Improving the Adaptation Process for a New Smart Home User

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Abstract. Artificial Intelligence (AI) has been around for many years and plays a vital role in developing automatic systems that require decision using a data- or model-driven approach. Smart homes are one such system; in them, AI is used to recognize user activities, which is a fundamental task in smart home system design.There are many approaches to this challenge, but data-driven activity recognition approaches are currently perceived the most promising to address the sensor selection uncertainty problem. However, a smart home using a data-driven approach exclusively cannot immediately provide its new occupant with the expected functionality, which has reduced the popularity of the data-driven approach. This paper proposes an approach to develop an integrated personalized system using a user-centric approach comprising survey, simulation, activity recognition and transfer learning. This system will optimize the behaviour of the house using information from the user's experience and provide required services. The proposed approach has been implemented in a smart home and validated with actual users. The validation results indicate that users benefited from smart features as soon as they move into the new home.

Keywords: Smart home · User adaptation · Activity recognition · Transfer learning

1 Introduction

"I'd rather die than be a burden on my daughter"— this sentiment is common among older people [8]. Older people desire to continue living independently. Nevertheless, it is natural for their families to be hesitant and worried, regardless of how well-managed the home may be. The dangers for elderly people who live alone are many, and unpredictable. Smart homes and associated conveniences could help improve their lives and mitigate most concerns [13].

Imagine a scenario in which Bob/Betty is an elderly person who has decided to continue living independently. Despite concerns about safety and proper care, his/her family decides to accommodate Bob/Betty in a new smart home where technology can facilitate their activities of daily living, such as personal hygiene and food preparation. The same home can also provide advanced functionalities such as fall detection, as well as other safety and security services.

In this scenario, a critical question might be raised: Will the chosen technology be able to provide the expected help to Bob/Betty immediately after he/she moves into this new home? The answer to this question might be “no” due to the reliance of smart homes on a sufficient amount of data to recognize, understand and predict user behaviour and to provide the required services. This data dependency may increase Bob’s/Betty’s familys concern about his/her independent living, especially when he/she first moves in, causing them to underestimate the long-term capabilities of the smart home.

From the description above, it could be concluded that a data-driven smart home cannot provide for all of a user’s needs from day one. Now, two scenarios will be created in which the house attempts to provide automated responses to Bob’s/ Betty’s needs as soon as he/she starts living there.

Scenario (Morning): *The user wakes up, uses the toilet, and then goes to the kitchen make their breakfast, eats breakfast, goes back to bedroom, gets ready, and goes outside. In this scenario, the user expects lights in the bedroom, corridor, toilet, kitchen, shower, and on the table to switch on automatically when required, as well as the kettle and radio in the kitchen. All automated devices will be switched off if the user forgets to switch them off before leaving the house*

Scenario (Evening): *The user come back from office, changes their clothes, uses the toilet, then goes to the sitting room, reads the newspaper, goes to the kitchen, makes dinner, eats dinner, and then goes to the bedroom to sleep. The user demands all automated devices turn on when appropriate and switch off after he is asleep.*

This research proposes a User-guided Transfer Learning (UTL) approach to develop a system that provides the occupant with an Assisted Living Facility (ALF). This article is structured as follows: Section-1 gives background information. Section-2 discusses the findings of related work, Section-3 explains the user-guided transfer learning method, and Section-4 describes the user-guided transfer learning interface. The process of system validation is explained in Section-5 and discussed in Section-6, while conclusions are presented in Section-7.

2 Related Work

User adaptation in smart homes is always a challenging and long-term process. Human activity recognition is one fundamental task of the adaptation process. There are two main approaches for activity recognition: knowledge-driven [12] and data-driven [10]. Knowledge-driven methods use prior domain knowledge to model current activities and involve knowledge acquisition, formal modelling and knowledge presentation. Logical reasoning tasks such as deduction, induction and abduction are used for activity recognition or prediction in knowledge-driven models. Their design is semantically clear, logically elegant and make it easy for the user to get started, offering a solution to the cold-start problem [3]. However, this model is weak in handling uncertainty and temporal information; thus, it is considered a static method.

