must be relevant to the user's context and ongoing activities. Activity recognition has been an active and fast growing research area. Whilst early work focused on the monitoring and analysis of visual information, such as images and surveillance videos, as a means to recognise activities, recent research has moved towards the use of multiple miniature dense sensors embedded within environments. These sensors are used to acquire the contextual data required for the process of activity recognition. Accordingly, a multitude of approaches and algorithms have been proposed and studied with the main differences between each being the manner in which the activities are modeled, represented, reasoned and used.

This chapter serves three main purposes: Firstly it aims to present an up-to-date summary of the state-of-the-art in activity recognition. We describe various existing approaches and their underlying algorithms. In particular we discuss and analyse dense sensor based activity recognition. Special emphasis is placed on approaches which utilize ontologies to enable and facilitate activity recognition. Secondly, the chapter introduces the concept of a domain knowledge driven approach to activity recognition. The approach adopts ontological modeling as the conceptual backbone covering the lifecycle of activity recognition in a sensorised pervasive environment. The compelling feature of the proposed approach is that activity recognition is performed through direct semantic reasoning making extensive use of semantic descriptions and domain knowledge. The approach supports progressive activity recognition at both coarse-grained and fine-grained levels. Thirdly, the chapter presents and discusses a number of research issues and directions the field will take. This intends to help all stakeholders in the field identify areas of particular importance, understand a coherent vision of the development of the area, its application domains and likely barriers to adoption.

The remainder of the chapter is organised as follows: Section 2 presents the approaches and algorithms of activity recognition. Section 3 describes the practice and lifecycle of the ontology-based approach to activity recognition. Section 4 outlines an exemplar case study for activity recognition in smart homes. Section 5 discusses the future research issues and trends about activity recognition. Section 6 concludes the chapter.

### **3.2. Activity recognition approaches and algorithms**

Activity recognition is the process whereby an actor's behavior and his/her situated environment are monitored and analysed to infer the undergoing activities. It comprises many different tasks, namely activity modeling, behavior and environment monitoring, data processing and pattern recognition. To perform activity recognition, it is therefore necessary to

- (1) create computational activity models in a way that allows software systems/agents to conduct reasoning and manipulation.
- (2) monitor and capture a user's behavior along with the state change of the environment.
- (3) process perceived information through aggregation and fusion to generate a high-level abstraction of context or situation.
- (4) decide which activity recognition algorithm to use, and finally
- (5) carry out pattern recognition to determine the performed activity.

Researchers from different application domains have investigated activity recognition for the past decade by developing a diversity of approaches and techniques for each of these core tasks. Based on the way these tasks are undertaken, we broadly classify activity recognition into the following categories.

### **3.2.1. Activity recognition approaches**

Monitoring an actor's behavior along with changes in the environment is a critical task in activity recognition. This monitoring process is responsible for capturing relevant contextual information for activity recognition systems to infer an actor's activity. In terms of the way and data type of these monitoring facilities, there are currently two main activity recognition approaches; vision-based activity recognition and sensor-based activity recognition.

**Vision-based activity recognition** uses visual sensing facilities, e.g., camera-based surveillance systems, to monitor an actor's behavior and its environment changes [3] [4] [5] [6]. It exploits computer vision techniques to analyse visual observations for pattern recognition. Vision-based activity recognition has been a research focus for a long period of time due to its important role in areas such as human-computer interaction, user interface design, robot learning and surveillance. Researchers have used a wide variety of modalities, such as single camera, stereo and infra-red, to capture activity contexts. In addition, they have investigated a number of application scenarios, e.g., single actor or group tracking and recognition. The typical computational process of vision-based activity recognition is usually composed of four steps, namely object (or human) detection, behavior tracking, activity recognition and finally a high-level activity evaluation. While considerable work has been undertaken and significant progress has been made, vision-based activity recognition approaches suffer from issues related to scalability and reusability due to the complexity of real world settings, e.g., highly varied activities in natural environment. In addition, as cameras are generally used as recording devices, the invasiveness of this approach as perceived by some also prevent it from large-scale uptake in some applications, e.g., home environments.

**Sensor-based activity recognition** exploits the emerging sensor network technologies to monitor an actor's behaviour along with their environment. The sensor data which are collected are usually analysed using data mining and machine learning techniques to build activity models and perform further means of pattern recognition. In this approach, sen-

sors can be attached to either an actor under observation or objects that constitute the environment. Sensors attached to humans, i.e., wearable sensors often use inertial measurement units (e.g. accelerometers, gyroscopes, magnetometers), vital sign processing devices (heart rate, temperature) and RFID tags to gather an actor's behavioural information. Activity recognition based on wearable sensors has been extensively used in the recognition of human physical movements [7] [8] [9] [10] [11]. Activities such as walking, running, sitting down/up, climbing or physical exercises, are generally characterised by a distinct, often periodic, motion pattern.

The wearable sensor based approach is effective and also relatively inexpensive for data acquisition and activity recognition for certain types of human activities, mainly human physical movements. Nevertheless, it suffers from two drawbacks. Firstly, most wearable sensors are not applicable in real world application scenarios due to technical issues such as size, ease of use and battery life in conjunction with the general issue of acceptability or willingness of the use to wear them. Secondly, many activities in real world situations involve complex physical motions and complex interactions with the environment. Sensor observations from wearable sensors alone may not be able to differentiate activities involving simple physical movements, e.g., making tea and making coffee. To address these issues object-based activity recognition, has emerged as one mainstream approach [12]. The approach is based on real world observations that activities are characterised by the objects that are manipulated during their operation. Simple sensors can often provide powerful clues about the activity being undertaken. As such it is assumed that activities can be recognised from sensor data that monitor human interactions with objects in the environment.

Object-based activity recognition has attracted increasing attention as low-cost low-power intelligent sensors, wireless communication networks and pervasive computing infrastructures become technically mature and financially affordable. It has been, in particular, under vigorous investigation in the creation of intelligent pervasive environments for ambient assisted living (AAL), i.e., the SH paradigm [2] [13] [14]. Sensors in a SH can monitor an inhabitant's movements and environmental events so that assistive agents can infer the undergoing activities based on the sensor observations, thus providing just-in-time context-aware ADL assistance. For instance, a switch sensor in the bed can strongly suggest sleeping, and pressure mat sensors can be used for tracking the movement and position of people within the environment.

It is worth pointing out that the approaches described above may be suitable for different applications. Taking this into account it is not possible to claim that one approach is superior to the other. The suitability and performance is in the end down to the nature of the type of activities being assessed and the characteristics of the concrete applications. In most cases they are complementary and can be used in combination in order to yield optimal recognition results.

### **3.2.2. Activity recognition algorithms**

Activity recognition algorithms can be broadly divided into two major strands. The first one is based on machine learning techniques, including both supervised and unsupervised learning methods, which primarily use probabilistic and statistical reasoning. Supervised learning requires the use of labelled data upon which an algorithm is trained. Following training the algorithm is then able to classify unknown data. The general procedure using a supervised learning algorithm for activity recognition includes several steps, namely, (1) to acquire sensor data representative of activities, including labelled annotations of what an actor does and when, (2) to determine the input data features and its representation, (3) to aggregate data from multiple data sources and transform them into the application-dependent features, e.g., through data fusion, noise elimination, dimension reduction and data normalization, (4) to divide the data into a training set and a test set, (5) to train the recognition algorithm on the training set, (6) to test the classification performance of the trained algorithm on the test set, and finally (7) to apply the algorithm in the context of activity recognition. It is common to repeat steps (4) to (7) with different partitioning of the training and test sets in order to achieve better generalisation with the recognition models. There are a wide range of algorithms and models for supervised learning and activity recognition. These include Hidden Markov Models (HMMs) [9] [15] [16], dynamic and naive Bayes networks [12] [17] [18], decision trees [19], nearest neighbour [10] and support vector machines (SVMs) [20]. Among them HMMs and Bayes networks are the most commonly used methods in activity recognition.

