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A Survey of User-Centred Approaches for Smart Home Transfer Learning and New User Home Automation Adaptation

S M Murad Ali, Juan Carlos Augusto, and David Windridge

Research Group on Development of Intelligent Environments, Department of Computer Science, Middlesex University, London, UK

ABSTRACT

Recent smart home applications enhance the quality of people's home experiences by detecting their daily activities and providing them services that make their daily life more comfortable and safe. Human activity recognition is one of the fundamental tasks that a smart home should accomplish. However, there are still several challenges for such recognition in smart homes, with the target home adaptation process being one of the most critical, since new home environments do not have sufficient data to initiate the necessary activity recognition process. The transfer learning approach is considered the solution to this challenge, due to its ability to improve the adaptation process. This paper endeavours to provide a concrete review of user-centred smart homes along with the recent advancements in transfer learning for activity recognition. Furthermore, the paper proposes an integrated, personalised system that is able to create a dataset for target homes using both survey and transfer learning approaches, providing a personalised dataset based on user preferences and feedback.

Introduction

"I'd rather die than be a burden on my daughter-like many old people." – This is a common opinion from older people (Hanson 2016) since they do not want to be considered a burden by their families. They desire to continue living independently, nevertheless, it is very 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 various and unpredictable. Smart homes and associated conveniences could help improve their lives and mitigate such concerns.

Recent improvements in technology, reasonable prices and the increasing availability of smart home appliances has made them more popular. The population of ageing people is rapidly increasing worldwide because of

CONTACT S M Murad Ali sa2305@live.mdx.ac.uk Research Group on Development of Intelligent Environments, Department of Computer Science, Middlesex University, The Burroughs, Hendon, London, UK

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advancements in health and medical practices. According to a United Nation's (UN) report, one out of eight people worldwide were at or over the age of sixty in 2015 (UN 2015). The same report also suggests this percentage will double by 2050. In Europe, the elderly population is also increasing very fast, and according to the World Health Organization (WHO), 30% of the European population will be 65 or older (Giannakouris et al. 2008).

It is a common experience that older people like to continue living independently in their homes despite the challenges of ageing. To fulfil the desire for comfort and a sense of security, there is an increased demand for smart home environments. Lutolf (1992) formalized the smart home concept, focusing on the integration of different services into the home using communication systems. Sat pathy (2006) proposed a clearer concept aiming to help users living independently and comfortably with the help of integration of different devices. Augusto and Nugent (2006) brought the smart home concept to the software-oriented AI (Artificial Intelligence) community, building a bridge between AI and smart homes that highlighting the need for smart home to be. Recently Leitner (2015) introduced a new paradigm, the wise home, offered an improved user experience by focusing on the users interaction experience (both explicit and implicit) rather than the technology that makes it possible. Currently, extensive research related to smart homes suggests the integration of various machine learning and artificial intelligence techniques for making smart homes more user-friendly.

Imagine a scenario where an user say Bob, is experiencing early stages of dementia, and he decides to continue living independently. Despite concerns about safety and proper care, his family decides to accommodate Bob in a new smart home where his daily living activities such as personal hygiene and food preparation can be facilitated by technology. The same home can also provide advanced functionality such as fall detection, as well as other safety and security services.

However, in this scenario, a critical question might be raised: Will the chosen technology be able to provide the expected help to Bob immediately after he moves into this new home? The answer to this question might be "no" because of the reliance of smart homes on large amounts of data. A smart home needs sufficient amount of data to recognize, understand and predict users behaviour and to provide the required services (Cook and Das 2004). This data dependency of the smart home may increase Bobs family concern about his independent living, especially when he first moves in, causing them to underestimate the long-term capabilities of the smart home.

One of the challenges of the new smart home would be the activity recognition where it would attempt to correctly classify Bob's daily activities of cooking, sleeping, and bathing based on a daily performance dataset. More generally, activity recognition is also important in areas requiring verification (Liu et al. 2015) including home automation, security surveillance, monitoring and anomaly detection.

There has been some progress in automated human activity recognition. For instance, machine learning algorithms have been adopted for smart home research because they offer advances in tackling the uncertainty problem of human activity recognition, e.g. (Mehr, Polat, and Cetin 2016), but the capability of machines to perform this task is still limited (Skocir et al. 2016).

The current scholarly work on activity recognition based on sensors demonstrates that knowledge-driven and data-driven techniques are common (Liu et al. 2015). Data-driven activity recognition systems work well if sufficient labelled data is available, and their performance increases proportionally by increasing the dataset though only up to a certain point. In contrast, some other approaches use unlabelled data for activity recognition (Liu et al. 2015; Ni et al. 2015; Skocir et al. 2016).