On the other hand, a data-driven approach mainly concentrates on designing a system that works smoothly without any user interruption. These approaches may not work at times because of the complex and irregular nature of human behaviours [4]. In both data-driven and knowledge-driven approaches, knowledge gained from monitoring user activity is used to improve the system during the development process. Only in very limited cases is the user engaged in the development of the system.

Currently, most research on activity recognition in smart homes focuses on the introduction of new machine learning algorithms [10]. However, machine learning algorithms cannot provide immediate benefit to the smart home user in cases where there is little or no training data. Few scholarly works have focused on the new smart home adaptation process using a data-driven approach. The approach proposed by Chiang and Hsu [5] illustrates a possible new smart home adaptation process. This method accommodates a user in a model of the new smart home in a laboratory environment for data collection. After data collection, a transfer learning approach is used to pass the data to the new smart home. Chiang et al. [6] showed that without target data (no data), the amount of transferred knowledge is insufficient, but it can be increased using a small amount of labelled data.

Data-driven approaches are still a challenging approach to adaptation for new smart homes. Researchers are trying to use transfer learning approaches [7] to diminish the problem. But purely transfer learning-based processes struggle to satisfactorily address the problem. This research aims to tackle the challenge by proposing an approach for development of an integrated system using a user-centric approach [1] comprising survey, simulation, activity recognition and a transfer learning approach.

3 User-guided Transfer Learning (UTL)

There is a specific gap in data-driven activity recognition whereby the system does not provide the prospective service immediately after installation. Here, we explain the method of data collection and illustrate how the scenario can be decomposed into activities.

In the above scenario in Section 1, Bob/Betty is expecting very basic functions from their smart home. It is possible to provide these functions if the home has an idea about their behaviour. Presently, data-driven activity recognition systems predict human behaviour via analysis of the user's dataset of past daily living. As Bob/Betty is a new occupant of the home, the system does not yet have any records about him/her.

At this point, we required a method which familiarizes the house with Bob's /Betty's habits before he/she moves in. We introduced an integrated system using user centric approach that brings four approaches— survey, simulation,

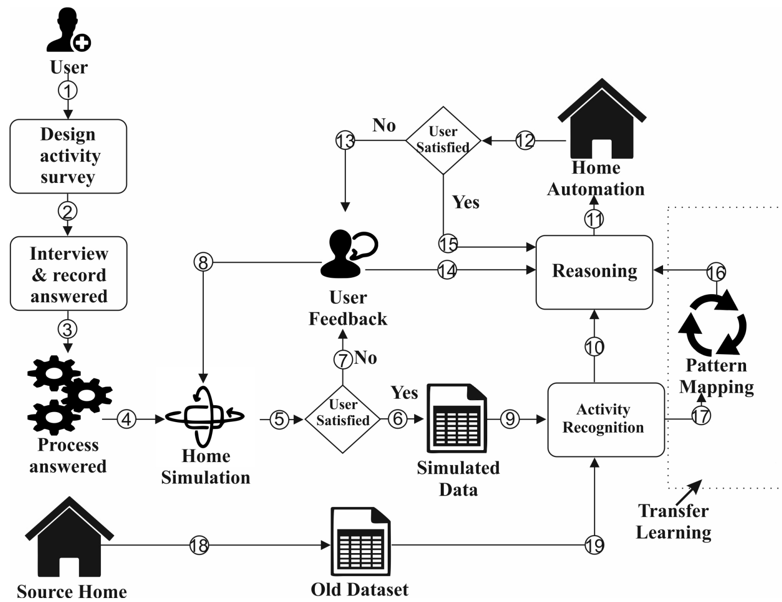

Fig. 1: Conceptual model of the proposed system.

activity recognition and transfer learning — together to provide a smart home facility from day one.