Unsupervised learning on the other hand tries to directly construct recognition models from unlabeled data. The basic idea is to manually assign a probability to each possible activity and to predefine a stochastic model that can update these likelihoods according to new observations and to the known state of the system. Such an approach employs density estimation methods, i.e., to estimate the properties of the underlying probability density or clustering techniques, to discover groups of similar examples to create learning models. The general procedure for unsupervised learning typically includes (1) to acquire unlabeled sensor data, (2) to aggregate and transforming the sensor data into features, and (3) to model the data using either density estimation or clustering methods. Algorithms for unsupervised learning include the use of graphical models [21] and multiple eigenspaces [20]. A number of unsupervised learning methods are also based on probabilistic reasoning such as various variants of HMMs and Bayes networks. The main difference between unsupervised and supervised probabilistic techniques is that, instead of using a pre-established stochastic model to update the activity likelihood, supervised learning algorithms keep a trace of their previous observed experiences and use them to dynamically learn the parameters of the stochastic activity models. This enables them to create a predictive model based on the observed agent's activity profiles.

A major strength of the activity recognition algorithms that are based on probabilistic learning models is that they are capable of handling noisy, uncertain and incomplete sensor data. Probabilities can be used to model uncertainty and also to capture domain heuristics, e.g., some activities are more likely than others. The limitation of the unsupervised learning

probabilistic methods lies in the assignment of these handcrafted probabilistic parameters for the computation of the activity likelihood. They are usually static and highly activity-dependent. The disadvantage of supervised learning in the case of probabilistic methods is that they require a large amount of labelled training and test data. In addition, to learn each activity in a probabilistic model for a large diversity of activities in real world application scenarios could be deemed as being computationally expensive. The resulting models are often ad-hoc, not reusable and scalable due to the variation of the individual's behaviour and their environments.

The second strand of activity recognition algorithms is based on logical modelling and reasoning. The rationale of logical approaches is to exploit logical knowledge representation for activity and sensor data modelling, and to use logical reasoning to perform activity recognition. The general procedure of a logical approach includes (1) to use a logical formalism to explicitly define and describe a library of activity models for all possible activities in a domain, (2) to aggregate and transform sensor data into logical terms and formula, and (3) to perform logical reasoning, e.g., deduction, abduction and subsumption, to extract a minimal set of covering models of interpretation from the activity model library based on a set of observed actions, which could explain the observations.

There exist a number of logical modelling methods and reasoning algorithms in terms of logical theories and representation formalisms. For example, Kauz [22] adopted first-order axioms to build a library of hierarchical plans for plan recognition. Wobke [23] extended Kauz's work using situation theory to address the different probabilities of inferred plans. Bouchard [24] used action Description Logic (DL) and lattice theory for plan recognition with particular emphasis on the modelling and reasoning of plan intra-dependencies. Chen [25] exploited the event theory - a logical formalism, for explicit specification, manipulation and reasoning of events, to formalise an activity domain for activity recognition and assistance. The major strength of Chen's work is its capabilities to handle temporal issues and undecidability. Logical activity modelling and reasoning is semantically clear and elegant in computational reasoning. It is also relatively easy to incorporate domain knowledge and heuristics for activity models and data fusion. The weakness of logical approaches is their inability or inherent infeasibility to represent fuzziness and uncertainty. Most of them offer no mechanism for deciding whether one particular model is more effective than another, as long as both of them can be consistent enough to explain the actions observed. There is also a lack of learning ability associated with logic based methods.

### **3.2.3. *Ontology-based activity recognition***

Using ontologies for activity recognition is a recent endeavor and has gained growing interest. In the vision-based activity recognition community, researchers have realized that symbolic activity definitions based on manual specification of a set of rules suffer from limitations in their applicability, i.e., the definitions are only deployable to the scenarios for which they have been designed. There is a need for an explicit commonly agreed representation of activity definitions, i.e., ontologies, for activities that are independent of algorithmic choices, thus facilitating portability, interoperability and reuse and sharing of

both underlying technologies and systems.

As such, researchers have proposed ontologies for specific domains of visual surveillance. For example, Chen [26] proposed an ontology for analyzing social interaction in nursing homes; Hakeem [27] used ontologies for the classification of meeting videos, and Georis [28] for activities in a bank monitoring setting. To consolidate these efforts and to build a common knowledge base of domain ontologies, a collaborative initiative has been made to define ontologies for six domains of video surveillance. This has led to a video event ontology [29] and the corresponding representation language [30]. For instance, Akdemir [31] used the video event ontologies for activity recognition in both bank and car park monitoring scenarios. In principle these studies use ontologies to provide common terms as building primitives for activity definitions. Activity recognition is performed using individually preferred algorithms, such as rule-based systems [27] and finite-state machines [31].

In the object-based activity recognition community, ontologies have been utilised to construct reliable activity models. Such models are able to match an unknown sensor reading with a word in an ontology which is related to the sensor event. For example, a Mug sensor event could be substituted by a Cup event in the activity model "MakeTea" as it uses a Cup. This is particularly useful to address model incompleteness and multiple representations of terms. For example, Tapia [39] generated a large object ontology based on functional similarity between objects from WordNet, which can complete mined activity models from the Web with similar objects. Yamada [32] used ontologies to represent objects in an activity space. By exploiting semantic relationships between things, the reported approach can automatically detect possible activities even given a variety of object characteristics including multiple representation and variability. Similar to vision-based activity recognition, these studies mainly use ontologies to provide activity descriptors for activity definitions. Activity recognition is performed based on probabilistic and/or statistical reasoning [32] [39].

More recently, ontology based modelling and representation has been applied in pervasive computing and in particular Ambient Assisted Living. For example, Latfi [33] proposed an ontological architecture of a telehealth based SH aiming at high-level intelligent applications for elderly persons suffering from loss of cognitive autonomy. Michael *et al.* [34] developed an ontology-centred design approach to create a reliable and scalable ambient middleware. Chen *et al.* [35] pioneered the notion of semantic smart homes in an attempt to leverage the full potential of semantic technologies in the entire lifecycle of assistive living i.e. from data modelling, content generation, activity representation, processing techniques and technologies to assist with the provision and deployment. While these endeavours, together with existing work in both vision- and object- based activity recognition, provide solid technical underpinnings for ontological data, object, sensor modelling and representation, there is a gap between semantic descriptions of events/objects related to activities and semantic reasoning for activity recognition. Ontologies are currently used as a mapping mechanism for multiple terms of an object as in [39] or the categorisation of terms as in [32] or a common conceptual template for data integration, interoperability and

reuse as in [33] [34] [35]. Specifically, there is a lack of activity ontologies, i.e., explicit conceptualisation of activities and their interrelationships.

Ontology-based activity recognition approach offers several compelling features: Firstly, ontological ADL models can capture and encode rich domain knowledge and heuristics in a machine understandable and processable way. This enables knowledge based intelligent processing at a higher degree of automation. Secondly, DL-based descriptive reasoning along a time line can support incremental progressive activity recognition and assistance as an ADL unfolds. The two levels of abstraction in activity modelling, i.e., concepts and instances, also allow coarse-grained and fine-grained activity assistance. Thirdly, as the ADL profile of an inhabitant is essentially a set of instances of ADL concepts, it provides an easy and flexible way to capture a user's activity preferences and styles, thus facilitating personalised ADL assistance. Finally, the unified modelling, representation and reasoning for ADL modelling, recognition and assistance makes it natural and straightforward to support the integration and interoperability between contextual information and ADL recognition. This will support systematic coordinated system development by making use of seamless integration and synergy of a wide range of data and technologies. In the following sections we use SH based ambient assisted living to further illustrate these concepts within the realms of ontological activity recognition.

### 3.3. The practice and lifecycle of ontology-based activity recognition

At the time of writing the mainstream approaches to activity recognition is based on probabilistic and statistical analysis methods. These methods are well-known and widely used with a plethora of work in the literature. On the other hands ontology-based approach to activity recognition has only emerged recently with little published work. As such this chapter intends to describe the general framework and lifecycle of the approach that can be used by researchers as a general reference.

Figure ?? shows the system architecture for the realisation of ontology-based activity recognition. Central to the architecture is the ontological modelling and representation of SH domain knowledge (refer to the components in the right-hand column). This provides Context and ADL Ontologies as conceptual knowledge models and User Profiles and Situations as knowledge entities in corresponding repositories. The context ontologies are used to semantically describe contextual entities, e.g., objects, events and environmental elements. The generated semantic contexts, i.e. Situations are used by the ADL Recognition component for activity recognition. The ADL ontologies are used, on the one hand, to create ADL instances for an inhabitant in terms of their ADL profiles, and on the other hand, to serve as a generic ADL model for activity recognition. In addition, archived data in these repositories can be mined for advanced features such as learning, high-level long-term trend recognition as well as automatic model creation.