The focus of this study is to apply transfer learning to help solve problems related to initializing a new smart home where no prior data is available for modelling user activities. In the context of machine learning, transfer learning addresses how to store knowledge garnered from one problem and apply it to a related but disparate problem (Weiss, Khoshgoftaar, and Wang 2016) without dependence on the size of the dataset (Pan and Yang 2010). The motivation behind it is to improve the performance of the present task by leveraging experience gained from previous tasks. In a new smart home, transfer learning can be applied to improve activity recognition (Pan and Yang 2010).

Transfer learning is adequate in cases where the targeted training data is limited, (Weiss, Khoshgoftaar, and Wang 2016). While machine learning techniques traditionally require training and testing data from the same population, (Weiss, Khoshgoftaar, and Wang 2016) such matched data might be difficult or even impossible to acquire.

Maximally data-driven activity recognition approaches typically focus on modelling a system for autonomous adaptation without user interaction (Liu et al. 2015). On the other hand, some smart home applications have a user-centred approach and aim to build a personalized system that fulfils certain user requirements. This approach involves continuous design, feedback, and modification, among other requirements (Amiribesheli and Bouchachia 2015; Haines et al. 2005; Hwang and Hoey 2012; Oguego et al. 2018).

It has been notice that critical analysis from a user-centred approach must be combined with transfer learning for it to be an effective method of activity recognition while establishing a new smart home. While there are several studies focused on transfer learning (Pan and Yang 2010; Weiss, Khoshgoftaar, and Wang 2016) and user-centric domains (Azimi et al. 2017; Röcker 2013), this survey mainly focuses on the new user adaptation process in a smart home, combining data-driven, transfer learning and user-centred approaches.

The rest of the paper is as follows: In "section 2: Activityrecognitioninsmarthomes" we will present an overview of sensor-based data-driven activity recognition processes for smart homes. The most recent approach to developing a user-centric smart home will be discussed in "section 3: User-centered smart home". In "section 4: Transfer learning" we will highlight recent advancements in transfer learning for activity recognition. We will review the latest smart home adaptation process together with our proposed improved methodology in "section 5: Discussion about". In "section 6: system" we will propose a system architecture and finally, sum up the state of the art and our proposed approach"section 7: conclusion".

Activity Recognition in Smart Homes

The baseline infrastructure for a home to be considered a smart home includes several sensors and actuators, user interfaces (such as voice control and graphic displays), building services (ventilation, heating and lights), and appliance networks (Weiss, Khoshgoftaar, and Wang 2016). The external network (mobile phones, internet) can be combined with the in-house network. In this context, a smart home is focused on an automated building as well as on integrated communication services via existing building infrastructure. Researchers generally agree that a smart home system is comprised of three primary elements: the internal network, home automation, and intelligent control (Rashidi and Cook 2009a).

To enable activity recognition in a smart home, there are three main stages. It is necessary to 1. Collect low-level data from the sensors (acquiring sensor data), 2. Process the data collected (processing and data analysis), and 3. Apply learning or reasoning methods to make inferences about activities based on the processed data (activity recognition)(Figure 1) (Akhavian and Behzadan 2015; Liu et al. 2015; Mehr, Polat, and Cetin 2016; Ni et al. 2015; Skocir et al. 2016).

Step 1: Acquiring Sensor Data

The first stage of data collection requires the use of sensors and actuators, small and affordable devices around the household capable of perceiving, monitoring and logging human activities (Bakar et al. 2016). While a wide range of sensors is available, few of those on the market are specifically designed for activity recognition (Bakar et al. 2016). Sensors can be categorized based on their type, purpose, output signals, and technical infrastructure.

Dense sensors can be split into two main categories: obtrusive, or vision-based sensors, and non-obtrusive sensors (Bux, Angelov, and Habib 2017). Vision-based sensors use video cameras for activity recognition; they are

