Multimedia Delivery in Smart Home Environments

Year 1 Progress Review

Zelin Wang

Academic Supervisors: Dr. Safak Dogan & Prof. Ahmet Kondoz

Industrial Supervisors: Dr. Milosh Stolikj & Prof. Dmitri Jarnikov

Institute for Digital Technologies, Loughborough University London

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Abstract

This report provides a review of year one background study for the research activities conducted on multimedia delivery in smart home environments. Focused on delivering user-preferred multimedia service, the contribution of this research will be made to achieving smart interaction between delivered multimedia service and user, where adaption to multimedia depends on user's activity and preference shall be realised. Three domains of knowledge are touched on, which involves user activity recognition, semantic interoperability and reinforcement learning.

State-of-the-art in each domain is presented for methodology comparison and discussions. A use case is discussed for the research corresponding to the functional modules. Tests of several classification methods carried out for user activity recognition, where performance of each classifier is assessed. Structure design of the ontology which suitable for the use case is illustrated. Besides, a multimedia dataset is being created which records the changing details of media setting for a user. Later, a proof-of-concept presentation considering this multimedia dataset is explained. In the end a schedule plan for future work is illustrated in a Gantt chart.

Key words: **multimedia delivery, smart home, activity recognition, semantic interoperability, reinforcement learning**

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Abbreviations

ADL	Activity of Daily Living
AI	Artificial Intelligence
ARAS	Activity Recognition with Ambient Sensor
AWS	Amazon Web Service
CASAS	Centre for Advanced Studies in Adaptive Systems
CNN	Convolutional Neural Network
HAVC	Heating Ventilating and Air Conditioning
IR	Infrared
IoT	Internet of Thing
IoT-O	Internet of Thing - Ontology
J48	J48 Decision Tree
KNN	K Nearest Neighbour
MavHome	Managing an Adaptive Versatile Home
MDP	Markov Decision Process
MNIST	Mixed National Institute of Standards and Technology
M2M	Machine to Machine
MUM	Mobile and Ubiquitous Multimedia
NBC	Naive Bayes Classifier
OWL	Web Ontology Language
RDF	Resource Description Framework
SAREF	Smart Applicances REFerence
SEMIC	Semantic Interoperability Community
SVM	Support Vector Machine
VR	Visual Reality
W3C	World Wide Web Consortium

1. Introduction

With rapid growth in the computing speed and the explosion of data in cloud media, different sources containing different aspects of an event can be quickly collected from smart devices and stored on the cloud. Over the years, the learning pattern inside a software program has become more and more dynamic. People nowadays are expecting a better user experience from their smart devices. This is what has been generally referred to as living in a smart environment (or *smart living* in short). To be more specific, a better user experience within the smart environment means that, a user shows a positive attitude or satisfaction on the dynamic adjustment, which is made to the delivered multimedia service. For example, indoor multimedia control decreases the media volume autonomously when user is speaking on the phone, or in another case, slightly increases the media volume when a kettle is boiling water which makes the environment noisy. Before the smart environment can do this adjustment for its inhabitants, the adjustment is made by inhabitants themselves manually that, with a TV remote controller, the volume is increased or decreased accordingly. Nevertheless, today's advancement in Artificial Intelligence (AI) has driven people to design smart homes that can observe phenomenon, reason from inputs, and make decision like a human brain. The multimedia delivery in a smart home shall start from defining the research problem within this field.

1.1 Problem Statement

A smart home [1] refers to an indoor living environment, where different kinds of devices such as media services, indoor sensors, lighting, etc., can interconnect together and interface among themselves accordingly, to make inhabitants' lives more comfortable. Multimedia delivery, which typically comes in the form of a digital media stream from cloud services and delivered to a set of home devices, has so far been seen as one of the popular services provided in smart environments. In the era of Big Data, the requirement for efficient computing, as well as massive data storage bring in the achievement and popularity of cloud computing. Owing to its development, information produced by various digital devices in a smart home environment can be shared and analysed using cloud services. Several well-known cloud computing platforms including Amazon Web Service (AWS)[1], Google Cloud Platform[2] have been developed and earn their value in areas such as neural networks[3], virtual machine[4], etc.

In the case of multimedia delivery within a smart home environment as illustrated in Figure 1 messages with regard to the user of a certain event as well as the surroundings can be captured by various sensors such as motion sensors, volume sensors, luminance sensors, etc. The relationship between user activity and indoor devices can be mapped out. Multimedia delivery which includes both video and audio can then adapt to the user's activity by learning the user's present and previous behaviours and habits.

1 https://aws.amazon.com/

2 https://cloud.google.com/

3 http://techblog.netflix.com/2014/02/distributed-neural-networks-with-gpus.html

4 https://cloudplatform.googleblog.com

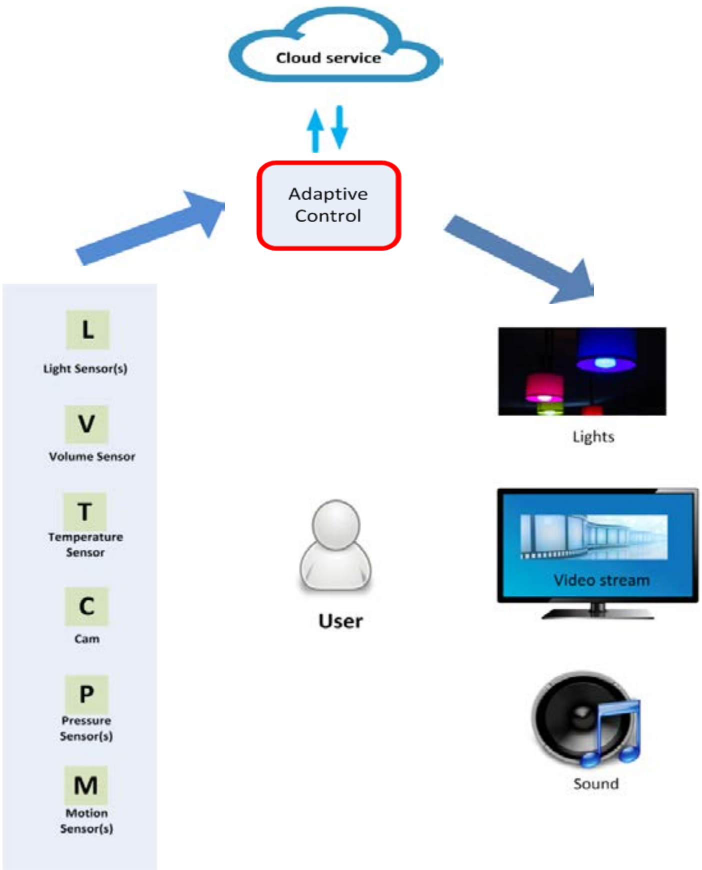


Figure 1. A brief illustration of multimedia delivery in smart home environments

With information from user, home environment and multimedia services, the research question is: how to achieve the home automation of multimedia adaption so that the user can experience the convenience and intelligence of the smart home, thus leading a life in a smart way by aid of the surroundings?

1.2 Current Applications and Techniques

The research with regards to smart home applications varies in a wide range according to different motivations. Activity recognition, which serves the purposes such as everyday living, medical aid, indoor energy consumption control, etc., has seen a few achievements in the past few decades [2].

On the entertainment aspect, the indoor multimedia has seen progress in the automatic adaption of streaming quality depending on the Internet conditions [3]. One application is video quality setting in YouTube, that if the displayed video runs on 'automatic' quality, the actual streaming quality would vary from time to time, delivering higher quality in good web connectivity condition. Moreover, one of the latest techniques to date is the development of Visual Reality (VR). With VR glasses as well as headphones, people can get to enjoy unique experience such as wandering on the moon, flying like a Spiderman. A good example is Sony's PlayStation for VR, to be released in October, 2016[5].

5 https://www.playstation.com/en-us/corporate/press-releases/2016/sony-interactive-entertainment-america-unveils-extraordinary-gaming-experiences-for-playstation-4-and-playstation-vr-at-e3-2016/

Linguistic-related research also finds its way in research areas such as user identification, speech recognition, multilingual transformation, etc. While linguistic user identification gains its value in personal security, speech recognition, which can realise the man-machine communication by providing useful information according to user's commands, has been applied in products such as Amazon Echo[6]. Multilingual transformation, on the other hand, can break down the obstacle of communication for people who speak different languages.

Communication techniques and standards such as WiFi, IEEE 802.15.4, etc., provide the intercommunication among devices within the smart home. The new advances in indoor lighting brings in smart bulbs such as Philips Hue[7], LIFX[8], which can adapt both colours and luminance in accordance with media delivery or user instruction when they are connected and work together with other indoor equipment such as smart TV, smart phone and so on.

1.3 Research Objectives

Driven by the existing research and technologies in smart home environments, the main aim of this research is to develop a framework to adapt multimedia delivery settings by analysing user's activity information, both present and historical, received from various sensors in smart home environments. To achieve this final goal, three areas of work shall be targeted.