Figure 1 shows the architecture of the system. The user is at the heart of this system; every step of the development process is concluded by considering user feedback and satisfaction. After simulation, the user is invited to become familiar with the house (Figure 1,step 5). This process helps the user gain confidence about the new house. After the system is implemented in the house and the user has started living in the house user feedback is collected again (Figure 1,step 12). The incorporation of feedback from the user at each stage may help in the development of trust in the system.

3.1 Survey

AI implemented automated house should act as a person. It should able to sense the house environment, process the information and react accordingly. Basically the process starts by the data collection.

In order to enrich the data available to the system from the beginning, a questionnaire has been designed for users in which he/she is asked questions (Figure 1,step 2) about activities of daily living. The questionnaire can be found here: `https://doi.org/10.22023/mdx.8789987`. The main objective of the questionnaire is to help the system learn about the user's daily activity and behaviours. To simplify the survey process, the activities are divided into two categories, called *simple activity* and *complex activity*. The number and sequence of actions in the simple activity category is the same for any user. As an example, the "wake up" activity is detected by three sensors, bed pressure, bedroom motion and bedroom light. So, the "wake up" activity is similar for all users, but the time at which it occurs is different. On the other hand, the number of actions and their sequence differs for complex activities. As an example, making tea could be different for users because tea can be made in different ways; some people use milk, some do not, and the sequence of actions in the process could also be different.

Table 1: Sample answers from the user for specific activity.

Activity	**Location**	**Object involve**	**Duration**	**Time**
Eating breakfast	Kitchen or sitting room	Plate, radio, tea, medicine	5-8 min	7:10-7:30 AM
Reading newspaper	Bedroom or sitting room	Sofa, table lamp	15-20 min	7:00-7:30 PM

In the survey process, first, target activities are selected, and afterwards, the user is asked to describe a day in which the target activities take place, including features such as the sequence of activities and start time of each activity. The activity's location is sometimes important, for instance, a particular user may want to read the newspaper in the bedroom instead of the sitting room. The objects used to complete each activity are also important, because this information suggests to the system what sensor(s) will be used to detect the activity. Finally, time is the most valuable parameter used to detect user behaviours. In case the user provides the wrong answered, it will be identified at the end of the process when the automation happened at the wrong time. As we are following the user-centred approach, the problem would be tackled by the user feedback (Figure 1, step 13). Table 1 gives a clearer picture of what type of answers are sought when users answer the questionnaire. Based on the collected answers, a simulation is designed.

3.2 Simulation

The purpose of the simulation (Figure 2, step 4) is to giving the user knowledge about the new house and model the user behaviour based on the user's answer and generate the dataset.

UbikSim [14] is used to design the simulation. UbikSim is open source, has a rich library, and is Java-based. These features make it easy to integrate with the rest of the part of the proposed system. Ubik was initially developed to study complex multi-agent systems (MAS); it has since been modified, including the addition of new features for this project. UbikSim is implemented in two phases, namely virtual house design and user behaviour design.

Virtual house design The first step is to design a 3D virtual house to look like the real smart house where the user will live. In the design stage, our aim is to provide knowledge about the house, so when the user starts living in the new house, he/she does not feel uncomfortable with any of the appliances, furniture

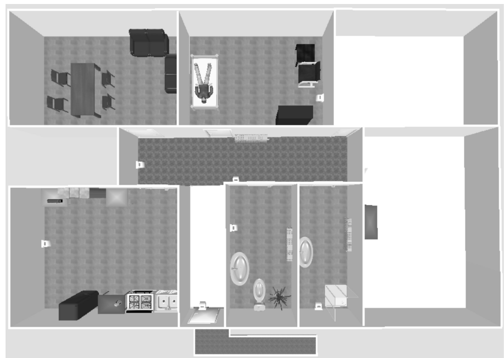

Fig. 2: A virtual design of real Smart Space Lab at Middlesex University.

and or other devices that may be integrated with the sensors. Some features of the home may not be available in UbikSim. In such cases, we can use the rich Sweet home library to improve the design. Figure 2 shows the virtual design of the real smart space lab at Middlesex University.