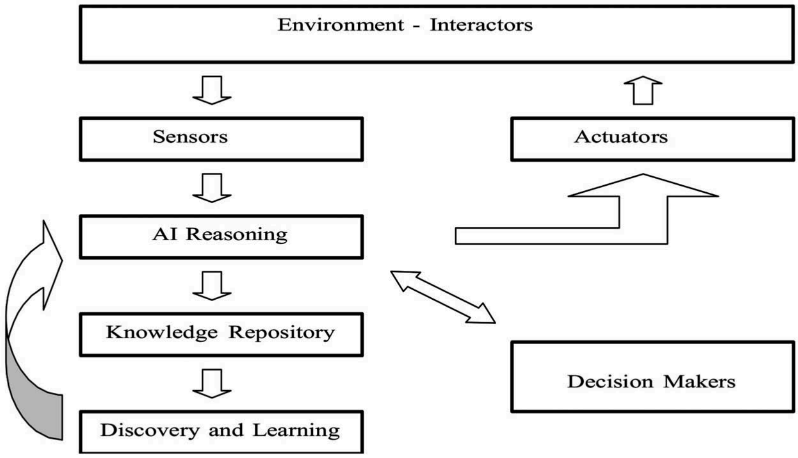

Figure 1. Information flow in smart home Augusto (2007).

popular for this purpose because the sensing device does not require human intervention. Non-obtrusive sensors can be further divided into two classes: wearable sensors and dense-sensing environment sensors (Yilmaz, Javed, and Shah 2006).

Wearable sensors are suitable for applications such as monitoring skin temperature, pulse, body position and movement. However, they have a number of limitations, notably short battery life due to their constant operation, and willingness of the user to wear them. To address these limitations, dense sensing has emerged, where the dense-sensing environment can collect all the necessary data without physical contact with the user.

Smart home applications continuously generate data, with the amount produced depending on the number of sensors, the number of occupants of the home, and the activities the occupants carry out. All sensors rely on wired or wireless communication and must have a unique identifier (ID), time stamps and status signals (Yilmaz, Javed, and Shah 2006). Sensors may fail from time to time, especially if the smart home environment is noisy . The data collected can be noisy and multidimensional; thus, temporal-ordered random data processing is used to isolate the necessary raw data for activity recognition.

Step 2: Processing and Data Analysis

Data analysis is a critical step for activity recognition in smart homes, mostly performed by machine learning algorithms and reasoning approaches (Akhavian and Behzadan 2015; Skocir et al. 2016). However, as future smart homes become more and more sophisticated, the data collected also becomes noisier, requiring additional processing before being subjected to next-level analysis. Data filtering becomes essential to smooth out the raw data by filtering out artefacts and removing outliers. Methods such as Bayes and particle filters, median filters, low-pass filters and Kalman filters can be used.

After filtering and handling missing values, the next step in data analysis is to put the data into a proper format depending on the algorithms used. Data segmentation is also necessary prior to classification, since smart home sensor data might be collected at requested or periodic intervals. The segmentation process divides collected data into smaller blocks before applying classification to improve classification performance. A smart home data segmentation process proposed by Ni et al. (2015) divides data into three main segments: temporal-based, activity-based and sensor-based (Ni et al. 2015).

Step 3: Activity Recognition

The last stage of the process outlined in (Figure 1) is recognition of an activity based on the acquired and filtered sensor data. There are two main approaches for activity recognition: knowledge-driven (Cook 2009; Mckeever et al. 2010) and data-driven (Rao and Cook 2004). Knowledge-driven methods use prior domain knowledge to model current activities (Bakar et al. 2016; Ni et al. 2015), 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 easy for the user to apply immediately; it is well known that they provide a solution to the cold-start problem (Azkune et al. 2015). However, these models are a static method, weak in handling uncertainty and temporal information.

In contrast with knowledge-driven models, data-driven models learn from pre-existing datasets that contain user behaviours by utilizing data mining and machine learning techniques. The models involve the use of probabilistic or statistical methods for overcoming data uncertainty and temporal issues. Based on the categorization proposed by Jebara (2004), data-driven approaches can be separated into two classes: generative and discriminative.

In the generative approaches, a probabilistic model is used to build a complete description of the input data (Lei et al. 2010). For example, the naive Bayes classifier (Sarkar, Lee, and Lee 2010) provides adequate results for activity recognition since it incorporates probability concepts. Discriminative approaches use previous submissions for assembling correct and in-correct data. For instance, the nearest-neighbour algorithm utilizes a large number of training samples which grow exponentially with the anticipated accuracy. Another popular generative approach is the Hidden Markov Model (HMM), which handles temporal information well (Moeslund, Hilton, and Krüger 2006). The model uses a probabilistic structure for efficient learning from the available data. Its main drawback is that a complete probabilistic representation requires adequate data.

There is also a need for discriminative approaches which solve the classification problem rather than the representation problem, like the generative approach. An example of the discriminative approach is the nearest-neighbour method (Bao and Intille 2004) that compares the training dataset and allocates the most closely matched sequences together.