The components in the left hand column denote the physical environment, sensors, devices and assistive services in a SH. The sensors monitor an inhabitant's ADL and use their observations, together with context ontologies, to generate semantic contexts. Assistive



Services receive instructions from the ADL Recognition component and further act on the environment and/or the inhabitant through various actuators.

Activity recognition is performed through a description logic based reasoner (the components in the middle column). The reasoner takes as inputs the semantic descriptions of a situation and performs reasoning against the ADL ontologies to provide incremental progressive activity recognition. To support fine-grained activity recognition, concrete sensor observations will be bound with context models to create an activity's description. By reasoning the descriptions against an inhabitant's personal ADL profile, specific personalized activities can be recognised. A full discussion related to activity assistance is beyond the scope of this chapter.

As most ADLs in the context of ambient assisted living are daily routines with abundant common sense patterns and heuristics from medical observations and psychological behavioral studies [36] [37], it is reasonable and straightforward to construct an ontological activity model using a description language. This avoids problems suffered by probabilistic algorithms such as the lack of large amounts of observation data, inflexibility, i.e. each activity model needs to be computationally learned, and reusability, i.e. one person's activity model may be different from others. Using ontological modeling the creation of user activity profiles is equivalent to creating activity instances in terms of a user's preferences and styles of performing ADLs. Hence it is relatively straightforward to undertake and is also scalable to a large number of users and activities in comparison with traditional approaches. Ontology-based activity recognition follows a typical knowledge engineering lifecycle involving knowledge acquisition, modeling, representation, storage, use/reuse and reasoning, which are described below in details in the context of smart home based ambient assisted living.

### **3.3.1. Domain knowledge acquisition**

A Smart Home (SH) is a home setting where inhabitants perform various ADLs in a location at a time using one or more items. As routine daily activities, ADLs are usually performed in specific circumstances, i.e., in specific environments with specific objects used for specific purposes. For example, brushing teeth usually takes place two times a day, in a bathroom, normally in the morning and before going to bed. This activity usually involves the use of toothpaste and a toothbrush. This is more generally referred to as the context for the corresponding activity. As humans have different life styles, habits or abilities, individuals' ADLs and the way they perform them may vary one from another. Even for the same type of activity, e.g., making white coffee, different people may use different items, e.g., skimmed milk or semi-skimmed milk, and in different orders, e.g., adding milk first and then sugar, or vice versa. As such ADLs can be categorized as generic ADLs applicable to all and personalised ADLs with subtlety of individuals. In addition, ADLs can be conceptualized at different levels of granularity. For example, Grooming can be considered to be comprised of sub-activities Washing, Brushing and Applying Make-up. There are usually a "is-a" and "part-of" relationships between a primitive and composite ADL. All these observations can be viewed as prior domain knowledge and heuristics that

can facilitate assistive living. The key is how to formally capture, encode and represent such domain knowledge.

There are two approaches to capture SH domain knowledge. The first is to derive relevant information through interviews, questionnaires and by studying existing documents [36], then to extract and construct patterns manually using some knowledge engineering tools. The second one is to use information extraction (IE) and data mining techniques to mine from the text corpuses on the Web a set of objects used for each activity and extract object usage information to derive their associated usage probabilities [38], [39]. The second approach is motivated by the observation that an activity can be viewed as the sequence of objects used, i.e., a probabilistic translation between activity names (e.g., "make coffee") and the names of involved objects (e.g., "mug", "milk"). As the correlations between activities and their objects used are common sense (e.g., most of us know how to carry out daily activities), such domain knowledge can be discovered in various sources such as how-tos (e.g., those at ehow.com), recipes (e.g., from epicurious.com), training manuals, experimental protocols, and facility/device user manuals or the generic global information space - the Web. Knowledge acquisition usually generates conceptual knowledge models that can be represented in various informal or formal forms, e.g., HTML, XML, tables, diagrams and graphs. Such models are normally be formalised later in terms of application scenarios.

### 3.3.2. Formal ontology modelling

Ontological modeling is a formal way of knowledge modeling that explicitly specifies key concepts and their properties for a problem domain. These concepts are organized in a hierarchical structure in terms of their shared properties to form super-classes and sub-class relations. For example, MakeTea is a subclass of MakeHotDrink. Properties establish the interrelations between concepts. For instance, hasDrinkType is a property of the MakeHotDrink activity that links the DrinkType concept (e.g., tea, coffee, chocolate) to the MakeHotDrink concept. The resulting ontologies, essentially knowledge models, are able to encode and represent domain knowledge and heuristics. This avoids manual class labeling, pre-processing and training processes in traditional data-centered approaches to activity recognition. In addition, ontologies allow agents to interpret data/information and reason against ontological contexts, thus enhancing the capabilities of automated data interpretation and inference. Once domain knowledge in smart home environment is captured, they can be formally modeled using ontologies, which include context ontologies and activity ontologies. Context ontologies consist of classes and properties for describing SH entities such as Device, Furniture, Location, Time and Sensor, and their interrelationships with an activity class. Each sensor monitors and reflects one facet of a situation. By aggregating individual sensor observations the contextual snapshots at specific time points, or say a situation, can be generated, which can be used to perform activity recognition.

Activity ontologies are the explicit representation of a hierarchy of activities that consists of activity types and their relationships in a problem domain. Activities in activity ontologies are modeled not only based on objects, environmental elements and events but

also the interrelationships between them, such as is-a or part-of relations. This allows an assistive system/agent to take advantage of semantic reasoning directly to infer activities rather than using the traditional probabilistic methods. Ontological activity recognition is closer to the logical approach in nature. It uses a logic based markup language, e.g. OWL or RDF [40] for specifying activities, and their descriptors and relationships. The major strength of ontology-based activity recognition is that the explicit commonly shared specification of terms and relationships for all relevant entities, e.g., objects, environment elements and events, facilitates interoperability, reusability and portability of the models between different systems and application domains.

### **3.3.3. Semantic sensor metadata creation**

In a SH sensor data are generated continuously, and activity assistance needs to be provided dynamically, both along a timeline. This requires that semantic enrichment of sensor data should be done in real time so that the activity inference can take place. To this end, domain specific dedicated lightweight annotation mechanisms and tools are required.

Given the nature of data in SH a two-phase semi-automatic approach to generating semantic descriptions is required. In the first phase data sources such as sensors and devices are manually semantically described. As the number of data sources in a SH is relatively limited, though large, it is manageable to create all semantic instances manually by generic ontology editors such as the Protégé OWL Plugin. In the second phase dynamically collected sensor data are first converted to textual descriptors. For example, a contact sensor returns a two-state binary value. It can be pre-processed to literals sensible for denoting two states such as on/off or open/close or used/unused, etc. The concrete interpretation of the state depends on the purpose of the sensor. For example, the two states of a contact sensor in a microwave could be open/close. If the contact sensor is attached to a milk bottle, the literal might be used or unused. The conversion of numerical values to descriptive terms is to facilitate interpretation and comprehension for both humans and machines. Pre-processed data can then be automatically attached to semantic instances of the corresponding data source to create a semantic knowledge repository. All these operations are performed through demon-like style software tools embedded in the implemented system.

### **3.3.4. Semantic sensor metadata storage and retrieval**

Once semantic data are generated, they can be archived in semantic repositories for later exchange or consumption by services and applications. Repositories may be centralised in one location or distributed in geographically dispersed sites. As all repositories share the same model, and often use the same type of access APIs, there is little difference in the retrieval of semantic data. Nonetheless, distributed repositories are required to deal with issues pertaining to security and communication bandwidth. Within SH based assistive living, data may be exchanged and shared between institutions in different countries at a global scale. It would be desirable for each institution to have a repository and its own authorisation and authentication control for the enforcement of local data usage policies.

and ethical issues. On the other hand, as the volume of various data in a single SH is expected to be reasonably low, a centralised repository should be cost effective and easy for management.