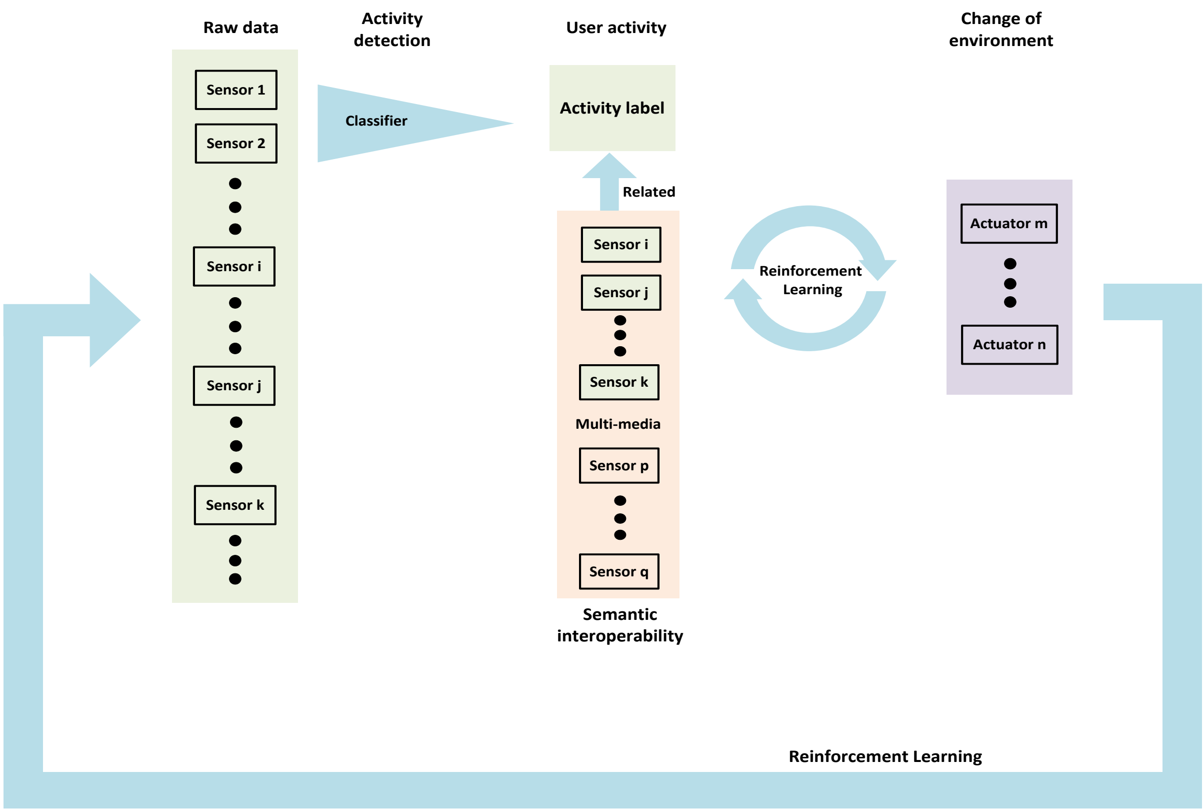


Figure 2. Functional modules of multimedia delivery in smart home environments

6 https://www.amazon.com/Amazon-Echo-Bluetooth-Speaker-with-WiFi-Alexa/dp/B00X4WHP5Ehttps://en.wikipedia.org/wiki/Amazon_Echo

7 http://www.developers.meethue.com/documentation/how-hue-works

8 http://www.lifx.com/

The first one is user activity recognition, followed by it is the semantic interoperability which maps out the relationship between the user activity and ambient environment, and then comes the reinforcement learning for allowing adaption to the multimedia services. Attention will be focused on the following key objectives:

- To compare and contrast the classifiers used in indoor activity recognition and provide their comparison results by testing on a chosen dataset.
- To develop an ontology framework that can be used to associate devices, multimedia service and user’s activity.
- To develop a control framework that can reason on the user’s activity and make necessary changes to the multimedia settings accordingly.

Figure 2 gives a detailed explanation of functional modules for the proposed research. Based on the research objectives described above, sensors inside the smart home first gather information about the user. The input collected by these sensors is referred to as raw data, which will be sent to the classifier for activity recognition. Different classifying methods can be used, however, the accuracy may vary due to the format of input data and the error control applied. The output of the classifier would give out the user activity label. Based on this label, semantic ontology which relates sensor information with regard to user activity from both the multimedia service (e.g., volume sensor) and ambient environment (e.g., luminance sensor) would be put together to compose the probable states and actions within reinforcement learning algorithms. The result of reinforcement learning algorithms will adapt the settings for multimedia service such as audio volume and other indoor actuators like luminance level until a final state is achieved which satisfies the user. As time goes by, classifier will analyse new sensors’ inputs to update the user activity, which will drive the new round of the semantic association and reinforcement learning. In this way multimedia adaption is achieved continuously.

1.4 Research Novelty and Impact

Despite the latest developments within smart home environments, where significant achievements have been made into areas such as activity recognition, machine-to-machine communication, semantic interoperability, there is limited research on interaction between multimedia and users in a smart home environment. Therefore, this research is driven by the novelty that a focus shall be cast upon adaption of the multimedia settings with regard to a study of behaviour and activities of the inhabitant.

This novelty will be realised by exploring appropriate learning algorithms for designing user-specified indoor multimedia delivery, driving the progress of new techniques developed in a smart home environment. Together with the newest techniques and popularity towards smart living, a variety of fresh ideas and methodologies are provided, promising an optimistic future for exploring and researching in this field. A smart way of delivering multimedia shall be realised where user can get rid of the media controller, as his preference and habit for multimedia entertainment are collected and studied by smart home. As a result, automatic adaption to the delivered multimedia are achieved, whether to become silent when user is occupied on the phone, close the curtain when the user want to enjoy a movie or to increase the volume when some noise from the kettle occurs, etc. A difference will be made in designing user-friendly multimedia service which pushes forward the state-of-the-art AI techniques in smart home application, bringing significant value in both academic domain (developing learning algorithms and training methods) and industrial domain (designing personalised multimedia service and entertainment).

1.5 Report Structure

Chapter 1 provides the introduction to this research. First, Section 1.1 states the general concepts of multimedia delivery, smart homes and cloud computing, with an open question with regard to research topic at the end. Section 1.2 presents the state-of-the-art topics and projects that relate to the multimedia delivery in smart home research. Followed by it, Section 1.3 discusses the motivation and research potential that lead to the statement of research objectives. Research novelty and impact is demonstrated in Section 1.4. In the end of this chapter, the outline structure for the whole report is given.

Chapter 2 contains the literature review which forms the main body of this report. By briefly illustrating a list of research articles to present previous work, the purpose of this chapter is to outline a general idea of what methods that are needed within this research. Followed by the functional modules given in Figure 1.2, this chapter is divided into three parts. Section 2.1 focuses on the literature within activity recognition. By listing several datasets and related approaches, a comparison of the main techniques is given. Section 2.2 presents the topic of semantic interoperability, with an illustration of both research work and existing indoor ontologies. Section 2.3 explore the state-of-the-art in learning methods.

In Chapter 3, the work progress to date is presented. With regard to the key points of research objectives shown in Section 1.3, a use case for user watching the TV is discussed in Section 3.1, besides three functional modules for the system designed is given. In Section 3.2, a comparison of several classifiers that are used in activity recognition is tested on the ARAS datasets. Discussion of their performance is given. Section 3.3 outlines the designed structure for semantic ontology based on the use case. In Section 3.4, a multimedia dataset is introduced to abstract user's preference for multimedia setting. Along with it, the Markov process is discussed for building up the learning agent via reinforcement learning method. At the end, the focus for the next period of work is given.

In the end, Chapter 4 summarises the first year work and presents a schedule for the rest period. Detailed plans are shown in a Gantt chart.

2. Literature review

Followed by the discussion in Section 1.3, this chapter delivers a literature review in three domains. Activity recognition is put as the first scenario as it collects the information of user's behaviour and habits, which provides an indication for multimedia adjustment. Classification methods are compared and summarised by studying the existing research using different datasets. Association of user activity and media services as well as indoor devices comes into the second scenario, where a review is made on semantic interoperability by comparing several ontologies designed for indoor devices. Learning methods mainly refer to reinforcement learning, for the purpose of learning user preference and achieving reinforced media adjustment. The latest progress with regard to reinforcement learning and the hybrid application usage with other methods such as deep learning are discussed.

2.1 Activity Recognition within Smart Home Environments

2.1.1 Introduction

From the last decade in 20th century, many researchers started to casted their interest in developing smart spaces in limited living environments [4-5] such as building automation [6]. Launched in 1998, the Aware Home Research Initiative[9] at Georgia Tech is one of the early research initiatives on smart environments [7-8]. Besides, there are several research papers showing progress in Managing an Adaptive Versatile Home (MavHome[10]) [9-10], which is used to provide a customised personal environment to the users of this space. It is a lab-based smart environment, aiming at providing safe and energy-saving living space. Such approaches, however, are very focused within the physical boundaries of the smart environment, whereas they do not guarantee application-level Quality of Service (QoS) for content delivery.

User activity recognition within smart home is of the first and baseline mission in the smart home research. Raw input collected from sensors would be interpreted by classifiers to give out an activity label of the user. Based on the certain activity, a study of user's preference to the multimedia setting is carried out.

General rules and steps for sensor-based activity recognition are [2]:

- Deploying appropriate sensors
- Collecting input data (building up dataset)
- Selecting classification algorithm

9 http://www.awarehome.gatech.edu/

10 http://ailab.wsu.edu/mavhome/

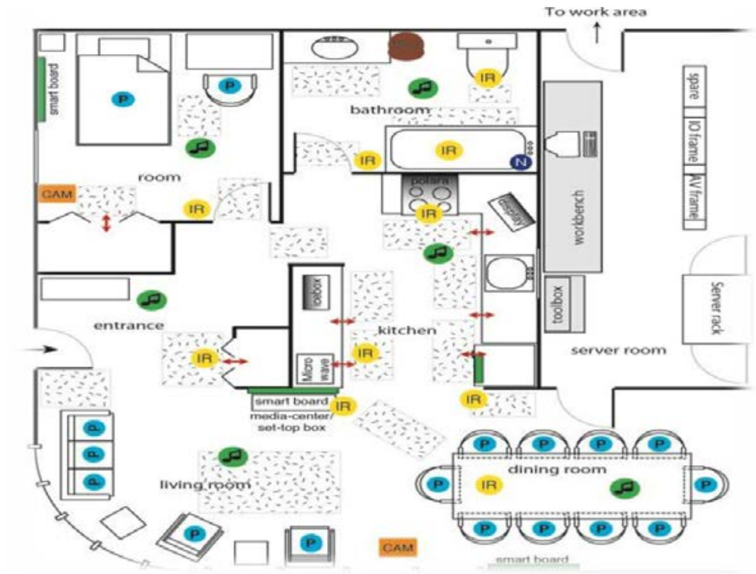


Figure 3. A smart home space plan in Domus project [14]

A number of research studies have been conducted within the scenario of Activity of Daily Living (ADL) [11-13] where activities such as preparing a meal, washing dishes, using the toilet, calling on the phone, etc., are involved. An example of a smart home space is given in Figure 3 from the Domus laboratory [14], where the user's activity space includes a living room, a kitchen, a bedroom and a toilet. Sensors that are applied here include Infrared (IR) motion sensors, pressure sensors, switch contact, flow meter and so on. Deployment such as pressure sensor (in blue) and IR (in yellow) can be seen in Figure 3.

