Engineering Knowledge for Assistive Living

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Abstract. This paper introduces a knowledge based approach to assistive living in smart homes. It proposes a system architecture that makes use of knowledge in the lifecycle of assistive living. The paper describes ontology based knowledge engineering practices and discusses mechanisms for exploiting knowledge for activity recognition and assistance. It presents system implementation and experiments, and discusses initial results.

Keywords: Smart home, ontology, knowledge engineering, activity recognition, assistive living

1 Introduction

Smart Home (SH) [1] has emerged as a mainstream approach to providing assistive living and supporting ageing-in-place. A SH is considered to be augmented living environments equipped with sensors and actuators, within which monitoring of Activities of Daily Living (ADL) and personalised assistance can be facilitated. Though a number of Lab-based or real living SHs has been developed and an abundance of supportive technologies provide fragments of the necessary functionality [2], existing SH technologies and solutions suffer from major drawbacks, including data heterogeneity, lack of interoperability, reusability and applicability of technologies and solutions as well.

To address these problems, this paper introduces a knowledge based approach to evolving current smart home technologies towards the future infrastructure that is needed to support the application and large-scale deployment of smart homes in real world context. The approach is motivated by the observations that ADLs as daily routines are full of commonsense knowledge and heuristics providing rich links between environments, events and activities. The proposed approach aims to exploit semantic technologies to engineer SH domain knowledge. Specifically, SH resources, i.e., sensors, sensor data, actuators, inhabitants, ADL and services, will be formally modelled and explicitly represented with well-defined meaning, rich contextual and/or heuristic knowledge. As such, the approach can support resource interoperability and reusability through semantic descriptions, realise advanced features in the lifecycle of assistive living by making extensive use of semantic/knowledge-based intelligent processing techniques.

The paper is organised as follows. Section 2 introduces a knowledge based system architecture. Section 3 describes knowledge engineering and management practices. Section 4 outlines some typical knowledge use scenarios. We present system implementation and experiments in Section 5 and conclude the paper in Section 6.

2 A Knowledge Enabled Approach to Assistive Living

Fig. 1 shows the proposed system architecture for a SH. The Physical Layer consists of physical hardware such as sensors, actuators, and various devices including medical equipment, household appliances and network components. This layer provides the means to monitor and capture the events and actions in a SH. The Data Layer collects and stores raw data in a number of data stores. These stores are usually disparate in data formats and access interfaces, with each of them being dedicated to individual application scenarios. The Application Layer contains application dependent services and systems for assistive living. Within this layer applications can process sensor data from the Data Layer and control actuators and/or devices in the Physical Layer to offer assistance. These three layers have so far been the major components underpinning existing SH application design and development. While each layer is indispensable for any SH application, the close coupling among sensors, data and applications, often having one to one, ad hoc relationships.

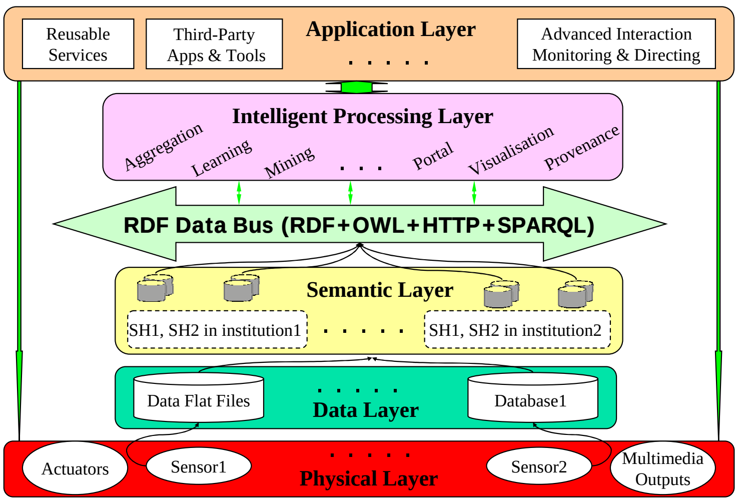

Fig. 1. The conceptual system architecture

The proposed approach incorporates a Semantic Layer, a RDF[1] Data Bus and an Intelligent Service Layer into the systems architecture. The goal of the Semantic Layer is to provide a homogeneous view over heterogeneous data, thus enabling seamless data access, sharing, integration and fusion across multiple organisations,

[1] RDF, OWL, HTTP, SPARQL are W3C standards, refer to W3C web site - www.w3.org.

providing interoperability and machine understandability. It achieves this by using SH ontologies as a unified conceptual backbone for data modeling and representation. Semantic modelling allows the markup of various data with rich metadata and semantics to generate semantic content. Multiple SHs in geographically distributed locations supported by various organisations can then aggregate and fuse their SH data. The uniform data models and representation, e.g., RDF or OWL, allow seamless data access through the RDF Bus based on the standard communication protocol HTTP and RDF query language SPARQL. The Semantic Layer is also responsible for providing tools and APIs for semantic data retrieval and reasoning.

The Intelligent Service Layer is built upon the semantic content and functionalities of the Semantic Layer. Its purpose is to exploit semantics and descriptive knowledge to provide advanced processing and presentation capabilities and services. The former provides added-values to the query interfaces of the RDF Bus through further analysis and reasoning over recorded SH data. The latter essentially visualises the contents of the repositories and the outputs of the processing services. The selection and use of such services will depend on the nature and availability of collected data as well as the personal needs of inhabitants and care providers, hence allowing for personalisation. They are accessible to third party developers, thus interoperable and reusable at both the service and application level.

3 Ontology-based Knowledge Engineering and Management

A SH is a home setting where 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. 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 ingredients, 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.