A centralised repository that consists of two interlinked components, as shown in Figure ?? can be developed for semantic data management. The first component contains semantic descriptions relating to the various sensors, devices, inhabitants and the services offered within an institution. These entities and their semantic descriptions are relatively stable for a care institution, i.e., static data. This component can functionally serve as a registry so that new SHs once built within the institution, devices once added to any individual SH, inhabitants once they take residence in a SH and new services once developed, can all be registered for later discovery and reuse. The second component is dedicated to the storage of dynamically generated sensor data and derived high level ADL data, which are time dependent, varying and extensible, i.e. dynamic data. Static data only need to be described and recorded once while dynamic data have the requirement to be recorded whenever they are generated. The separation of their storage saves storage space and also increases recording efficiency. Another advantage with this design is its ability to supports dynamic, automatic discovery of devices, device data, services and inhabitants, thus facilitating reuse of data and services. Further details of these concepts will be presented in the following Section.

### 3.3.5. Activity recognition

In ontological SH modeling, activities are modeled as activity classes in the ADL ontologies and contextual information such as time, location and the entities involved is modeled as properties for describing activity classes. As such, a situation at a specific time point is actually a concept description created from SH contextual ontologies, denoting an unknown activity. In this case, activity recognition can be mapped to the classification of the unknown activity into the right position of the class hierarchy of the activity ontologies and the identification of the equivalent activity class. This is exactly the subsumption problem in DL, i.e., to decide if a concept description  $C$  is subsumed by a concept description  $D$ , denoted as  $C \subseteq D$ . The commonly used tableau proof system uses negation to reduce subsumption to unsatisfiability of concept descriptions, which can be described below.

- Reduce subsumption to check unsatisfiability of concept description, i.e., a concept  $C$  is subsumed by a concept  $D$  can be reduced to the checking of satisfiability of concept  $C$  and the negation of concept  $D$ , which can be written below  

$$C \subseteq D \mapsto C \cap \neg D$$
- Check whether an instance  $b$  of this resulting concept description can be constructed
- Build a tree-like model for the concept description
- Transform the concept description in Negation Normal Form
- Decompose the description using tableau transformation rules
- Stop when a clash occurs or no more rules are applicable

- *If each branch in the tableau contains a clash, the concept is inconsistent*

Specifically a situation, i.e., an unknown concept description at a specific time point can be generated by linking sensor observations to properties of the context ontologies and incrementally fusing a sequence of sensor observations. For example, the activation of the contact sensors in a cup and milk bottle can link the cup and milk to the unknown activity through `hasContainer` and `hasAddings` properties. By aggregating sensor observations along a time line, a specific situation, that corresponds to an unknown activity, could be constructed, e.g., `hasTime(10am)`, `hasLocation(kitchen)`, `hasContainer(cup)` and `hasAddings(milk)`. If the closest ADL class in the ADL ontologies that contains as many perceived properties as possible to the situation can be found, e.g., `MakeDrink`, then it can be deemed to be the type of ADL for the identified situation.

### 3.3.6. Activity model learning

As activity models play a critical role in mining real-time sensor data for activity recognition, to make sure that activity models are complete and accurate are of paramount importance. While ADL ontologies have the advantage of providing knowledge-rich activity models, it is difficult to manually build comprehensive ADL ontologies. In particular, given the complexity of ADLs, the differences of ways and capabilities of users carrying out ADLs and also the levels of granularity that an ADL can be modeled, building complete one-for-all ADL ontologies is not only infeasible but also rigid for adapting to various evolving use scenarios. To address this problem, we can use the manually developed ADL ontologies as the seed ADL ontologies. The seed ontologies are, on one hand, used to recognize activities as described in Section 5.1. On the other hand, we developed learning algorithms that can learn activity models from sensor activations and the classified activity traces. As such, ADL ontologies can grow naturally as it is used for activity recognition. This is actually a self-learning process in order to adapt to user ADL styles and use scenarios.

Consider that an activity description denoted by a number of sensor activations can be subsumed by an abstract ADL, but no matching equivalent ADL concept is found. This means that the situation represents a new activity. The activity is a subclass of the high-level abstract ADL but does not belong to any of its existent subclasses in the seed ontologies. If such a situation appears frequently, it is reasonable to declare the description as a new ADL class and insert the class into the corresponding place within the seed ontology hierarchy.

As an example, consider the following scenario: If sensors attached to a kitchen door, a container and a bottle (beer or wine) are activated in a regular pattern for a period of time, it is reasonable to assume that the contextual description described by these sensor observations represents a regular activity. By performing recognition reasoning, an agent can classify the contextual description as a subclass of `MakeColdDrink`. But it cannot be categorized into any subclasses of `MakeColdDrink`, e.g., `MakeIceWater`, `MakeJuice`. In this case a new ADL such as `MakeAlcoholDrink` can be declared as a new ADL class and inserted into the hierarchy below the `MakeColdDrink` class. With this refined ADL model,

when the same sensor activation pattern happens again, the assistive agent will be able to recognize the MakeAlcoholDrink ADL and be capable of providing assistance if necessary. While new ADL models can be learnt and added into ADL ontologies, a software agent will not be able to assign a proper term for the learnt ADL and also validate the model. Therefore, human intervention, in particular with regard to model evaluation, validation, naming, is indispensable. Nevertheless, the learning mechanism has the ability to automatically indentify the trends and make the recommendation on how the ADL models are to be improved.

### 3.3.7. Activity assistance

With activity ontologies as activity models, and activity instances from a specific inhabitant as the inhabitant's activity profile, the propose approach can support both coarse-grained and fine-grained activity assistance. The former is directly based on subsumption reasoning at concept (or class) level, i.e., TBox while the latter on subsumption reasoning at instance level, i.e., ABox - an inhabitant's ADL profile. For coarse-grained activity assistance, the process is nearly the same as activity recognition described in section 5.1. The extra step is to compare the properties of the recognized activity with the properties identified by sensor observations. The missing property(ies) can then be used to suggest next action(s). For example, if the recognized activity is MakeTea with properties hasContainer, hasAddings and hasHotDrinkType, and the sensor activations indicate tea as HotDrinkType and cup as Container, then advice on Addings such as milk or sugar can be provided.

For fine-grained personalized activity assistance, it is necessary to identify how an inhabitant performs the recognized type of activity in terms of its ADL profile. The discovered ADL instance can then be compared with what has already been performed to decide what need to be done next in order to accomplish the ongoing ADL. For example, a unknown ADL has been identified in the context of hasContainer(cup), hasAddings(milk) and hasHotDrinkType(coffee). Using the aforementioned recognition mechanism, the MakeHotDrink ADL can be firstly recognised. Suppose the inhabitant has specified her/his MakeHotDrink ADL profile as hasContainer(cup), hasAddings(milk), hasHotDrinkType(coffee), hasAddings(sugar) and hasHotWater(hotWater). Through comparison, an assistive system can infer that sugar and hot water are needed in order to complete the ADL. As the matching happens at the instance level, i.e., based on the way the inhabitant performs the activity and what actually happened, it can provide inhabitants with personalised assistance.

Activity assistance can be provided in a progressive manner, i.e., initially at coarse-grained level and then fine-grained level. For instance, the MakeDrink ADL may be first identified before proceeding to recognise a concrete MakeDrink activity, such as MakeHotDrink or MakeColdDrink. In this case ADL assistance can be provided first at coarse-grained level, i.e., an assistive system suggests the immediate subactivity classes to a inhabitant without specifying concrete actions. For the above example, the system will simply offer a reminder that the following ADL could be MakeHotDrink or MakeColdDrink. Once an inhabitant takes further actions by following the coarse-gained assistance, the unknown

activity will unfold gradually towards the leaf activity. The increasing sensor data will be available to help recognise the leaf activity. Once at this stage fine-grained activity assistance can be provided.

### 3.4. An exemplar case study

We use the "MakeDrink" ADL as an application scenario to demonstrate the ontology-based activity recognition. In the case study we firstly build SH ontologies using the Protégé ontology editor covering both context and ADL ontologies, as shown in Fig. 3.3.