User behaviour design User behaviour design is based on the user's answers. Here, we follow an interactive approach, using an avatar-an interactive object that can move within the virtual smart home and passively or actively interact with the virtual sensors-to represent the behaviour of the real inhabitant. The avatar interacts with virtual sensors and data on these interactions is saved in the server.

In the scenario, Bob/Betty wants to live independently in a smart home. After an interview in which he/she completes the questionnaire, Bob/Betty is invited to interact with the simulation. Thus, Bob becomes familiar with the new house and its facilities before he/she starts living in it. Bob's/Betty's activities are simulated according to their answers. If he/she is satisfied with the activity processes, the next step is initiated; otherwise, the step is repeated.

The simulation model is generated after complete user satisfaction is reached. Finally, the simulation data are generated based on the requirements of the activity recognition tools. Figure 3 shows user daily living activity data generated using a virtual smart home.

3.3 Activity recognition

To provide the user smart home automation services, we need to detect the habits of the user. Automatically habit detection possible when machine learn and understand the user activity. To detect the user habit we consider LFPUBS [4]. LFPUBS is used as an activity recognition tool, capable of finding the most frequent patterns from a dataset. Like UbikSim, LFPUBS is also open source and Java-based. LFPUBS uses its own language, called LLFPUBS, based on Event-Condition-Action (ECA). The output created by its application is also in ECA format. Its architecture has translation, learning and application layers.

idMeasure	idUser	idDevice	oldValue	newValue	time
87245	1	446	1	0	04/06/2019 14:10
87244	1	505	1	0	04/06/2019 14:10
87243	1	35	1	0	04/06/2019 14:10
87241	1	505	0	1	04/06/2019 14:09
87242	1	446	0	1	04/06/2019 14:09
87240	1	35	0	1	04/06/2019 14:09
87239	1	450	1	0	04/06/2019 14:09
87238	1	505	1	0	04/06/2019 14:09
87237	1	35	1	0	04/06/2019 14:09

Fig. 3: Daily living activity data for a user generated by Simulation.

Each of these layers plays a vital role in understanding data. The translation layer receives raw data, processes it, and splits it into sequences to create a sensible dataset. The learning layer is the core of LFPUBS, which probes for patterns, creates a frequency set of actions, quantitative time relations and specific conditions. The application layer shows and saves the knowledge discovered by the learning layer.

After detecting user behaviour, a reasoning system needed that acts in real time and provide the automation services based on the acquired knowledge. Although quite well known in the AI community, the actions of the reasoning system will be caught by the learning system. For reasoning, we use Mreasoner [9]. Mreasoner is a reasoning system capable of handling causality in context-aware systems. As LFPUBS and Mreasoner both have different functionality and data format. So, use a translator LFPUBS2M [15] that translate LFPUBS pattern to M rules which we can use for the Mreasoner.

3.4 Transfer learning

A novel method is proposed to allow the user enjoy the smart homes automation services as soon as he/she starts living there. To provide the user with more accurate smart home automation services, we integrate the transfer learning technique with the proposed method. As discussed above, a simulation is designed and a dataset generated based on each users answers and the designers experience. However, no activities were practised in a real house. As a result, the duration of each activity could be different in a real house, which may affect the users experience as he/she tries to receive the desired services. As an example, the user could say, or the designer assume, that traveling from the bedroom to the kitchen will take 3 sec, or making a cup of tea 5 min, but these durations may not apply to the real house. Thus, at this point, we must find a way to improve the systems knowledge about the real house.

With transfer learning, a system can leverage experience from previous tasks to improve the performance of a new task. We propose an interface (Figure 1, step 17) to analyse the activity recognition patterns developed from the simulated and real datasets. The pattern will be finalize based on user preference; however, any conflict detected will be solved using the method of Oguego et al. [11]. The proposed method assumes that source data have been collected from a house with the same layout as the experimental house.