2.1.2 Datasets

When collecting the sensor inputs, two main approaches are used. One is sequential form, and the other is parallel form. Dataset with sequential form read in new data when the change of a sensor state occurs. Usually, no fixed time interval is applied. By contrast, dataset with a parallel format applies a fixed time stamp such as every 30 seconds, every 1 minutes, etc. New data therefore is recorded at each time stamps, with state information of every sensor.

A comparison of the datasets is given in Table 1. They are accessible online and widely used in smart home-related research studies.

Centre for Advanced Studies in Adaptive Systems (CASAS[11]) has been established by researcher Diane J. Cook[12] and her team from the Washington State University since 2007. It is a dataset which focuses on creating shared datasets related to indoor everyday living activities and health care [2, 15-17]. The format of datasets in CASAS is sequential while the number of users and activities vary accordingly.

11 http://ailab.wsu.edu/casas/datasets/

12 http://eecs.wsu.edu/~cook/

Table 1. A comparison of three popular datasets within smart home scenarios

Name	Country	Year	Description
CASAS	US	From 2007	• Centre for Advanced Studies in Adaptive Systems in WSU • Contains various datasets for remote health monitoring and activity for daily living • Sequential data format for one or multiple users
Domus Lab (Sherbrooke)	France	2010	• Activity space including bedroom, kitchen, dining room, living room and bathroom • IR, pressure sensors, light switches, contacts (door, locker, fridge), flow meters, etc. • 6 separate users' data collected for 10 days detecting 7 activities • Sequential data format
ARAS	Turkey	2013	• Activity Recognition with Ambient Sensor • Similar sensor types as Sherbrooke • Combined 2 users' data for more than 20 activities • Parallel data format recording state of 20 binary sensors

Sherbrooke[13], generated by the Domus Lab in France in 2010, is a home-based living environment dataset. It records the seven main living activities from 6 individuals, each lasts for 45 minutes and with a total length of 10 days. Activity space ranges from bedroom, kitchen, to bathroom and sensors used here involve Infrared (IR) sensors, pressure sensors, light switches, etc. Similar to the datasets in CASAS, Sherbrooke also records data in a sequential format [14].

The ARAS[14] dataset was generated by a research group from Turkey (H. Alerndar, H. Ertan, O. Incelt and C. Ersoy) in 2013. It contains binary sensors which keep track of two users' activity at the same time. Different from the above two, ARAS makes use of parallel format where all sensor inputs are collected at each second throughout 24 hours for 30 days [18].

13 http://domus.usherbrooke.ca/jeux-de-donnees/

14 http://cmpe.boun.edu.tr/aras/

2.1.3 Selected Classification Methods

Classification methods used for activity recognition include Support Vector Machine (SVM), Naive Bayes Classifier (NBC), K Nearest Neighbour (KNN), Decision Tree (J48), etc. Among these approaches, J48 Decision Tree is one of the most popular methods due to its high accuracy rate and low calculation time [19].

NBC [21] makes use of probability model. The idea behind NBC is that it tries to estimate probabilities for each class and then picks the class with maximum probability. It goes with the assumption that each attribute is independent and contributes equally to the decision. However, the practical case is that, even if the assumption of independence is not satisfied, it still works well as long as the greatest probability is assigned to the correct class (classification does not need accurate probability estimate).

KNN [22] works in the following way. To classify a new sample, the KNN algorithm searches the whole training set for one sample that is most similar to this new test sample. Then by calculating the similarity function (distance function), the instances between the new sample and each training sample can be measured, thus ‘ K nearest neighbor (s)’ of the new sample can be picked out regarding to the ‘distance’. According to the class label of its neighbor(s), the class for the new sample can be determined. $K = 1$ means each training instance is defined as a region space, and the distance function is used to measure which region the new sample falls into. Usually K is set to 1 for accuracy concern. However, it is also clear that the drawback of the KNN algorithm is time consuming, as it needs to calculate distances throughout the whole training set. This would occupy large amount of time in large datasets.

J48 Decision Tree [23] is a top-down classification method. It uses a recursive algorithm that keeps splitting the data from the one initial attribute (root node) until samples in one attribute ends up belonging to a pure category. The ‘splitting’ generate the ‘tree branch’ where the end ‘pure category’ forms the ‘tree leaves’. The problem within decision tree is overfitting, which means the tree structure is too large (too many branches and leaves to consider whereas the tree becomes tailored or not generic be the training sample). Therefore, the initial attribute should be carefully selected that the tree can end up with smallest structure (the least total number of leaves and branches possible). One way to choose the best initial attribute is by calculating the information gain of the each attribute (entropy of distribution before the split – entropy of distribution after the split) and then choose the attribute that has the highest information gain as the initial attribute; then continue to split by choosing the next attribute that has the highest information gain until the splitting reaches a pure category.

2.2 Semantic Interoperability

2.2.1 Introduction

According to the definition given by Veltman [24], semantic interoperability is the “ability of information systems to exchange information on the basis of shared, pre-established and negotiated meanings of terms and expressions”.

At the end of 20^{th} century, the concept of "Semantic Web[15]", which has the ability of gathering, comparing and transforming annotations of webpage, brings about the early notation for the semantic interoperability. It makes use of ideas in ontology such as adding in data, linking components and sharing vocabularies among the related categories. Semantic data can be treated as a group of ontologies that build up the entities for the whole system, and items which are produced, exchanged and consumed among different entities [25].

Ontologies are formal definitions of vocabularies. They enable the definition of complex structures as well as new relationships between vocabulary terms and members of the classes, which are needed in the structures. Thus ontologies have seen a huge popularity in intelligent knowledge management. By making use of hierarchical properties based on a vocabulary of concepts, ontologies can provide a smart way of structuring knowledge in resource domains [26].

One popular building tool for ontology design is based on Resource Description Framework (RDF) language, termed Web Ontology Language (OWL), where RDF[16] originates from the family of World Wide Web Consortium (W3C) specification. In RDF, a triple (subject-predicate-object) is used to describe data. This will be further explained in Section 2.2.3.

2.2.2 State-of-the-Art in Ontologies

As a method for information management, the recent years have seen its development in healthcare such as electric health records [27], Internet of Things [28, 29], smart environments including multimedia deployment and context-awareness [30-32], system infrastructure [33], etc. Besides, the Semantic Interoperability Community (SEMIC[17]) is an European organisation that aims to improve semantic interoperability of interconnected e-Government systems.

Hunter's work [30] merged several multimedia terms such as MPEG-7 and MPEG-21 to encourage a superior way of multimedia representation, management and delivery. The study presented in [32] introduced a context-awareness infrastructure, which is able to interpret the on-play video and transfer it into word description. However, these studies focus on multimedia services quality itself which lacks the user-multimedia interaction aspects.

The authors in [33] proposed a concept of semantic smart home that aims at designing the smart home system architecture, including semantic modelling, content generation and management. By involving the user activity and its living environment, this work makes contribution to improve ontologies for ADL, which can be applied in user preference study and assistive living. Nevertheless, the semantic interoperability presented here does not consider the issues of multimedia delivery.

However, [31] presents a progress that can correspond to user's using an ontology-based model. In this work, an example is given by adapting the video quality displayed on smart phone according to user's outdoor location. Although a number of extra factors such as weather, time, user's profile are considered, it focuses mainly on adjustment of location-based Quality of Service (QoS) other than adaption of indoor multimedia delivery with regard to user activities and behaviours.

15 https://www.w3.org/standards/semanticweb/

16 https://www.w3.org/RDF/

17 https://joinup.ec.europa.eu/community/semic/description

2.2.3 Existing ontologies within indoor environments

This section will introduce two ontologies corresponding to the smart environments. They are th Smart Appliances REFerence (SAREF[18]) [34] ontology and the Internet of Thing Ontology (IoT-O[19]) [25].

SAREF is an ontology to interleave data and semantics from smart appliances in buildings and households. In SAREF ontology, a device is used to provide a function such as turning on the light, decreasing temperature, etc. Three categories of devices are considered in SAREF, i.e., *building related*, *energy related* and *function related*, among which, *function related* category consists of the devices which offering services such as indoor lighting (*Lighting*), entertainment (*Multimedia*), indoor thermal comfort (*Heating Ventilating and Air Conditioning, i.e., HVAC*), etc. According to different devices, object properties are described such as *has state, has command*, etc.

However, there are a few problems within SAREF ontology. First, the component description within *Data Properties* is not clear. For example, there is no description stating *on/off*, which may be the data property of those individuals such as *Door*, *Light* and so on. Second, for most individuals that appear in SAREF, such as *Multimedia*, *HVAC*, it lacks the specific illustration for what object property and data property they have, which is the core concern for semantic interoperability.

In general, the SAREF ontology gives an ontology design for an indoor smart environment scenario. It outlines the different modules that may be considered for home design, including facility management such as time and location, energy consumption and entertainment. Nevertheless, there is not enough explanation in structure design, such as *Entities* and *Data Properties*. Moreover, the interconnection for individuals among various classes is weak, and detailed illustrations of object property and data property for most certain individuals are missing.

The second ontology introduced here is the IoT-O. The latest version was released in April 2016 [25]. IoT-O is an ontology for Internet of Things (IoT) with regard to the recent Machine-to-Machine (M2M) standard [29], named oneM2M Standard[20]. Early M2M standards operate only on the communication level and lack the actuation model. Therefore the goal of oneM2M Standard is to promote interoperability at semantic data level, achieve autonomic actuation for efficient system design, and provide a standard and scalable function support. Encouraged by the aim of oneM2M Standard, IoT-O is developed as an ontology that can associate among sensors, actuators as well as services.

IoT-O ontology is built upon several already existing ontologies to handle issues for M2M devices such as standardised data model for interoperability at a semantic data level. The contribution in IoT-O is that it defines the missing concepts in the previous IoT ontology such as actuator and actuation. Furthermore, a new module is designed to describe actuators and their related concepts.