The MakeDrink scenario is designed based on our Smart Lab [2] environment that consists of a real kitchen. In the kitchen various sensors are attached to objects pertaining to ADLs. For example, contact sensors are attached to the entry door, containers of teabag, sugar, milk, coffee and chocolate, and a cup. The activation of a sensor indicates the occurrence of an action involving the object to which the sensor is attached. The event will be interpreted and mapped to a corresponding concept or property in the SH ontologies giving specific contextual information. For instance, the activation of a door sensor means that the location of a user is in kitchen. The activation of a coffee container means that coffee is used for an ADL as a drink type. Other sensors such as motion detectors and pressure sensors are also used in the lab for various purposes, e.g. the detection of an inhabitant and their exact location. To simplify the description, we only use a number of properties to illustrate the mechanism in the following manner.

The scenario runs as follows: In first instance the kitchen door sensor is activated. Then the system detects the activation of the sensors attached to a cup, a teabag container and a milk bottle in a temporal sequence. Suppose no other sensors were activated during this period that the above sensors become active. The question is therefore which ADL just took place?

To infer the ADL, it is necessary to map sensor activations to the state changes of the objects to which sensors are attached. The mapping relations are modelled by the Sensor and HomeEntity classes in the SH ontologies. The hasSensor property in the HomeEntity class links each home object such as sugar, fridge, microwave and cup to the attached sensor such as a contact sensor. Then the sensor readings contained in the hasSensorState property in the Sensor class can be mapped to the values of the hasEntityState property in the HomeEntity class. For example, the activation of a contact sensor in a sugar container is mapped to the "used" state for the hasEntityState property of the Sugar class. As the Sugar class is a subclass of the Addings class in the ontology and the Addings class is a filler class for the hasAdding property, this means that an anonymous ADL has the hasAdding property. In this way, the sequence of sensor activations in the above scenario can denote an anonymous ADL that is described by the following contextual properties, i.e. hasLocation, hasContainer, hasAdding and hasHotDrinkType. Based on the situational context and the context ontologies, ADL inference can be performed in a number of ways, which are described below using Protégé Version 4.

**ADL Recognition:** The ADL recognition algorithm described in Section 5 can be per-

formed in the FaCT++ reasoner [41] that has been bundled with Protégé 4 as a backend reasoner. Protégé 4 provides a query frontend, i.e. DL Query tab through which complex query expressions can be framed. Fig. 3.4 shows the implementation process of the ADL recognition. We first input the situational context described above into the class expression pane using a simplified OWL DL query syntax. When the Execute button is pressed, the specified context is passed onto the backend FaCT++ reasoner to reason against the ontological ADL models. The results which are returned are displayed in the Super classes, Sub classes, Descendant classes, Instances and Equivalent classes panes, which can be interpreted as follows:

- If a class in the Super classes pane is exactly the same as the one in the Sub classes pane, then the class can be regarded as the ongoing ADL.
- If a class in the Super classes is different from the one in the Sub classes, then the inferred ADL can be viewed as an intermediate ADL between a superclass and a subclass. In our example, the situation can be interpreted as that a type of MakeHotDrink ADL has been performed. Even though MakeTea is a sub class of the inferred ADL it is not possible to claim that it is a MakeTea ADL. This means some descriptive properties may be missing, e.g. a hasHotWater property may be needed in order to ascertain the inferred ADL as the MakeTea ADL.
- In both cases described above, the Instances pane contains recognised concrete instances of the inferred ADL. These instances usually model and represent a user's preferred way of performing the class of inferred ADL.

The activities recognised in the above cases a and b are coarse-grained, i.e., an assistive agent can only suggest a type (class or subclass) of activity to an inhabitant as the ongoing ADL, e.g. to remind an inhabitant "are you going to make tea?". To recognise fine-grained personalised ADLs, an assistive agent needs to compare the perceived sensorised contextual information with the specified property values of the instances in the Instance pane. Fig. 3.5 shows the main properties of the *UserA\_Prefered\_Tea ADL*. In comparison with the perceived context of cup, hot water, location and teabag, an assistive agent can recognise that the user is making a Chinesetea with skimmed milk and sugar along with a China cup. Based on fine-grained activity recognition, advice on completing the ongoing ADL can be tailored to a user's ADL preferences.

**Progressive ADL Recognition under incomplete sensor observations:** The proposed ontology based domain driven approach can perform progressive incremental ADL recognition under incomplete sensor observations. Fig. 3.6 shows the screenshots of recognition operation at three sequential time points. As can be seen, with only location context, i.e. the kitchen door sensor activated, the agent can infer that the ongoing ADL is definitely a KitchenADL and one of the five ADL instances as shown in Screenshot (i). As the ADL progresses, more contextual information can be captured and used to reason against the ontological ADL models. This will allow incremental ADL recognition. For example, with the hasContainer, has Adding and hasHotWater properties, the agent can infer the ongoing ADL as the MakeHotDrink ADL with three instances. With the hasHotDrinkType property



captured, the agent can further recognise that this is a type of MakeTea ADL with only one instance.

It is worth pointing out that the discussions in this section are based on the simplified application scenario, i.e., "MakeDrink" ADL recognition. Its main purpose is to demonstrate the proposed approach, its implementation and operation. Though the experiments involve only part of the SH ontologies, the methods and mechanisms can be extended and applied to complex scenarios. Our experiments have been carried out using the latest Protégé toolsets. As all tools in Protégé consists of application programming interfaces, it is straightforward to develop an integrated system as outlined in Section 3.

### 3.5. Emerging research on activity recognition

#### 3.5.1. Complex activity recognition

Most existing work on activity recognition is built upon simplified use scenarios, normally focusing on single-user single-activity recognition. In real world situations, human activities are often performed in complex manners. These include, for example, that a single actor performs interleaved and concurrent activities and/or a group of actors interact with each other to perform joint activities. Apparently existing research results, i.e., the approaches and algorithms described in previous sections cannot be applied directly for recognising complex activities. Researchers in related communities have realised this knowledge gap and more attention is being focused towards to this area. This shift of research emphasis is also driven by the increasing demand on scalable solutions that are deployable to real world use cases. Nevertheless, research endeavors in this niche field are still at an infancy.

In the modelling and recognition of complex activities of a single user, Wu *et al.* [42] proposed an algorithm using factorial conditional random field (FCRF) for recognizing multiple concurrent activities. This model can handle concurrency but cannot model interleaving activities and cannot be easily scaled up. Hu *et al.* [43] proposed a two-level probabilistic and goal-correlation framework that deals with both concurrent and interleaving goals from observed activity sequences. They exploited skip-chain conditional random fields (SCCRF) at the lower level to estimate the probabilities of whether each goal is being pursued given a newly observed activity. At the upper level they used a learnt graph model of goals to infer goals in a "collective classification" manner. Modayil *et al.* [44] introduced Interleaved Hidden Markov Models to model both inter-activity and intra-activity dynamics. To reduce the size of the state space, they used an approximation for recognizing multitasked activities. Gu *et al.* [45] proposed an Emerging Patterns based approach to Sequential, Interleaved and Concurrent Activity Recognition (epSICAR). They exploit Emerging Patterns as powerful discriminators to differentiate activities. Different from other learning-based models built upon the training dataset for complex activities, they built activity models by mining a set of Emerging Patterns from the sequential activity trace only and applied these models in recognizing sequential, interleaved and concurrent activities.

In the modeling and recognition of complex activities of group or multiple occupants,

existing work has mainly focused on vision analysis techniques for activity recognition from video data. Various HMM models have been developed for modeling an individual person's behavior, interactions and probabilistic data associations. These include the dynamically multi-linked HMM model [46], the hierarchical HMM model [47], the Coupled HMM [48], the mixed-memory Markov model [49] and the Layered Hidden Markov Models (LHMMs) [50]. DBN models are also extensively used to model human interaction activities [51] [52] both using video cameras. Lian *et al.* [53] used FCRF to conduct inference and learning from patterns of multiple concurrent chatting activities based on audio streams. Work on using dense sensing for complex activity recognition is rare. Lin *et al.* [54] proposed a layered model to learn multiple users' activity preferences based on sensor readings deployed in a home environment. Nevertheless, their focus is on learning of preference models of multiple users rather than on recognizing their activities. Wang *et al.* [55] used CHMMs to recognize multi-user activities from dense sensor readings in a smart home environment. They developed a multimodal sensing platform and presented a theoretical framework to recognize both single-user and multi-user activities. Singla *et al.* [56] proposed a single HMM model for two residents. The model can not only represent transitions between activities performed by one person, but also represent transitions between residents and transitions between different activities performed by different residents. As such their probabilistic models of activities are able to recognize activities in complex situations where multiple residents are performing activities in parallel in the same environment.