4 User-guided Transfer Learning (UTL) interface

The system has been designed to integrate multiple systemUbikSim, LFPUBS, LFPUBS2M and MReasoner. Each of these systems requires a specific format for its input data and outputs data in its own format. To overcome compatibility problems, we designed the UTL interface (Figure 4), which automatically converts each systems output to the appropriate format for the next system to use as input.

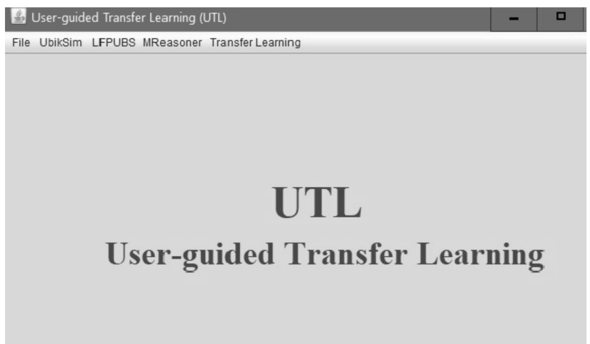

Fig. 4: User-guided Transfer Learning (UTL) Interface.

5 Validation

The key objective of the validation process to examine the system designed using the proposed the method to ensure it is capable of providing a user with automation services as soon as he/she starts living in the new smart home.

As we mentioned above, the user is at the heart of our system development process. To simplify the validation process, instead of validating the whole system at once, we can perform validation in three steps: data validation, simulation validation, and automation validation. Every step consists of a loop which allows refinements to the system based on user feedback. Any intelligent environment (IE) requires the interfacing of hardware, software, networks, and physical space. This type of system also involves different simulations be designed for each user, and the number of iterations required may require a long development time. Thus, in this work, five users participated in the validation process. Validation is carried out at the Smart Spaces lab at Middlesex University (Figure 5, Left), most part of which is set up as a smart home. This area consists of a living room, a bedroom, a kitchen, a toilet, a shower room and a corridor space. 6 Motion, 11 door, 3 object and 6 light sensors are installed. The smart home behaviour

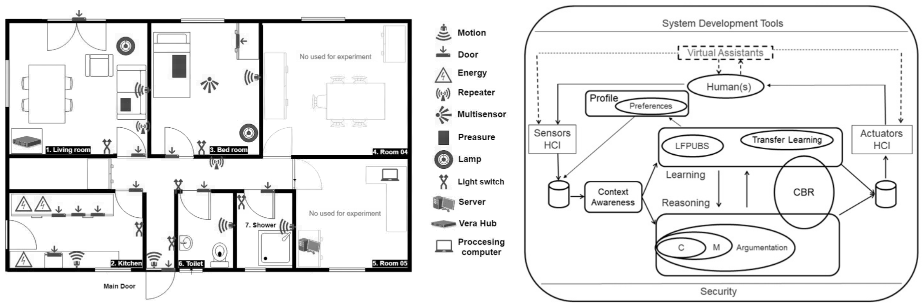

Fig. 5: A map of the lab including sensor hardware (Left); SEArch Architecture (Right).

is driven by the SEArch architecture [2](Figure 5, Right). The system uses rule based reasoning [9] [11] and performs the user behaviour learning [4].

Data validation This step gathers detailed user activity data via face-to-face interviews. Participants are asked pre-designed questions (see Section 3.1). In the interview, the user naturally explains how he/she performs morning and evening activities of daily living. The user may perform various types of activities in morning and evening, but we consider only the preselected activities the system can monitor and provide automation to support.

At this step, the simulated home is displayed to the participants so they can become familiar with new home and devices; this is intended to reduce future discomfort with new devices. Users' answers are processed to sequence activity based on the scenarios, to separate data into complex and simple activities, to organise action sequences that are involved with particular activities, and to rename complex activities (Tables 2, 3,4).