Five domains are considered in IoT-O, including domains of *sensor*, *observation*, *actuator*, *actuation* and *manager*. Within each domain, several modules may be involved. Each module consists of one or two existing ontologies. Five initial modules correspond to the *sensing module (SSN)*, *actuating module (SAN)*, *service module (MSM* and *hRest)*, *lifecycle module (schema* and *iot-Lifecycle)* and *energy module (powerOnt)*. Besides, an ontology termed *DUL* is used for defining a few general

18 https://sites.google.com/site/smartappliancesproject/ontologies

19 https://www.irit.fr/recherches/MELODI/ontologies/IoT-O.html

20 http://www.onem2m.org/

concepts such as quality, measure unit, amount, region, etc. *Time* ontology records time information needed.

For example, the *observation* domain has *SSN:Observation*, which is the result obtained from *SSN:SensorOutput* with specific value of *SSN:ObservationValue*. *DUL* regulates the categories of *SSN* information. To be more specific, *SSN:Observation* is a sub-class of *DUL:Situation*; *SSN:Output* belongs to *DUL:InformationObject*; *SSN:ObservationValue* is under the *DUL:Region* category. Besides, *SSN:ObservationValue* has time information recorded by *Time:Instant*.

Table 2. Constitution of ontologies among different domains in the IoT-O

	Sensor	Observation	Actuator	Actuation	Service
SSN	√	√			
ACT			√	√	
DUL	√	√	√	√	
Time		√		√	
MSM					√
hRest					√

Compared to the SAREF ontology, IoT-O shows a better construction in detailing out the categories such as functionality (under the path *owl:Thing – Abstract – Functionality*), devices and family appliance (under the path *owl:Thing – PhysicalObject – BuildingThing*). *Entertainment* with regard to multimedia devices is specified as *DVD*, *HiFi*, *Radio* and *TV*. Besides, a largely enriched family appliance varies from lighting, kitchen devices to window shade, all categorised under *BuildingThing*. In [25], the author also provides a smart building use case of autonomic lighting using a smartphone. Here the service manager registers the lamp on the smartphone, thus a link is established between the smartphone and lamp. By associating the command from the smartphone sent by the user, service manager can then adapt the luminosity of the lamp; luminosity sensor keeps record of luminance level and provides real time measurement value to the smartphone. This example shows the semantic interoperability of the service and corresponding sensors and actuators involved in the operation.

Although a significant advantage is achieved when compared to SAREF, the IoT-O ontology lacks the association of devices which reflects the user activity. Nevertheless, the background study of semantic interoperability casts light on the main idea and methods that can be used for ontology design which matches the research objective. In Section 3.3, an initial ontology is developed to relate multimedia service, devices and user activity by referring to the ontology introduced here.

2.3 Learning Methods

2.3.1 Introduction

Regarding to the third objective in Section 1.3, while delivering multimedia service to the user, the multimedia control shall take into consideration the user's present activity, so that the multimedia service can reach the user's satisfaction dynamically and accordingly. This involves methods that can collect user's behaviour in accordance with the delivered multimedia, learn about user's preference settings and apply the appropriate multimedia settings in different cases. In other words, methods applied in a smart home to develop algorithms which achieve dynamic automatic multimedia control are needed. Followed by this induction, appropriate methods may be found by a brief survey of the literature on AI.

Back in the 1950s, when computers were new to the world, the first generation of AI researchers started their career and predicted the prosperity in AI was right around the corner. In the 1980s, one better way to develop AI seemed to be machine learning in neural networks. These systems promised to learn their own rules from scratch, and offered the pleasing symmetry of using brain-inspired mechanics to achieve brain-like functions. The networks need a rich stream of examples to learn from, like a baby gathering information about the world [35]. This leads to the development of deep machine learning, i.e., Deep Neural Network (DNN) and reinforcement learning. The mechanism for DNN involves a multi-layered neural network with a group of neurons for each layer, whereas reinforcement learning explores the unknown and tries out different possibility types to reach the best answer [36].

In general, there exist two approaches when developing learning algorithms, supervised learning and the opposite, unsupervised learning [37]. Supervised learning refers to the method that during algorithm training, a correct label is given to the training sample, thus the parameters in the learning algorithms can be updated and optimised according to the correct label. A well-known example to apply supervised learning is Mixed National Institute of Standards and Technology (MNIST[21]) dataset for image recognition. MNIST was developed by Yann LeCun and his colleagues for recognising handwriting digits. Every sample in the dataset consists of two parts, digit image and its correct label.

However, algorithms developed for unsupervised learning have no correct "label" to refer to, but are informed when their outcome is wrong, learn from their failures and shortcomings, and thus make improvement to their parameters. While supervised learning depends on correct labels to make progress, unsupervised learning is more suitable for brand new learning conditions where little prior knowledge is acquired or given.

The mechanism of reinforcement learning is more similar to unsupervised learning where algorithms learn from scratch. Nevertheless, reinforcement learning has a reward given for each taken action and this reward can be treated as the concept of "correct label" appearing in supervised learning. Therefore, a recent approach has been made to integrate deep learning into reinforcement learning methods in game scenario [38]. More information on reinforcement learning is provided in Section 2.3.3.

21 http://yann.lecun.com/exdb/mnist/

2.3.2 Deep Learning

Getting inspired from neural science, deep learning uses multiple processing layers, each consists of a group of neurons, to learn representations of data and build computational models with multiple levels of abstraction. A good review for methodology and algorithms applied in deep learning is shown in [38] where Convolutional Neural Network (CNN) is highlighted. Compared to the traditional neural network, CNN has the advantage of decreasing computation cost especially when the neural network is experiencing large size [39]. Therefore it gains a huge popularity in deep learning algorithms. To update the neuron weights, backpropagation method [40] is applied to indicate how a machine should adapt its parameters between nearby layers. Besides, the classic method for measuring cost function is cross entropy [41] and gradient decent [42] can be applied to minimise the cost. The state-of-the-art improvement has been seen in source recognition such as speech [43-45], visual object [46-48], and also in detection and discovery areas [49].

A neural network consists of three parts, i.e., input layer, hidden layer(s) and output layer. Deep neural network means that usually there are several hidden layers to make the network "deep". The reason for this is to abstract multi-level features of an input. If human face recognition using CNN is taken as an example, the input will be the raw pixel of a picture that may contain a human face. Then the feature abstracted in the first hidden layer would be the small curves that make up the lines appearing in the human face, such as the outline of the eyes, the ears, etc. In the second hidden layer, a more complex feature such as an eye, a nose, a mouth would be detected. When the third hidden layer is considered, the detection may be made to even more complex feature such as a combination of two eyes, a nose and a mouth that plots out the basic image for detecting a human face. With more hidden layers, a higher level of facial features can be detected for better recognition, but at a cost of computational complexity. A detailed explanation of CNN can be found in CS231n[22] provided by the Stanford University.

2.3.3 Reinforcement Learning

Among the different categories of machine learning, the mode of reinforcement learning appeals to the function of the human brain. It is somewhere between supervised machine learning and unsupervised machine learning [37], which means the algorithm developed for reinforcement learning would get told when the answer is wrong but it does not receive the right answer immediately. The algorithm needs to try out several times to figure out the right answer by itself. Companies like Google DeepMind[23] have successfully developed reinforcement learning algorithm in accomplishing computer games.

An illustration of the reinforcement learning framework is shown in Figure 4. On the left side, the AI system or study agent is depicted, which finds itself in some kind of an environment that it is trying to achieve a goal. The environment can be real world or virtual. The AI system interacts with its environment by observing the condition (state) and responding with an action. To be more specific, AI system makes observation about the environment through its sensory apparatus. The observation is always noisy and incomplete, which is typically the situation in real world. In the beginning, there is no full information about the surrounding given to the AI system, so the first job is to build a good model of the world based on the known information. Usually, a statistical model has to be built on the

22 http://cs231n.stanford.edu/

23 https://deepmind.com/

noisy observation. The second job of the AI system is to pick the best action that will get it closest to the goal from the set of actions that are available to it at that moment in time. Once the system decides on the action, it outputs the decided action, and the action gets executed, which may or may not have some change on the environment that drives new observation.

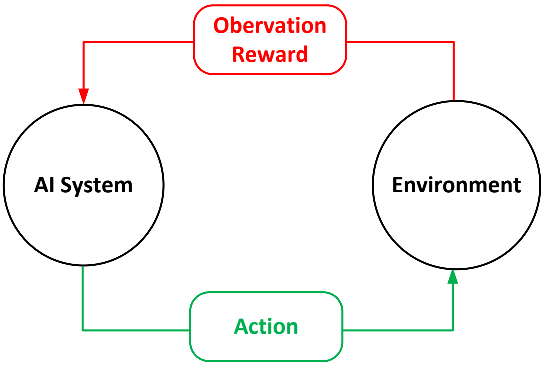


Figure 4. Reinforcement learning framework

The recent development of reinforcement learning usually comes with a deep learning inside, as is mentioned at the end of Section 2.3.1. A well-known example is from Demis and his team in Google DeepMind. In 2015, they used an Atari game as the test bed to test the intelligence of the algorithm and published their result in the Nature magazine [38]. Inputs here are the raw pixels, just like a human looking at a screen. Then a novel reinforcement learning agent termed Deep Q-Network (DQN) is demonstrated to learn successful policies from the inputs and to maximise the score in the game. One year later, they published another research article [50] on their approach applied in their AI AlphaGo[24] to play game Go. Their approach has two initial networks. One is the value networks that can evaluate board positions; the other is the policy networks to make the next move. Reinforcement learning here is applied for self-play training.