### 3.5.2. Domain knowledge exploitation

As can be seen from the above discussions, at present, there is a multitude of sensing technologies, multimodal devices and communication platforms being developed and deployed in smart environments for activity monitoring. There is an abundance of approaches and algorithms for activity recognition in various scenarios, including a single user performing a single activity, a single user performing interleaved multiple activities and multiple users performing complex activities. Nevertheless, existing endeavors for activity monitoring and recognition suffer from several main drawbacks.

Firstly, sensor data generated from activity monitoring, in particular in the situations of using multimodal sensors and different types of sensors, are primitive and heterogeneous in format and storage, and separated from each other in both structure and semantics. Such data sets are usually ad hoc, lack of descriptions, thus difficult for exchange, sharing and reuse. To address this problem researchers have made use of domain knowledge to develop high-level formal data models. Nugent *et al.* [57] proposed a standard XML schema HomeML for smart home data modelling and exchange; Chen *et al.* [58] proposed context ontologies to provide high-level descriptive sensor data models and related technologies for semantic sensor data management aiming to facilitate semantic data fusion, sharing and intelligent processing. We believe knowledge rich data modelling and standardisation supported by relevant communities is a promising direction towards a commonly accepted framework for sensor data modelling, sharing and reuse.

Secondly, current approaches and algorithms for activity recognition are often carefully handcrafted to well-defined specific scenarios. Existing implemented proof-of-concept systems are mainly accomplished by plumbing and hardwiring the fragmented, disjointed, and often ad hoc technologies. This makes these solutions subject to environment layout, sensor types and installation, and specific application scenarios, i.e., lack of interoperability and scalability. The latest experiments performed by Biswas *et al.* [59] indicated it is difficult to replicate and duplicate a solution in different environments even for the same, simplest single-user single-activity application scenario. This highlights the challenge to generalise approaches and algorithms of activity recognition to real world use cases. While it is not realistic to pre-define one-size-fits-all activity models due to the number of activities and the variation of the way activities are performed, it is desirable if rich domain knowledge can be exploited to produce initial explicit generic activity models. These models are later used, on the one hand, to generate fine-grained individual-specific activity models, and on the other hand, to evolve towards completion through learning. Chen *et al.* [60] proposed activity ontologies for this purpose and initial results are promising. It is expected further work is needed along this line.

Domain knowledge will certainly play a dominant role when activity recognition is designed as a component of a complete system, e.g., as an input to support inference and decision making. An envisioned application is to use activity recognition to perform behavioural or functional assessment of adults in their everyday environments. This type of automated assessment also provides a mechanism for evaluating the effectiveness of alternative health interventions. For example, Patel *et al.* [61] used accelerometer sensor data to analyse and assess activities of patients with Parkinson's disease. They developed analysis metrics and compared the results with assessment criteria from domain experts to estimate the severity of symptoms and motor complications. This demonstrates that domain knowledge about activity profiling and assessment heuristics are valuable for providing automated health monitoring and assistance in an individual's everyday environment.

### 3.5.3. Infrastructure mediated activity monitoring

Although many sensor-based activity recognition systems have been developed in the past decade, most of them are still set in experimental environments. To be deployed in real-life settings, activity recognition systems must be scalable, in-expensive, easy to install and maintain. Instead of installing an extensive sensing infrastructure or a large number of low-cost sensors, it is important to leverage a home's existing infrastructure to "reach into the home" with a small set of strategically-placed sensors [63]. Infrastructure mediated activity monitoring requires selecting appropriate sensors and designing elaborate methods for combining the sensors with the existing infrastructure. Patel *et al.* [62] detected human movement by differential air pressure sensing in HVAC system ductwork. Fogarty *et al.* [63] deploy a small number of low-cost sensors at critical locations in a home's existing water distribution infrastructure. The authors infer activities in the home based on water usage patterns. These systems would be useful to explore this direction.

### 3.5.4. Abnormal activity recognition

The existing systems recognize activities in various levels such as action level, ADL (Activity of Daily Living) level, and high level. But they all are normal activities. Another kind of activity that we should pay attention is abnormal activity. Detecting abnormal activities is a particularly important task in security monitoring and healthcare applications. Nevertheless it is challenging to solve the problem. First what is an abnormal activity; we might have a variety of definitions. For instance everyone do activity A, one person does activity B; we can call it an abnormal activity. Yin *et al.* [64] defined abnormal activities as events that occur rarely and have not been expected in advance. Second there is an unbalanced data problem in abnormal activity detection. Much larger proportion of sensing data is about normal activity, while the data for abnormal ones is extremely scarce, which makes training the classification model quite difficult.

### 3.6. Conclusions

There is no doubt that intelligent pervasive environments and applications will pervade future working and living spaces, transform our lives and impact our society. Activity recognition is becoming an increasingly important determinant to the success of context-aware personalised pervasive applications. Synergistic research efforts in various scientific disciplines, e.g., computer vision, artificial intelligence, sensor networks and wireless communication to name but a few, have brought us a diversity of approaches and methods to address this issue. In this chapter we first presented a focal review on the state-of-the-art of activity recognition and described their strengths and weaknesses of both approaches and algorithms. It becomes evident that new approaches and methods are required to deal with the sensor data of multiple modalities and the large number of activities of different nature and complexity in the context of ever-growing novel pervasive applications. In particular, such approaches and methods should tackle technical challenges in terms of their robustness to real-world conditions and real-time performance, e.g., applicability, scalability and reusability.

Ontology-based approach to activity recognition has recently emerged and initial results have proved it is a promising direction. As such we introduced the practice and lifecycle of the ontology-based approach covering ontological modelling, representation and inference of sensor, objects and activities in the lifecycle of activity recognition. We have outlined an integrated system architecture to illustrate the realisation of the proposed approach. In the context of ambient assisted living, we have analysed the nature and characteristics of ADLs and developed the concepts of ADL ontologies. We have described the algorithms of activity recognition making full use of the reasoning power of semantic modelling and representation. We have used a simple yet convincing example scenario to illustrate the use of the approach for a real world problem. Compared with traditional approaches, ontological ADL models are flexible and can be easily created, customised, deployed and scaled up. Description reasoning can provide advanced features such as exploitation of domain knowledge, progressive activity recognition and multiple levels of recognition.

We also outline and discuss future research problems and specific issues. In particular, we highlight the necessity of moving from simple activity scenarios to complex real world situations, e.g., interleaved, concurrent activities and multiple users. To address the challenges we highlight the importance of using domain knowledge and a number of issues to be addressed. We fully believe this chapter provides an overview and a reference for researchers in this active research community.