The users are then invited for another interview, shown the summary from the previous interview, and asked for feedback. All users expressed satisfaction with the processed data.

Simulation validation This step seeks to ensure the users are satisfied with the simulation. UbikSim is chosen from the UTL interface to design the simulation, and morning and evening scenarios are designed separately. The simulation, in which an avatar performs daily activities as previously described by the user, is played for the user. This step required repetition; users 1 and user 2 accepted the first iteration, users 4 and user 5 the second, and user 3 the third.

After the simulation is accepted by the user, the data is converted to a particular format so that it can be use in LFPUBS as an input. LFPUBS is a learning system that acquires knowledge of user behaviour from the user activity dataset. A sample of such acquired knowledge is shown in Figure 6. It is a fraction of the activity pattern, where *General Conditions* are calendar information boundaries representing when the action is performed. There *ON* clause defines the event, *IF* defines the necessary condition, and *THEN* defines the action that needs to be carried out. Then, *Action Pattern 1* describes that when Entrance sensor is OFF

Table 2: User's weekday activity sequences

User	Time range	Scenario	Activities and sequences
User1	08:30-09:30AM	Morning	Wake Up → Use Toilet →Make Tea →Go Outside
	07:00-10:00PM	Evening	Enter Home → Use Toilet →Relaxing →Make Tea →Sleeping
User2	06:00-07:00AM	Morning	Wake Up → Use Toilet →Make Tea →Use Shower →Go Outside
	08.00-10.00PM	Evening	Enter Home →Make Tea→Relaxing→Make Tea →Sleeping
User3	08:30-09:00AM	Morning	Wake Up → Use Toilet →Use Shower →Make Tea →Go Outside
	08:00-10:00PM	Evening	Enter Home →Make Tea →Sleeping
User4	06:00-07:00AM	Morning	Wake Up → Use Toilet →Use Shower →Make Tea →Go Outside
	08:00-11:00PM	Evening	Enter Home → Use Toilet →Make Tea →Sleeping
User5	08:30-09:00AM	Morning	Wake Up → Use Toilet →Make Tea →Use Shower →Go Outside
	08:00-10:00PM	Evening	Enter Home → Make Tea →Relaxing →Sleeping

Table 3: Example of simple and complex activities.

Scenario	Simple Activity	Complex Activity
Morning	Wake up, use toilet, use shower, go outside	Make tea
Evening	Enter home, Use toilet, sleeping	Make tea, relaxing

and Corridor sensor is OFF, and then the Toilet sensor expected to be OFF after 230s. If *THEN* clause mentions an actuator, then triggered otherways it is used for monitoring purposes. This way LFPUBS creates links between two events. As stated in Section 3.3, that pattern is not directly executable by Mreasoner. So LFPUBS2M used to translate the dataset to Mreasoner executable format. Figure 7 shows part of the rules that are sequentially executed by the Mreasoner to accomplish the automation task. Here the rules define that the kitchen Light will be turned on when Pattern_0 to Pattern_9 are satisfied. Where each of the patterns satisfied with a certain state of the sensors for example, Pattern_8 will be satisfied if kitchen door open between 13:41:32 to 13:57:41 on Monday to Friday.

Smart home automation validation The objective of this step is to activate the devices and provide the user with the promised automation. To accomplish

Table 4: Users' Action Sequences for Particular Activities.