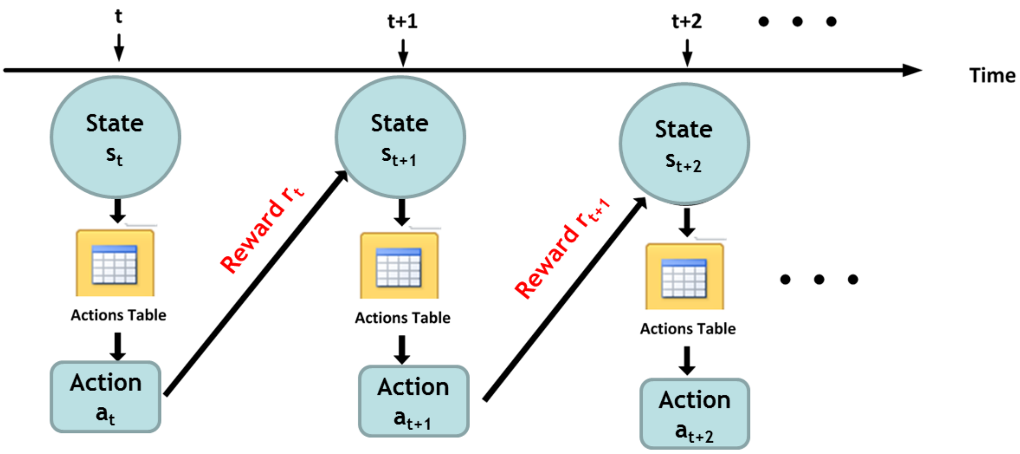


Figure 5. State-action-reward in a Markov Decision Process

24 https://deepmind.com/alpha-go

For reinforcement learning, a Markov model is used where a group of states covers all of the possible observations for a learning case. Figure 5 depicts the details of the state-action-reward concept in a Markov Decision Process (MDP) [20]. Observation is abstracted at each time interval, say, t, to demonstrate the state at that time s_t and each state has an action table which involves all the possible actions that may be taken under that state. Policy strategy is then applied to help choose an action. The execution of the action a_t may or may not bring in some change to the environment, and gives a reward r_t as feedback. At the next time interval $\mathrm{t}+1$, a new observation is made with state s_{t+1}. Again by looking up the action table of s_{t+1} and applying the policy strategy, action a_{t+1} is executed to trigger a new observation s_{t+2}, get reward r_{t+1}, and drive this process onward.

From the mathematical point of view, the MDP episodic setting and target function can be defined via the following process:

$$s_0 \sim \mu(s_0)$$

$$a_0 \sim \pi(a_0|s_0)$$

$$s_1, r_0 \sim P(s_1, r_0|s_0, a_0)$$

$$a_1 \sim \pi(a_1|s_1)$$

$$s_2, r_1 \sim P(s_2, r_1|s_1, a_1)$$

$$\dots$$

$$a_{T-1} \sim \pi(a_{T-1}|s_{T-1})$$

$$s_T, r_{T-1} \sim P(s_T|s_{T-1}, a_{T-1})$$

$$f_{target} = Maximize\ E[R|\pi]$$

$$where\ R = r_0 + r_1 + \cdots + r_{T-1}$$

In general, an MDP is defined by $(\mathrm{S}, \mathrm{A}, \mathrm{P})$, where S represents the state space, A refers to the action space and $\mathrm{P}(\mathrm{r}, s'|\mathrm{s}, \mathrm{a})$ is the transition (from state s to state s') probability distribution. Besides, μ regulates the initial state distribution in an episode, which refers to the starting state; policy π decides on which action to take. For a learning process correlated to the MDP, the goal is to maximise the average reward R for every episode.

At the beginning of an episode, initial state s_0 is given by $\mu(s_0)$. The first action a_0 is decided by $\pi(a_0|s_0)$. Upon the execution of a_0, the transition probability distribution $P(s_1, r_0|s_0, a_0)$ then convert state s_0 to s_1, with a reward delivered by r_0. At state s_1, policy applied again $\pi(a_1|s_1)$ to pick a new action a_1 and lead to the next state s_2 with reward r_1. In this way, the MDP keeps moving on until the end of an episode and the average reward will be calculated by f_{target}.

Therefore, the policy strategy is the key factor towards MDP average reward and shall be applied according to a practical use case. The policy strategies can be divided into three categories [37]. The simplest one is the deterministic policy where the action only depends on the present state. The second category is the stochastic policy where the action is a stochastic process of the state distribution. The third kind is the parameterised policy where the action relies on a parameter vector. The choose of the policy is important to the reinforcement algorithms and directly influence the algorithm performance. Further job shall be done into the policy strategy in the next period of research.

Presently, a toolkit named OpenAI Gym[25] is popular for developing and comparing reinforcement learning algorithms. It contains a group of environment suitable for algorithms applied in Atari games, simulated robots, etc. Frameworks such as Tensorflow, Theano and Keras are compatible with OpenAI Gym, which makes it easier to generate and develop new learning algorithms.

To sum up, reinforcement learning and is among one of the popular machine learning methods nowadays. The mechanism of the rewards which relates to the decision making behind reinforcement learning can make the agent learn how to achieve goals in a complex and uncertain environment. With the existing tools such as Open AI Gym, an agent that could achieve an improved performance on learning its user's preference and behaviours are expected to be developed via the idea of reinforcement learning. Issues here for building up appropriate learning algorithms would be defining the appropriate states, designing policy strategies, etc.

25 https://openai.com/blog/openai-gym-beta/

3. Research Progress

This section will demonstrate the up-till-now progress. First, a use case of watching TV is illustrated with system design based on the research objectives in Section 1.3 and functional modules described in Figure 2. Then, the work will go into details on each functional module. For user activity recognition, a few tests are given to compare the classifiers' performance on the ARAS datasets. Followed by it is the designed structure of components to be considered in the ontology for semantic interoperability. The last part of the chapter would focus on the idea of reinforcement learning where a Markov model is illustrated with the description of a being built multimedia dataset.

3.1 Overall system design for the use case of watching TV

Consider a case of a user watching TV in a smart home. The goal here is to deliver the multimedia services while enhancing user-preferred interaction by analysing data from user, media (streaming video) and ambient environment (lights, curtains, windows, etc.). To achieve this, three functional modules, regarding to activity recognition, semantic interoperability and reinforcement learning given in Figure 2 shall be established. The information from both the streaming media and ambient (luminance, volume) environment indicate user's preference for media setting, while user's present activity shall be used as in the policy strategy to adapt the media and home settings accordingly.

According to the brief statement above, the elements involved here are: the streaming media, user activity, and devices (sensors and actuators). Table 3 gives the detailed examples of the sensors and actuators considered in this use case. The sensors and actuators can be categorised into user-related, media-related, and environment-related sensors. Media play sensor refers to integrated software which record different states of multimedia such as play, pause, volume level, etc. Acoustic sensors refer to those that can record sound from hot pot (heating water), phone (ringing) and noise outside the window. Appliance detectors refer to sensors that can get the state of home appliance, such as whether a hotpot is heating water, the window is closed, etc.

Table 3. Sensors and actuators categorisation

	User-related	Multimedia-related	Environment-related
Sensors	location sensors pressure sensors voice sensors	media play sensor	luminance sensors acoustic sensors appliance detectors
Actuators	smart phone	TV screen and loudspeaker	lights, blinds controller, window controller

Here the multimedia refers to the steaming video which contains the TV programs. A TV screen is used for projecting the media source and a loudspeaker is used to adjust the sound volume. The light control can adjust indoor lightness as well as colours of the lights according to the projected scene on the screen. The blinds controller is used to close or open the curtain according to the luminance requirement from the user's preference when watching the delivered media source.

During the media delivery, there is a possibility that the user is occupied with doing something else, such as talking on the phone, cooking, making tea, etc. To detect user's activities, the sensors deployed in the home environment are used. For example, from a pressure sensor on the couch, a motion sensor that covers the couch area, as well as the multimedia sensors which suggest a movie is being streamed, the smart home system may indicate that the user is watching the movie on the couch. At a certain time stamp, an acoustic sensor picks up the signal that the phone is ringing and later the voice sensor gets information that the user is speaking on the phone, the system can conclude that at this moment, a call is coming in and the user is talking on the phone. In this case, an appropriate setting for the multimedia delivery is to decrease the volume of the loudspeaker, so that the streaming movie will not disturb the user's phone call. In another example, if an appliance detector detects the kettle is operating, with additional information from the acoustic sensor detecting an obvious noise of boiling water, the smart home system will infer that the user is making a hot drink. At this moment, as the noise level from the kettle is high and may influence the audibility of the sound of the movie, the system will increase the volume of the loudspeaker.

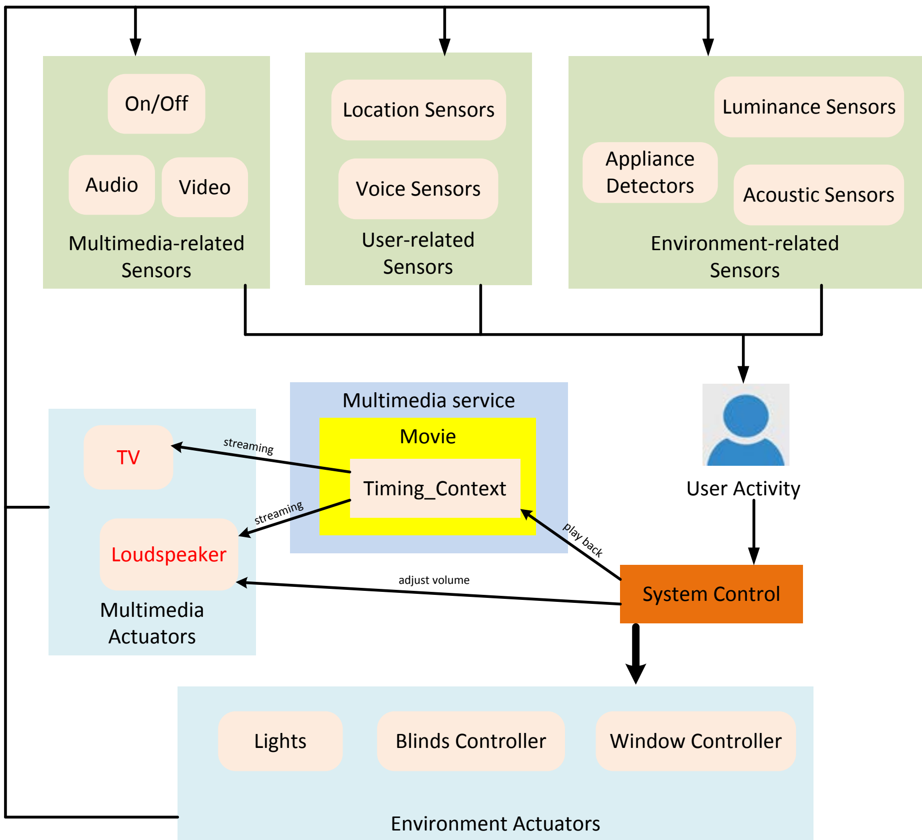


Figure 6. Information flow among different components in the use case of watching a movie

As a further step, it can be considered that the user-related voice sensor not only records the user's voice context, but also can indicate user's emotion. Research in this area has been explored and the related progress has been reported as a result of the MixedEmotions[26] project [52-53]. Thus, a further adaption can be integrated here, which makes use of the user's emotions recorded by speech. Besides, as in the earlier case, the blinds controller may close the curtain when the movie is on. The detection of the noise level outside the window may lead to closing the window in attempt to lower the noise interference from outside.