## References

- [1] Weiser, M., (1991) The computer for the twenty-first century, *Scientific American*, Vol.265, No.3, pp.94-104.
- [2] Nugent, C.D., (2008) Experiences in the Development of a Smart Lab, *The International Journal of Biomedical Engineering and Technology*, Vol.2, No.4, pp319-331
- [3] Ivano, Y. and Bobick, A., (2000) Recognition of Visual Activities and Interactions by Stochastic Parsing, *IEEE Trans Pattern Analysis and Machine Intelligence*, Vol.22, No.8, pp.852-872.
- [4] Stauffer, C. and Grimson, W.E. (2000) Learning Patterns of Activity Using Real-Time Tracking, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol.22, No.8, pp.747-757.
- [5] Bodor, R., Jackson, B., Papanikolopoulos, N. (2003) Vision based human tracking and activity recognition, In *Proceedings of the 11th Mediterranean Conference on Control and Automation*.
- [6] Fiore, L., Fehr, D., Bodor, R., Drenner, A., Somasundaram, G. and Papanikolopoulos, N. (2008) Multi-Camera Human Activity Monitoring, *Journal of Intelligent and Robotic Systems*, Vol.52, No.1, pp.5-43.
- [7] Bao, L. and Intille, S. (2004) Activity recognition from userannotated acceleration data, In *Proc. Pervasive*, LNCS3001, pp.1-17.
- [8] Huynh D. T. G. (2008) Human Activity Recognition with Wearable Sensors, PhD thesis, TU Darmstadt.
- [9] Patterson, DJ., Fox, D., Kautz, H. and Philipose, M. (2005) Fine-grained activity recognition by aggregating abstract object usage, In *Proc. of IEEE International Symposium on Wearable Computers*, pp.44-51.
- [10] Lee, SW. and Mase, K. (2002) Activity and location recognition using wearable sensors, *IEEE Pervasive Computing*, Vol.1, No.3, pp.24-32.
- [11] Parkka, J., Ermes, M., Korpipaa, P., Mantyjarvi, J., Peltola, J. and Korhonen, I. (2006) Activity classification using realistic data from wearable sensors, *IEEE Transactions on Information Technology in Biomedicine*, Vol.10, No.1, pp.119-128.
- [12] Philipose, M. , Fishkin, K. P., Perkowitz, M., Patterson, D. J., Hahnel, D., Fox, D. and Kautz, H. (2004) Inferring Activities from Interactions with Objects, *IEEE Pervasive Computing: Mobile and Ubiquitous Systems*, Vol.3 No.4, pp.50-57.
- [13] Chan, M., Estéve, D., Escriba, C., Campo, E. (2008) A review of smart homes-Present state and future challenges” *Computer Methods and Programs in Biomedicine*, Vol.91, No.1, pp.55-81.
- [14] Helal, S., Mann, W., El-Zabadani, H., King, J., Kaddoura, Y., Jansen, E. (2005) The gator tech smart house: a programmable pervasive space, *IEEE Computer*, Vol.38 No.3, pp.64-74.
- [15] Ward, J.A., Lukowicz, Troter P., and Starner, T. G. (2006) Activity recognition of assembly tasks using body-worn microphones and accelerometers, *IEEE Trans.Pattern Analysis and Machine Intelligence*, Vol.28 No.10, pp.1553-1567.
- [16] Boger, J., Poupart, P., Hoey, J., Boutilier, C., Mihailidis, A. (2005) A Decision-Theoretic Approach to Task Assistance for Persons with Dementia, In *Proc. of the International Joint Conference on Artificial Intelligence (IJCAI’05)*, pp.1293-1299.
- [17] Wang, S., Pentney, W., Popescu, A.M., Choudhury, T., Philipose, M. (2007) Common Sense

- Based Joint Training of Human Activity Recognizers, In Proc. International Joint Conference on Artificial Intelligence.
- [18] Albrecht, D.W., Zukerman, I. (1998) Bayesian Models for Keyhole Plan Recognition in an Adventure Game, User Modelling and User-Adapted Interaction, Vol.8, pp.5-47.
  - [19] Tapia, E. M., Intille, S. (2007) Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart rate monitor, In International Symposium on Wearable Computers (ISWC).
  - [20] Huynh, T., Schiele, B. (2006) Unsupervised Discovery of Structure in Activity Data using Multiple Eigenspaces, In 2nd International Workshop on Location- and Context-Awareness (LoCA), LNCS vol.3987.
  - [21] Liao, L., Fox, D., and Kautz, H., Extracting Places and Activities from GPS Traces Using Hierarchical Conditional Random Fields. The International Journal of Robotics Research, 26(1):119, 2007.
  - [22] Kautz, H. (1991) A Formal Theory of Plan Recognition and its Implementation, Reasoning About Plans, Allen J., Pelavin R. and Tenenbergs J. eds., Morgan Kaufmann, San Mateo, C.A., pp.69-125.
  - [23] Wobke W. (2002) Two Logical Theories of Plan Recognition, Journal of Logic Computation, Vol.12 No.3, pp.371-412.
  - [24] Bouchard, B., Giroux, S. (2006) A Smart Home Agent for Plan Recognition of Cognitively-impaired Patients, Journal of Computers, Vol.1, No.5, pp.53-62.
  - [25] Chen, L., Nugent C., Mulvenna M., Finlay D., Hong X., Poland M. (2008) A Logical Framework for Behaviour Reasoning and Assistance in a Smart Home, International Journal of Assistive Robotics and Mechatronics, Vol. 9, No.4, pp. 20-34.
  - [26] Chen, D., Yang, J., and Wactlar, H.D. (2004) Towards automatic analysis of social interaction patterns in a nursing home environment from video, in Proc. 6th ACM SIGMM Int. Workshop Multimedia Inf. Retrieval, pp. 283-290.
  - [27] Hakeem, A. and Shah, M. (2004) Ontology and Taxonomy Collaborated Framework for Meeting Classification, In Proc. Int. Conf. Pattern Recognition, pp.219-222.
  - [28] Georis, B., Maziere, M., Bremond, F. and Thonnat, M. (2004) A video interpretation platform applied to bank agency monitoring, in Proc. 2nd Workshop Intell. Distributed Surveillance System, pp.46-50.
  - [29] Hobbs, J., Nevatia, R., and Bolles, B. (2004) An Ontology for Video Event Representation, In IEEE Workshop on Event Detection and Recognition.
  - [30] Francois, A.R.J., Nevatia, R., Hobbs, J., Bolles, R.C. (2005) VERL: An Ontology Framework for Representing and Annotating Video Events, IEEE MultiMedia, Vol.12, No.4, pp.76-86.
  - [31] Akdemir, U., Turaga, P., Chellappa, R. (2008) An ontology based approach for activity recognition from video, Proceeding of the 16th ACM international conference on Multimedia, pp.709-712.
  - [32] Yamada, N., Sakamoto, K., Kunito, G., Isoda, Y., Yamazaki, K., Tanaka, S. (2007) Applying Ontology and Probabilistic Model to Human Activity Recognition from Surrounding Things, IPSJ Digital Courier, Vol.3, pp.506-517.
  - [33] Latfi, F., Lefebvre, B., Descheneaux, C. (2007) Ontology-Based Management of the Telehealth Smart Home, Dedicated to Elderly in Loss of Cognitive Autonomy, CEUR Workshop Proceedings, vol.258, (online) available: <http://ftp.informatik.rwth-aachen.de/Publications/CEUR-WS/Vol-258/paper42.pdf>.
  - [34] Michael, K., Schmidt, A., Lauer, R. (2007) Ontology-Centred Design of an Ambient Middleware for Assisted Living: The Case of SOPRANO, In Proc. of the 30th Annual German Conference on Artificial Intelligence
  - [35] Chen, L., Nugent, C.D., Mulvenna, M., Finlay, D. and Hong, X. (2009) Semantic Smart Homes: Towards Knowledge Rich Assisted Living Environments, Studies in Computational