User	Activity name	Action involves	New name
User1	Make Tea	KitchenDoor ON → KitchenMotion ON →Kettle ON →Cupboard ON →Fridge ON	Milk Tea
	Relaxing	SittingroomMotion ON → SittingroomLight ON →SittingroomSofa OFF	Relaxing in sitting
User2	Make Tea	KitchenDoor ON → KitchenMotion ON →Kettle ON →Cupboard ON	Red Tea
	Relaxing	SittingroomMotion ON → SittingroomLight ON →SittingroomSofa OFF	Relaxing in sitting
User3	Make Tea	KitchenDoor ON → KitchenMotion ON →Kettle ON →Cupboard ON	Red Tea
	Relaxing	SittingroomMotion ON → SittingroomLight ON →SittingroomSofa OFF	Relaxing in sitting
User4	Make Tea	KitchenDoor ON → KitchenMotion ON →Kettle ON →Cupboard ON →Fridge ON	Milk Tea
	Relaxing	BedroomMotion ON → BedroomLight ON →BedPressure OFF	Relaxing in Bed
User5	Make Tea	KitchenDoor ON → KitchenMotion ON →Kettle ON →Cupboard ON →Fridge ON	Milk Tea
	Relaxing	BedroomMotion ON → BedroomLight ON →BedPressure OFF	Relaxing in Bed

this, each user is invited to visit the lab twice, once in the morning and once in the evening. The Mreasoner from UTL was chosen to perform the real-time home automation based the on rules generated (as described in the previous section). User feedback about the automation services is collected from each user and used as a basis to modify the rules. After finishing the validation process, we

Table 5: Study questions for measuring the acceptance of the system and user satisfaction.

no	System acceptance and user satisfaction question
1	How useful is it that the smart home provides services from day one?
2	How similar did you find the simulated and real smart home?
3	How close was the simulated behaviour to the answers you provided?
4	How useful was the simulation in adjusting to the real house?
5	How will did the house provide its automation services?
6	What improvements would you make to the system?

```
Action Map 0

(General Conditions)

 context (DayOfWeek (=,Monday,Tuesday,Wednesday,Thursday,Friday))&
 context (TimeOfDay(>,09:24:08)) & context (TimeOfDay(<,00:00:00))

(Action Pattern 0)
ON occurs (start,--,t0) Frequency: 7
IF context ()
THEN do (unordered,((OFF,Entrance (0)) & (OFF,Corridor (0))), t) when --

(Action Pattern 1)
ON occurs (unordered,((OFF,Entrance (0)) & (OFF,Corridor (0))), t0) Frequency: 21
IF context ()
THEN do (simple,(OFF,ToiletMove (0)) , t) when t = t0 + 230.6107692718506 s.

(Action Pattern 2)
ON occurs (unordered,((OFF,Entrance (0)) & (OFF,Corridor (0))), t0) Frequency: 2
IF context ()
THEN do (simple,(OFF,CupboardKitchen6 (0)) , t) when t is after t0

(Action Pattern 3)
ON occurs (unordered,((OFF,Entrance (0)) & (OFF,Corridor (0))), t0) Frequency: 9
IF context ()
THEN do (simple,(ON,CupboardKitchen6 (0)) , t) when t is after t0
```

Fig. 6: Sample of LFPUBS generated pattern.

```
ssr( ( weekDayBetween(monday-friday ) ) ->actionMap_day_context ) ;
ssr( ( #weekDayBetween(monday-friday ) ) ->#actionMap_day_context );
ssr( ( clockBetween(13:41:32-13:57:41 ) ) -> actionMap_time_context );
ssr( ( #clockBetween(13:41:32-13:57:41 ) ) -> #actionMap_time_context );

ssr( ( BedRoomDoor ^ actionMap_time_context ^ Pattern_1 ^ actionMap_day_context ) -> Pattern_0 );
ssr( ( [-][06s.]#BedRoomMotion ^ actionMap_time_context ^ Pattern_2 ^ actionMap_day_context ) -> Pattern_1 );
ssr( ( BedRoomMotion ^ actionMap_time_context ^ Pattern_3 ^ actionMap_day_context ) -> Pattern_2 );
ssr( ( #EntranceDoor ^ actionMap_time_context ^ Pattern_4 ^ actionMap_day_context ) -> Pattern_3 );
ssr( ( EntranceDoor ^ actionMap_time_context ^ Pattern_5 ^ actionMap_day_context ) -> Pattern_4 );
ssr( ( [-][02s.]#EntranceMotion ^ actionMap_time_context ^ Pattern_6 ^ actionMap_day_context ) -> Pattern_5 );
ssr( ( EntranceMotion ^ actionMap_time_context ^ Pattern_7 ^ actionMap_day_context ) -> Pattern_6 );
ssr( ( [-][14s.]#KitchenDoor ^ actionMap_time_context ^ Pattern_8 ^ actionMap_day_context ) -> Pattern_7 );
ssr( ( KitchenDoor ^ actionMap_time_context ^ actionMap_day_context ) -> Pattern_8 );
ssr( ( #BedRoomDoor ^ actionMap_time_context ^ Pattern_0 ^ actionMap_day_context ) -> Pattern_9 );
ssr( (Pattern_9 ) ->KitchenLight );
```