26 http://mixedemotions-project.eu/publications/

Figure 6 depicts the information flow for this use case where sensors' data which indicates the user's activity would adapt both multimedia steaming and ambient devices such as lights. To achieve it, the research work correlates with three main areas, i.e., user activity recognition, semantic interoperability and system control. The system control, or the adaption while delivering the multimedia, is the core mission to be targeted here, which involves the research work for investigating and developing the necessary machine learning methods such as deep neural network, reinforcement learning, etc. It should give prior concern to user's habits and preferences, which rely on the knowledge of activity recognition and semantic interpretation. In the following sections, works that has been carried out for each scenario until now shall be delivered separately.

3.2 Comparison of Classifiers Using the ARAS Datasets

In Section 2.1, activity recognition including datasets and main classification approaches has been introduced via a list of papers. In this section, the performance of several classifiers for activity recognition will be tested and compared on WEKA 3.7. WEKA is a software tool for data mining and pre-processing [51]. It contains various classification algorithms and requires a parallel format of the dataset. Therefore, the datasets used here are chosen from ARAS. The classifiers chosen here include NBC, KNN and J48. Besides, a 'dumb' classifier ZeroR is also used to show what the worst accuracy a classifier may achieve and how much improvement can the other classifiers make. ZeroR classifier only searches for one category which has the highest number of instances and labels all the instances in the dataset to that category. Therefore it is the simplest classifier which draws the bottom line accuracy of a classifier performance.

ARAS [18] contains two house deployments (House A and House B). Each house consists of 20 binary sensors which records daily activities of two users, providing a variety of more than 40 activities combination. In the test given below, a total number of 12 days' datasets are used, including *House A* and *House B*, each from *Day 1* to *Day 6*. The number of instances in each datasets is more than 80, 000. Activities recorded from *Day 1* to *Day 6* in *House A* have a richer categories up to 47 whereas in *House B*, the highest categories is 32.

Figure 7 gives an example of the test environment in WEKA. The dataset shown in Figure 7 comes from *Day2-in-house-A* in ARAS. The table at the left side of Figure 7 lists out 21 attributes of the dataset. For each data instance, the first 20 attributes represent sensors states and the last attribute gives out the user activity (*User_event*). Here, 17 user activities are recorded, shown in the colourful bars at bottom right in Figure 7 and are labelled from 1 to 17. A total number of 85095 instances tracked in this dataset.

For accuracy verification, a 10-fold cross validation is applied during the classification training. This means the samples will be divided into 10 groups. Each time 9 of them are used for training and the last one group is used for testing. Each group would be used as training for 9 times and used for testing for one time.

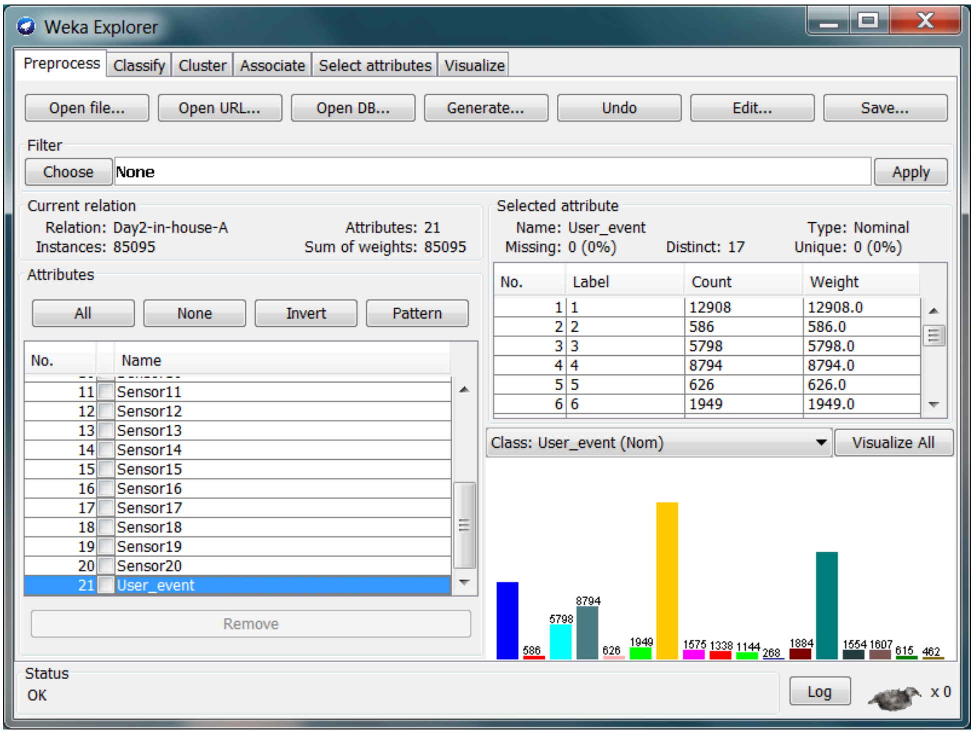
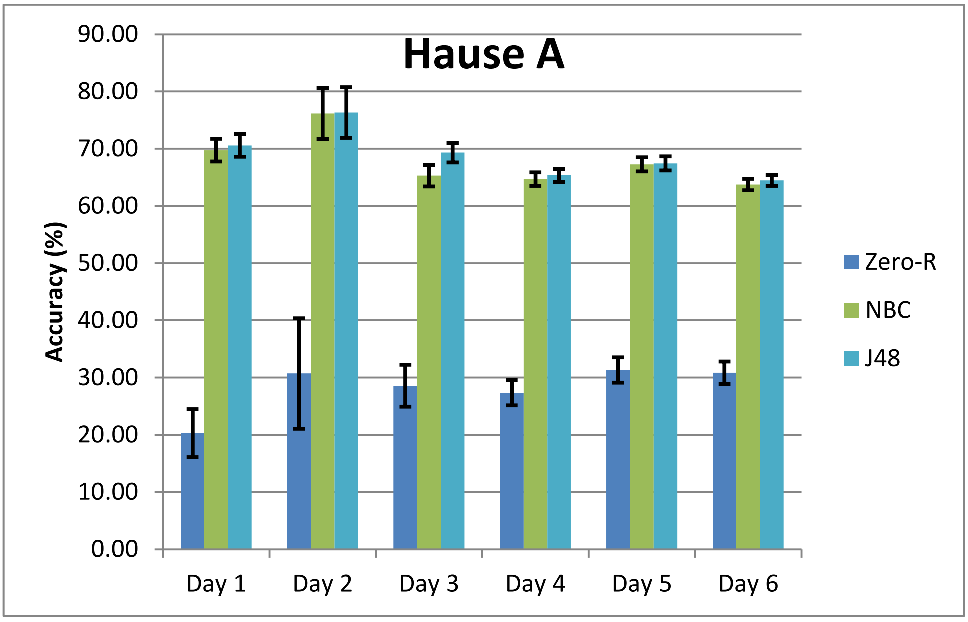
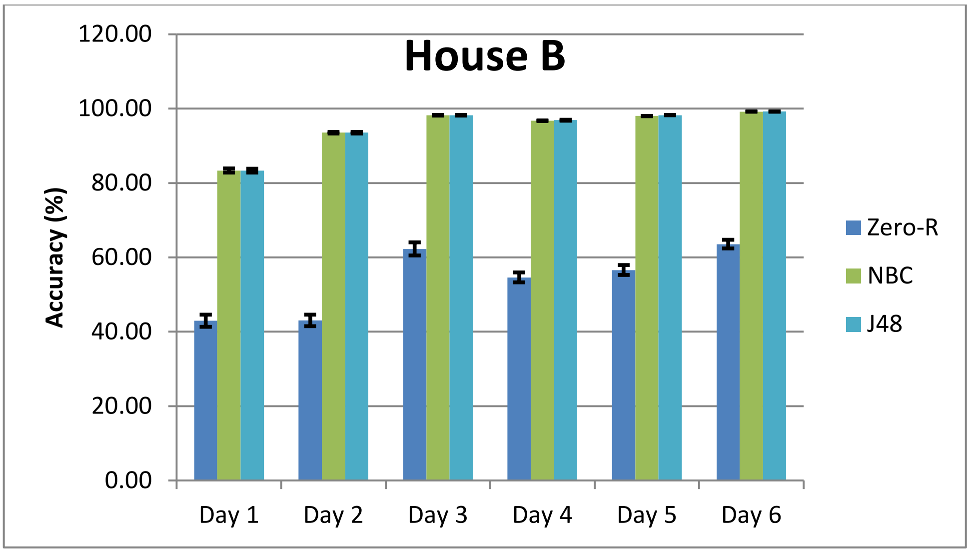


Figure 7. WEKA test environment

First, the classifiers performance is tested on the whole data of those 12 datasets. Bar charts plotted in Figure 8 (a) and (b) give the performance comparison of the chosen classifiers. Attention should be paid that there is no data for KNN, due to significant computational & memory demands.