- Intelligence, Vol.189, pp.279-296.
- [36] James, AB. (2008) Activities of daily living and instrumental activities of daily living, In: Crepeau EB, Cohn ES, Schell BB, editors. Willard and Spackman's Occupational Therapy. Philadelphia: Lippincott, Williams and Wilkins. pp.538-578.
  - [37] WHO, World Health Organization, International classification of functioning, disability and health (ICF), <http://www.who.int/classifications/icf/en/>
  - [38] Wyatt, D., Philipose, M., Choudhury, T.: Unsupervised activity recognition using automatically mined common sense, in: Proc. of AAAI 2005 (2005)
  - [39] Tapia, M.E., Choudhury, T., Philipose, M. (2006) Building Reliable Activity Models using Hierarchical Shrinkage and Mined Ontology, Proceedings of the 4th International Conference on Pervasive Computing, pp.17-32.
  - [40] OWL and RDF specifications, <http://www.w3.org/>
  - [41] Horrocks, I., Sattler, U., Tobies, S. (1999) Practical reasoning for expressive description logics, Lecture Notes in Artificial Intelligence, No.1705, pp.161-180.
  - [42] Wu, T.Y., Lian, C.C., Hsu, J.Y. Joint recognition of multiple concurrent activities using factorial conditional random fields, in: Proc. AAAI Workshop Plan, Activity, and Intent Recognition, California, 2007.
  - [43] Hu, D. H., Yang, Q. Cigar: concurrent and interleaving goal and activity recognition, in: Proc. AAAI, Chicago, Illinois, USA, 2008.
  - [44] Modayil, J., Bai, T., Kautz, H., Improving the recognition of interleaved activities, Proceedings of the 10th international conference on Ubiquitous computing, UbiComp; Vol. 344, pp.40-43, 2008
  - [45] Gu, T., Wu, Z., Tao, X.P., Pung, H.K., Lu, J. epSICAR: An Emerging Patterns based Approach to Sequential, Interleaved and Concurrent Activity Recognition. In Proc. of the 7th Annual IEEE International Conference on Pervasive Computing and Communications (Percom '09), pp.1-9, 2009.
  - [46] S. Gong, T. Xiang, Recognition of group activities using dynamic probabilistic networks, in: Proc. of ICCV 2003, Nice, France, 2003, pp. 742-749.
  - [47] Nguyen, N., Bui, H., Venkatesh, S., Recognising behaviour of multiple people with hierarchical probabilistic and statistical data association, in: Proc of the 17th British Machine Vision Conference (BMVC 2006), Edinburgh, Scotland, 2006.
  - [48] Oliver, N., Rosario, B., Pentland, A., A bayesian computer vision system for modeling human interactions, in: IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 22, 2000, pp. 831-843.
  - [49] Choudhury, T., Basu, S., Modeling conversational dynamics as a mixed memory markov process, in: Advances in Neural Information Processing Systems 17, MIT Press, Cambridge, MA, 2005, pp. 281-288.
  - [50] Oliver, N., Garg, A., Horvitz, E., Layered representations for learning and inferring office activity from multiple sensory channels, in: Computer Vision and Image Understanding, November 2004, pp. 163-180
  - [51] Du, Y., Chen, F., Xu, W., Li, Y., Recognizing interaction activities using dynamic bayesian network, in: Proc. of ICPR 2006, Hong Kong, China, 2006.
  - [52] Wyatt, D., Choudhury, T., Bilmes, J., Kautz, H., A privacy sensitive approach to modeling multi-person conversations, in: Proc. IJCAI, India, 2007.
  - [53] Lian, C., Hsu, J., Chatting activity recognition in social occasions using factorial conditional random fields with iterative classification, in: Proceedings of the Twenty-Third AAAI Conference on Artificial Intelligence (2008), Chicago, Illinois, 2008.
  - [54] Lin Z. Fu, L., Multi-user preference model and service provision in a smart home environment, in: Proc. of IEEE International Conference on Automation Science and Engineering (CASE 2007), 2007.

- [55] Wang, L., Gu, T., Tao, X., Lu, J., Sensor-Based Human Activity Recognition in a Multi-user Scenario, *Aml* 2009, LNCS 5859, pp. 78-87, 2009.
- [56] Singla, G., Cook, D., Schmitter-Edgecombe, M., Recognizing independent and joint activities among multiple residents in smart environments. *Ambient Intelligence and Humanized Computing Journal*, 1(1):57-63, 2010.
- [57] Nugent C.D., Finlay D.D., Davies R., Wang H.Y., Zheng H., Hallberg J., Synnes K., Mulvenna M.D., homeML - An open standard for the exchange of data within smart environments, *Proceedings of 5th International Conference on Smart homes and health Telematics, Lecture Notes in Computer Science (Vol. 4541)*, pp.121-129, 2007
- [58] Chen L., Nugent C.D., (2009), Semantic Data Management for Situation-aware Assistance in Ambient Assisted Living, the proceedings of the 11th International Conference on Information Integration and Web-based Applications & Services (iiWAS2009), ACM ISBN 978-1-60558-660-1, pp. 296-303
- [59] Biswas, J., Tolstikov, A., Phyo Wai, A., Baumgarten, M., Nugent, C., Chen, L., Donnelly, M., Replicating Sensor Environments for Ambient Assisted Living : A Step Towards Scaled Deployment, accepted for International Conference on Smart homes and health Telematics (ICOST2010), 2010
- [60] Chen L., Nugent C.D., (2009), Ontology-based activity recognition in intelligent pervasive environments, *International Journal of Web Information Systems*, vol.5, no.4, pp.410-430
- [61] Patel, S., Lorincz, K., Hughes, R., Huggins, N., Bonato, Monitoring Motor Fluctuations in Patients With Parkinson's Disease Using Wearable Sensors, *IEEE Transaction on Information Technologies in Biomedicine* , Vol.13, No.6, Nov. 2009
- [62] Patel, S.N., Reynolds, M.S., Abowd, G.D., Detecting Human Movement by Differential Air Pressure Sensing in HVAC System Ductwork: An Exploration in Infrastructure Mediated Sensing. *Proc. of the 6th International Conference on Pervasive Computing (Pervasive 2008)*, pp. 1-18, Sydney, Australia, 2008.
- [63] Fogarty, J., Au, C., and Hudson, S. E., Sensing from the Basement: A Feasibility Study of Unobtrusive and Low-Cost Home Activity Recognition, *UIST'06*, 91-100.
- [64] Yin, J., Yang, Q., Pan, J., Sensor-based abnormal human-activity detection. *IEEE Trans. Knowl. Data Eng.*, 20(8):1082-1090, 2008.



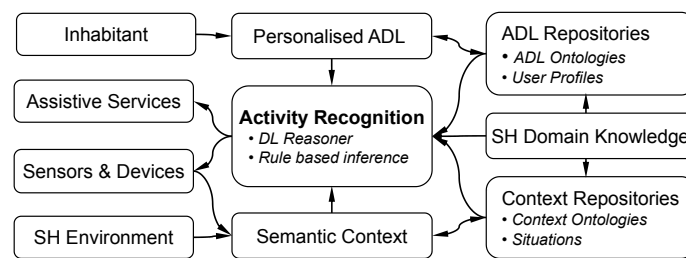


Fig. 3.1. The system architecture

Fig. 3.2. The system architecture

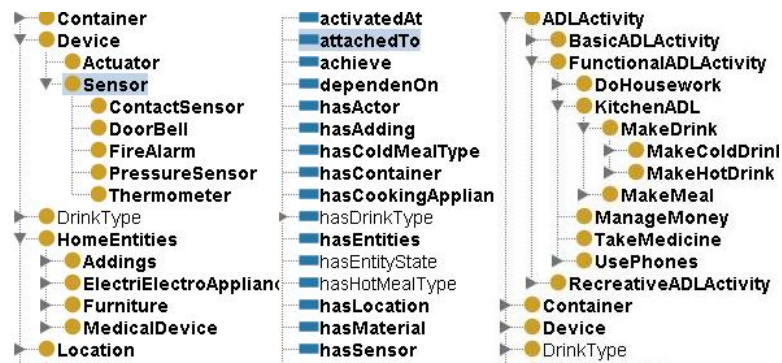


Fig. 3.3. A fragment of the SH context and ADL ontologies



Fig. 3.4. A fragment of the ADL recognition process

| Property assertions: UserA_Prefered_Tea |                  |
|---|------------------|
| Object property assertions              |                  |
| hasHotDrinkType                         | ChineseTea       |
| hasContainer                            | ChinaCup         |
| hasHotWater                             | 80DegreeHotWater |
| hasAdding                               | SkimmedMilk      |
| hasAdding                               | SandSugar        |

Fig. 3.5. An example of a user’s ADL profile

Query (class expression)

hasLocation **some** Kitchen

Execute Add to ontology

Query results

Super classes (1)

ADLActivity

Sub classes (1)

KitchenADL

Instances (5)

UserA\_Prefered\_Water

UserA\_Prefered\_Chocolate

UserA\_Prefered\_Juice

UserA\_Prefered\_Tea

UserA\_Prefered\_Coffee

Query (class expression)

hasLocation **some** Kitchen **and** hasContainer **some** Container **and** hasAdding **some** Addings **and** hasHotWater **some** HotWater

Execute Add to ontology

Query results

Super classes (1)

MakeDrink

Sub classes (1)

MakeHotDrink

Instances (3)

UserA\_Prefered\_Chocolate

UserA\_Prefered\_Tea

UserA\_Prefered\_Coffee

Query (class expression)

hasLocation **some** Kitchen **and** hasContainer **some** Container **and** hasAdding **some** Addings **and** hasHotWater **some** HotWater **and** hasHotDrinkType **some** Tea

Execute Add to ontology

Query results

Super classes (1)

MakeHotDrink

Sub classes (1)

MakeTea

Instances (1)

UserA\_Prefered\_Tea

Fig. 3.6. Screenshots of progressive ADL recognition