We carry out knowledge acquisition through interviews, questionnaires and by studying existing documents from which we derive the conceptual models for describing activities and their relations with sensors and objects. Based on SH characterization and the conceptual activity model we develop ADL ontologies using Protégé [3] as shown in **Fig.** 2. The ADL ontology consists of an activity hierarchy in which each node, also called a class, denotes a type of ADL. Each class is described with a number of properties. In a similar way we develop SH context ontologies that 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.

Given the nature of sensor data in SH we develop a two phase semi-automatic approach to generating semantic descriptions. In the first phase data sources such as sensors and devices are manually semantically described. In the second phase dynamically collected sensor data are first converted to textual descriptors. They are then automatically attached to semantic instances of the corresponding ontological classes to create a semantic knowledge repository. All these operations are performed through demon-like style software tools embedded in the implemented system. the generated semantic data and metadata are archived in a knowledge repository.

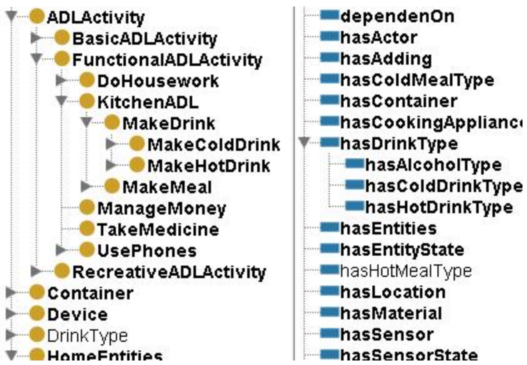

Fig. 2. A fragment of the ADL ontologies

4 Using Knowledge for Assistive Living

Once knowledge is modeled, captured and stored in knowledge repositories, it can be exploited in a diversity of ways. Three key use cases in the context of assistive living are described below.

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 can be mapped to the subsumption problem in Description Logic, i.e., to decide if a concept description $\mathcal{C}$ is subsumed by a concept description $\mathcal{D}$, denoted as $\mathcal{C} \sqsubseteq \mathcal{D}$.

Activity Model Learning - As activity models play a critical role in mining real-time sensor data for activity recognition, complete and accurate activity models 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 inflexible for adapting to various evolving use scenarios. To address this problem, we can use the manually developed ADL ontologies as the seed ADL models. The seed activity models are, on one hand, used to recognize activities as described above. 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.

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, while the latter on subsumption reasoning at instance level, i.e., based on an inhabitant's ADL profile. For coarse-grained activity assistance, the process is nearly the same as activity recognition. 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 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.

5 System Implementation and Evaluation

We have implemented a feature-rich context-aware assistive system, as shown in **Fig.** 3. The system is developed with C# while the front-end is developed using ASP.NET with Ajax and Silverlight support for audio and graphical user experience. We use the SemWeb semantic technologies for C# [4] to create and manage semantic data in persistent storage, and use SPARQL to query persistent storage via simple graph matching. We use the Euler inference engine to implement logic-based proof mechanism for reasoning. The implemented system has been deployed in a physical kitchen environment in our SmartLab [5]. We conducted two types of experiment for evaluation purposes. The first type of experiment is aimed to evaluate the performance and accuracy of activity recognition. To do this, we design a number of activity scenarios, e.g., performing *MakeTea* activity, and then ask an actor to perform an activity following the corresponding scenario. Each time the actor uses an object, the sensor attached to the object activated. The generated sensor observations are, on one hand, collected and passed onto the system for activity recognition. On the other hand, they are manually recorded and labelled. In this way, each time a sensor is activated during the activity performance, both the system and a human evaluator can produce potential activities that might be performed by the actor. By comparing the recognition results from the system and the evaluator step by step during the performance of a designated activity scenario we are able to evaluate the accuracy of activity recognition. The second type of experiment is aimed to evaluate the applicability and robustness of the system. To do this, we used the same activity scenarios but changed the system setting using system configuration tools. Then we ask an actor to perform an identical activity twice in different system settings. We compare the recognition results from the two same-activity-scenario but different-system-setting experiments to evaluate how different system configuration can affect its performance and applicability.

All experiments have yielded desired satisfactory results demonstrating that the system is fully working and the approach is viable. The system is also evaluated by healthcare professionals from local health Trusts. From users' perspectives, they have thoroughly tested the system with very positive feedback and constructive suggestions.

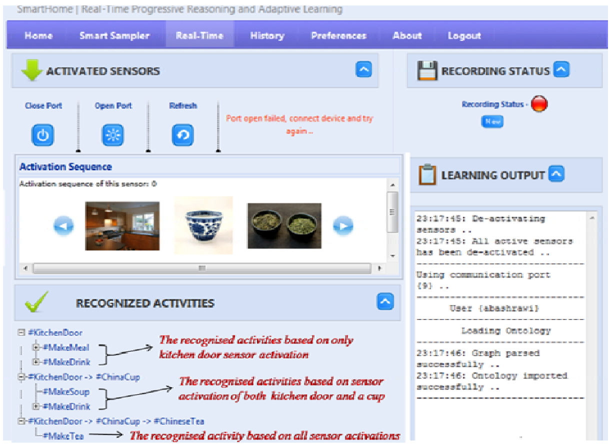

Fig. 3. The system interface in real time mode

6 Conclusions

In this paper we have applied ontology based knowledge engineering into the lifecycle of assistive living. We have discussed the system architecture, core functionalities, methodologies and technologies. Specifically we described the use of knowledge engineering and management for activity recognition, learning and assistance, and further detailed implementation, experiments and evaluation. Initial results have been positive and promising. While real world deployment of the system and large-scale evaluation of a diversity of use scenarios can be investigated in the future, the work has laid a solid architectural and methodological foundation.

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