(a) datasets of *Day1* to *Day 6* from *House A*



(b) datasets of *Day1* to *Day 6* from *House B*

Figure 8. Comparison of classifiers performance on whole datasets

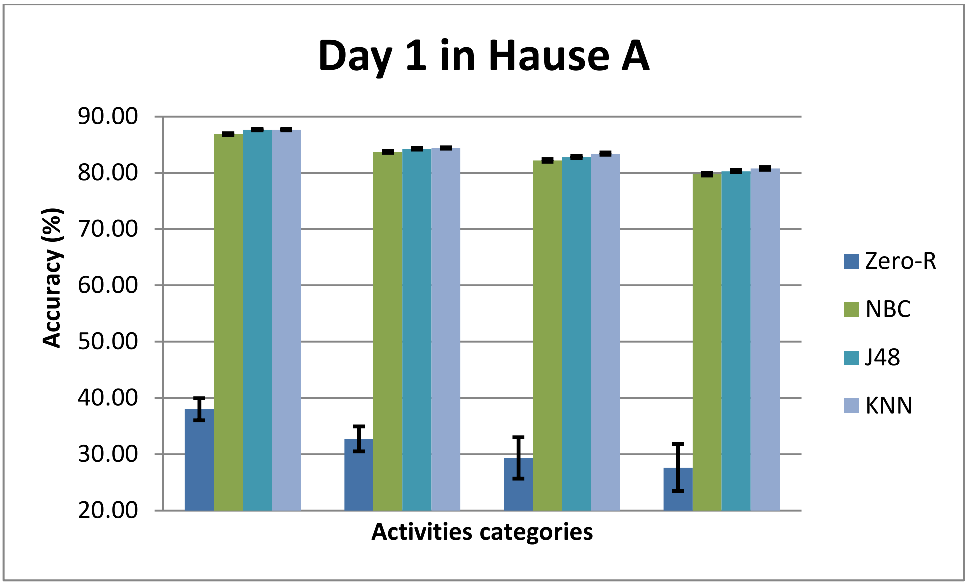
In general, classifiers performance shown in *House A* is worse than that in *House B*, both in accuracy and the mean absolute error range. This may be due to the variety of activities categories in *House A* is significantly larger than in *House B*. Moreover, NBC and J48 shows a higher performance compared to the accuracy given by ZeroR. In *House A*, the difference is much obvious, indicating that NBC and J48 have the potential when dealing with complex data.

While comparing the performance within NBC and J48, both the accuracy and mean absolute error range of J48 are slightly better and that of NBC. Nevertheless, when it comes to computation time, NBC takes around 20 seconds to gives out result while J48 needs approximately 30 seconds to finish. Therefore, result of J48 is more trustworthy with regards to accuracy as well as error range. However, NBC demonstrates only two thirds of the J48' computation time at a small scarification of accuracy performance. As a contract, ZeroR completes the computation within 6 seconds, which is much shorter than that of J48 and NBC, but at a huge sacrifice on the accuracy and mean error rate performance.

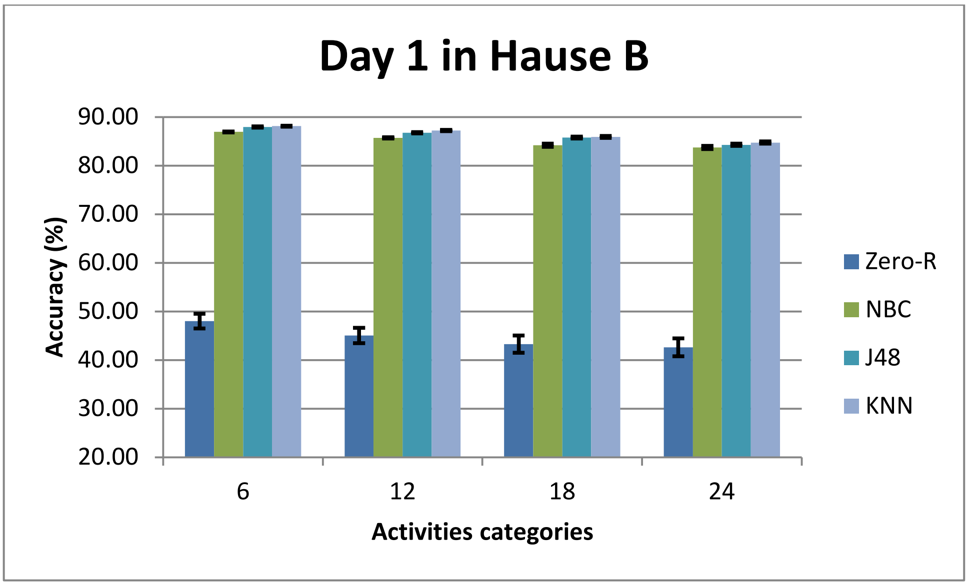
The test on the whole datasets indicates that:

- Computation complexity of KNN is much higher than the other classifiers
- J48 and NBC has a significant improvement on accuracy as well as credibility compared to ZeroR, while at a cost of computation time
- The complexity of activities categories has a detrimental influence on accuracy performance

Based on the above hypothesises, the second test chooses several subsets of datasets which contains fewer activities categories. Each of 4 subsets are selected from *Day 1* in *House A* and *Day 1* in *House B*, where the activities categories ranges among 6, 12, 18 and 24. Bar charts given in Figure 9 show the classifiers performance against the rise of activities categories.



(a) Classifiers accuracy vs. activities categories from *Day1* in *House A*



(b) Classifiers accuracy vs. activities categories from *Day1* in *House B*

Figure 9. Comparison of classifiers performance on segments of datasets

This time, KNN is able to give out result as the necessary calculation complexity decreases when involved instances drop significantly. Nevertheless, compared to the other three classifiers, the time that KNN costs is still much larger. For example, when activities categories equal to 12, ZeroR gives out immediately, NBC and J48 finish running within 2 seconds, but KNN takes around 15 seconds to show up result. From the chats in Figure 9 (a) and (b), accuracy performance of KNN wins over J48 and NBC a little bit, around 1%. Mean absolute error, however, has no much different among these three. In general, there is a decrease of accuracy when activities categories rise. Result from the second test verifies those hypothesises given at the end of first test. Although KNN does better at accuracy performance, the scarification on computation time is too large, whereas J48 and NBC run much faster at very small decrease in accuracy performance. Therefore, J48 and NBC would be chosen as the appropriate classification methods for the research.

3.3 Designed Structure for Semantic Ontology

To associate user's activity with multimedia service, as well as other home devices such as lights and window controller, a structure of components for semantic ontology that are involved in this use case is illustrated here. In Section 2.2.3, two existing ontologies, the SAREF ontology and the IoT-O ontologies, are introduced. Both of them are designed for indoor environment where the IoT-O ontology is more suitable for home application. However, as mentioned before, the illustration to the multimedia part in the IoT-O ontology is very simple whereas major instruction is given to areas such as indoor energy consumption and description of family devices. Moreover, the IoT-O ontology targets no specific user. Therefore, it lacks of association among user, multimedia delivery and the home environment.

In this section, the components considering devices, media services as well as user are put together to design a structure for semantic association. Figure 10 shows the hierarchy and relationship among them.

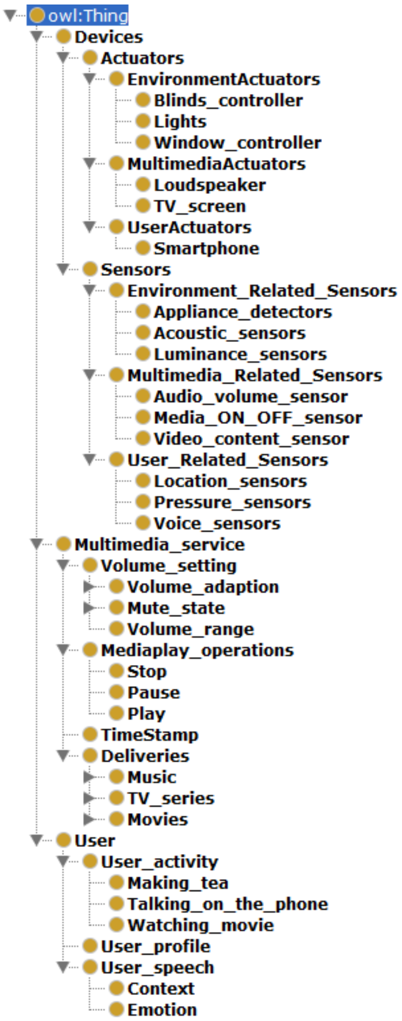


Figure 10. Class hierarchy of ontology for the use case of watching TV

The three main components under *owl:Thing* are *Multimedia_service*, *User*, *Devices*. Sensors and actuators are under the *Devices* category. *Multimedia_service* includes the deliveries such as movie, TV series, music, etc. Besides, volume information, media operations with regards to time stamp are also structured here.. The *User* category records the user's profile, activity and speech. From user's speech, emotions as well as context shall be collected and used for reasoning the media adaption. User activity considered here are two fold. The basic activity is about watching the movie, above which, additional short-time activities may include making a phone call, making tea, etc.

Queries can be made such as:

- *Acoustic_sensors* has input from *Smartphone* indicating *User A* has activity *Talking_on_the_phone*.
- *User A* has activity *Talking_on_the_phone* makes *Volume_setting* to *Decrease_volume*

The purpose of the designed structure is to illustrate the association among different components in the watching TV use case. Based on the outline of the IoT-O ontology, the structure given in Figure 9 can be shown as a partial expansion according the needs of the research.

3.4 Multimedia Dataset and Design for Reinforcement Learning

To learn about a user's preference for multimedia setting, a dataset is being created in company Irdeto that will record the initial multimedia streaming information. This dataset keeps track of dataflow of the home-based multimedia service (streaming video) and media play devices (TV and loudspeaker). As is mentioned earlier, the media play sensor will collect the streaming information of the media service. The streaming video is obtained from either a local computer or online sources. With a user involved, all the details of the changes in the streaming multimedia for the user's operation can be obtained with regard to time, where the accuracy of current play position is updated every three seconds.

From the sequence of current play position, whether the streaming resource is played forward/backward can be acquired. The playing status of the multimedia service involves the play, pause, stop; and the change in the volume level (higher or lower and mute or not) of the audio. Furthermore, by comparing the time duration between playing length and original length of the displayed multimedia, a conclusion can be made on whether user is interested in the present show. For example, if the playing length is approximately to the original length, it may infer that the user is either fond of or indifferent to the delivered multimedia. However, if the playing length is obviously shorter than the original length, this may indicate that user is not interested in the content, either because user does not like it or he has seen it before.