Fig. 7: Sample of LFPUBS2M translated rules.

asked the participants six questions (Table 5) to measure their acceptance of and satisfaction with the new system. We used a three-point Likert scale to analyse participants responses (Figure 8). Four (80%) of users felt that smart home automation from day one is very useful, and that the smart home simulation helped the user adapt to their new home. Users did not find substantial similarity between the simulated and real homes; however, they suggested that it gave them a basic idea about how the actual house would be. Users were generally satisfied with house automation time; Three paricipants (60%) agreed the automation happen on correct time. Most users agreed that the actual behaviours were similar to those in the simulation based on their answers.

All of the resources which gather used and generated in from the validation process, such as questionnaires, users answered, simulation, simulated data, LFPUBS-produced patterns, LFPUBS2M-generated rules, and the results of house actuation when user exercised the scenarios can be found here at `https://doi.org/10.22023/mdx.8789984`.

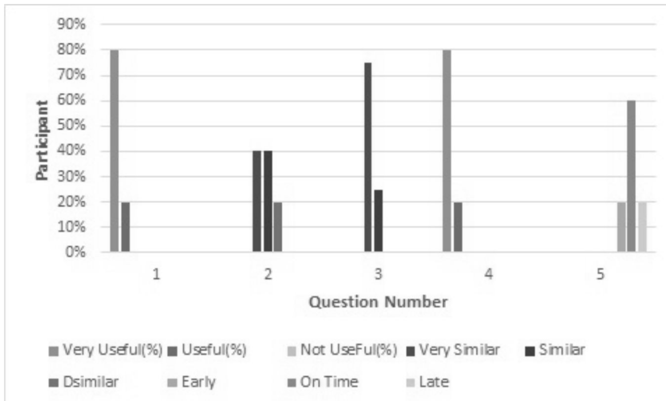

Fig. 8: Users' responses based on questions in Table 5.

6 Discussion

We performed validation considering the two scenarios described in Section 1. Our aim was to provide the user with home automation services as soon as he/she starts living in the house. Five users participated in the user-centred validation process. The user-centred nature of the process makes it highly unlikely the user will be unsatisfied with the resulting system. Participants response results show that a user expect automation functionality as soon as he/she start living in the house. Our design system was able to provide appropriate automation immediately over 60% of on time; user feedback shows our design is useful in helping new users understand the features of their new smart home.

7 Conclusion

Data-driven activity recognition is one of the most active and challenging lines of research in the field of smart home development. The goal in this work was to create a user-centric approach to develop a system that immediately provides smart home automation services to new users, thereby increasing user satisfaction and acceptance of the technology. To that end, this research designed an integrated systems that pre-determines user behaviour patterns using user-provided data. These approach complement of unsupervised existing strategy. These patterns are used to feed a reasoning system that can help provide the functionality that the user requires. The resulting system is user-centric, with every step incorporating user feedback. This minimizes the chance that users will be unsatisfied with the results. We successfully designed and implemented the system and validated it in a real smart home. The system shows promise; participants report that the system is very useful for adapting to their new smart home. Our next step will be validating the transfer learning process to further increase automation accuracy.

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