Next, reinforcement learning is supposed to be fit in this picture. Upon building up the learning agent, a MDP needs to be designed first. The information recorded by the dataset includes:

- ***Streaming resource***
  Information includes resource name and type (Movie, TV series, TV show, Music, etc.), format (mp4, mkv, etc.), quality (1080p, 720p, etc.).
- ***Current play position***

Range from [00:00:00 to HH:MM:SS] where “HH:MM:SS” represents the end of the streaming resource.

- ***Playing status***
  Includes PLAYING, STOPPED, PAUSED
- ***Volume level***
  Ranges from 0 to 100
- ***Mute states (true or false)***
  “Mute 0” which is false and “Mute 1” which is true

The arrangement is as follows:

- Action: (Volume) UP, DOWN, MUTE, DO NOTHING

- Inputs:

  Volume: [0,1,2,3, …, 100]

  Media play status: [PLAY, PAUSE, STOP, SEEK_FORWARD, SEEK_BACK]

  Media play position: [00:00:00, 00:00:03, 00:00:06,…,]

  Media play ID: [1, 2, 3, …,]

  Media play type: [History, News, Science, Sport, Movie, TV series]

From the combination of inputs, the states space which involves all combination of inputs can be built up. For example, one possible state is:

[Making phone call, 90, PLAY, 35:35:23, 7, Movie]

- Reward: Keep it as close to zero as possible. If the user changes the volume by a certain amount, the learning agent will get a negative score. However, this record shall not be simply replaced or permanently settled. There may be a chance that when the same event happens again later, the user may slightly modify the ‘comfortable volume amount’, so the learning agent may consider a moving average result.

The goal of the agent is to get as fewer negative points as possible which indicates the media setting is user-preferred. At this point, an environment, some data about user’s multimedia setting is established to work in. The goal for reinforcement learning is clearly addressed. From here on, the next period of work will be focused on policy strategy that can make the learning agent to score higher that can makes the multimedia setting appeal to the user’s preference.

4. Conclusion and Future Work

4.1 Summary of Year-1 Work

This Year-1 Review report is based on the first-year's research work conducted since the beginning of the PhD enrolment. The main task for the first year's work has been to clarify the research problem targeted.

The previous research initiatives and projects related to the smart home environments have made achievements on indoor activity detection, automatic adaption of media streaming quality, and several ontology models for scalable semantic interoperability in smart environments. However, the area of smart home related multimedia delivery, which takes into account of user activity and preferences, and makes use of methods of reinforcement learning, remains as a large research potential, thus is worth exploring.

The role of a smart environment in this project is to go beyond the traditional ways of delivering information by providing contextual services to users in various settings. This research focuses on delivering multimedia services in smart home environments, by establishing reinforcement learning loop between the user information and indoor devices. The goal is to develop reinforcement learning algorithms that carry out real-time adaption to the multimedia setting, which is based on the user's real time activities and historical habits, to bring in satisfaction and improved user experience within a smart home environment.

Therefore, the report introduces the research goal from three domains. The user activity recognition based on indoor environment is the first scenario to study. The second scenario is about the related ontology, illustrating the semantic interoperability which plots out the interconnection among the user activity, devices and media services. The last scenario focuses on the learning methods, where a Markov model is discussed with regard to the states which consist of different combinations of input factors from both the user and delivered multimedia service. The idea of reinforcement learning is discussed to be the main approach for developing the learning algorithms.

In the following sub-section, a Gantt chart is presented for addressing the work plan and targeted deliveries for each phase of the research activities to be conducted in the remaining period.

4.2 Time Schedule and Future Plan

The duration of this research is 36 months, starting from December 2015 and ending in November 2018. In accordance with the pre-set research objectives as well as the training and placement activities in the Netherlands, the research time schedule is divided into five phases. Figure 11 shows the Gantt chart schedule of the PhD research.

Generally, there are five phases. Early in February 2016, Phase 1 ended with a background report delivered as part of Marie-Curie contract to the European Commission on discussing the research proposal and work framework for the whole period. From March 2016 to September 2016, the work has been carried out with the research partners TU/e and Irdeto in Eindhoven, Netherlands.

A number of training courses with regard to IoT, smart environments and machine learning were delivered by TU/e during March. In the beginning of April, the research proposal was reviewed with colleagues at Irdeto and it was further focused on a home-based smart environment for multimedia delivery. On 13th June, a research progress meeting was carried out at Hoofddorp with group members from both UK and NLs. By that time, the research work on activity recognition came to an end. During the meeting, an agreement was reached that all three scenarios, including activity recognition, semantic interoperability and reinforcement learning would be studied, where the reinforcement learning is the core scenario for the research progress. The background study for semantic ontologies started after the progress meeting and ended at the end of July. Subsequently, a use case of watching TV has been discussed and a setup concerning the multimedia dataset is being built. This Year-1 progress review report will be delivered on 2nd September 2016.

In the end of Phase 2, building the multimedia dataset will be completed. The learning result from the dataset about the user's preferences for the delivered multimedia is expected to be published as a conference publication, such as at the *International Conference on Mobile and Ubiquitous Multimedia (MUM)*, or the *International Conference on Control, Robert and Human Interaction Communication.*

Phase 3: Prototyping and Testing. This period is about testing the algorithms that are built in Phase 2. The training model is concerned only with multimedia in the beginning, which would be later on added into other factors such user activity, user emotion, ambient lighting, etc. While training with different complexity, parameters such as learning rate, discount factor, etc., shall be adjusted accordingly based on the algorithm learning performance. Besides the accuracy, computation efficiency should also be considered. In the end of Phase 3, a journal paper is expected to be published about the algorithms developed and tested.

Phase 4: Solution Evaluation. According to the tested outputs from Phase 3, a detailed analysis on the results will be provided for conclusion in Phase 4. The deployment and dissemination will be made. Lastly, the final results according to the work in this phase will be published as a journal paper in a peer-reviewed journal, such as the *Intelligent Systems*, *Knowledge and Data Engineering*.

Phase 5: Continued Research towards PhD Completion. This period is about the continued research after the training and cooperation with the project partners. It occupies the last year of the research. By reviewing the previous work and achievements, producing the second PhD annual report is expected to be carried out. New methods that may modify and further optimise the algorithm structure are expected to be explored for making further progress. The overall proposed, tested and further optimised solution will be disseminated as a final journal publication. Finally, the PhD dissertation will be written up and submitted in the end of November 2018.

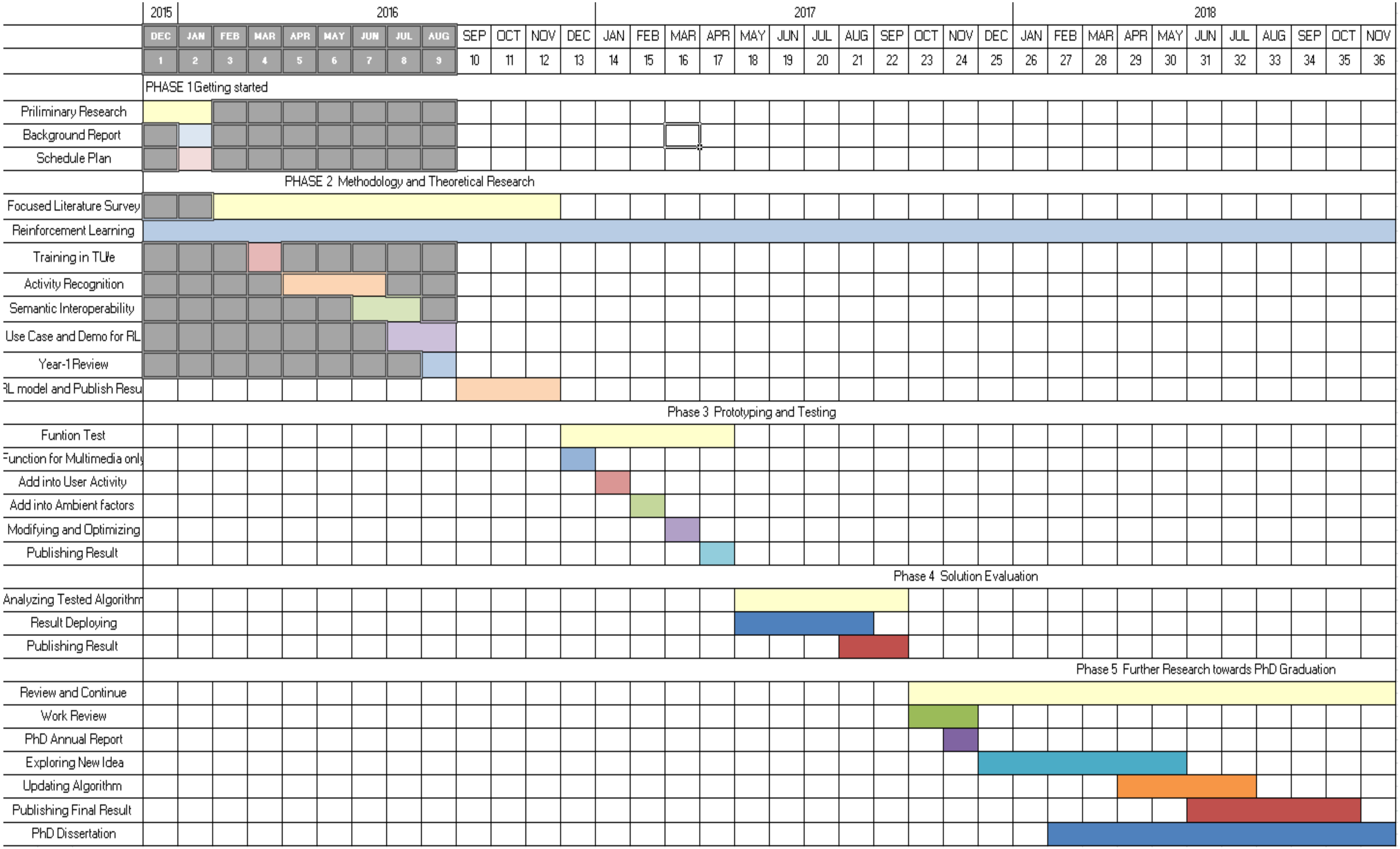


Figure 11. Research Gantt chart

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