Decision trees are another example of a discriminative technique. Decision trees are used to learn logical descriptions of activities from complex sensor readings (Pal and Mather 2001; Stankovski and Trnkoczy 2006). Many available descriptive approaches classify activities based on decision boundaries, where the main challenge is to find the hard data points (those closest to the boundary). These data points, known as support vectors, are used in the well-known Support Vector Machines (SVM) machine learning technique (Brdiczka, Crowley, and Reignier 2009). SVMs are established and well-known classification methods that classify data in a non-probabilistic way. Other popular algorithm types include Artificial Neural Networks (ANN) which offer various advantages for both activity recognition and learning process in smart home applications (Mehr, Polat, and Cetin 2016). Popular ANN applications in deep learning include recurrent neural networks, deep feed-forward networks and convolutional neural networks. These algorithms perform better than SVM, NB, and HMM (Arifoglu and Bouchachia 2017; Hammerla, Halloran, and Plötz 2016).

There are some other approaches that do not fall clearly into the categories of discriminative and generative. For instance, the Independent LifeStyle Assistant (ILSA) uses rule-based and statistical models (Guralnik and Haigh 2002). The Learning Frequent Pattern of User Behavior System (LFPUBS) also uses rules of association to find the most frequent patterns and distil and implement event condition action rules to detect patterns in real time (Guralnik and Haigh 2002).

Bakar et al. (2016) classified activity models into supervised Activity Recognition (AR) and unsupervised Activity Discovery (AD) based on the data instance. Supervised AR follows a supervised learning approach where labelled training data is available for activity classification. For example, decision trees, neural networks and support vector machine models are in the AR domain.

Unsupervised AD entails data flow analysis for discovering the most frequent patterns or knowledge through unsupervised approaches. The data can be represented using rules and, as mentioned above, LFPUBS is an example that falls within this category. There are also some approaches that could be classified as both AR and AD.

For instance, Bourobou and Yoo (2015) proposed a method that first uses an unsupervised learning method, the K-pattern clustering algorithm, to detect discontinuous and interleaved user activity patterns and group them into appropriate clusters. In the next step, an ANN is used to recognize and predict user activity based on Hamblins and Allens interval-based temporal relations (Augusto 2001a).

Activity Discovery (AD) entails data flow analysis for discovering the most frequent patterns or knowledge through unsupervised approaches. The data can be represented using rules and, as mentioned above, LFPUBS is the example of this category. There are also some approaches that could be classified as both AR and AD. For instance, Bourobou, Mickala, and Yoo (2015) proposed a method that uses firstly an unsupervised learning method called the K-pattern clustering algorithm for detecting discontinuous and interleaved user activity patterns and groups them into appropriate clusters. In the next step, an ANN is used to recognize and predict user activity based on Hamblin's and Allen's interval-based temporal relations (Augusto 2001a).

In summary, current smart home research focuses on learning algorithms and reasoning approaches (Bakar et al. 2016; Ni et al. 2015). There are many studies devoted to user-centred approaches for data-driven smart home development, and it will be beneficial to compare user-centric smart homes against non-user-centred (Table 1).

User-Centred Smart Home

It is well-reported in the current literature that one of the main current drivers for smart home applications is to fulfil the desires of the elderly people who want to continue to live independently (Al-Shaqi, Mourshed, and Rezgui 2016; Ni et al. 2015). Throughout the literature related to user-centred smart homes, there are a number of terminology ambiguities. Terms such as smart home and Ambient Assisted Living (AAL) are often found together, since smart homes have been a core instrument of AAL.

Table 1. Comparison between user-centred and non-user-centred smart homes.

User-centred smart home	Non-user-centred smart home
Users are more involved during system development. Hence, users feel a sense of ownership of the house.	Focuses more on the user generated data rather than direct user involvement.
The adaptation process starts from the development period.	The adaptation process starts when the user starts living in the house.
There are fewer chance to redesign the home because every design step only concludes after user acceptance.	May require redesign when the user starts living in the home.
User contribution is directly used in the validation process. Thus, there is only a small chance the user will refuse the house.	The design model is usually first validated by user data, and then directly by the user. There are more chances for the user to refuse the house.
User-centred design is time-consuming and costly because of intensive stakeholder involvement. Validation with the user requires more time.	Comparatively less time consuming and cheaper.
The final product is more effective and safe, especially for vulnerable users.	Product is less effective and safe.

The existing literature highlights that most approaches to creating user-centric smart homes focus on providing facilities for the elderly and disabled people. However, there are some user-centric approaches that focus on other areas, such as smart home power consumption (Chen et al. 2017). Another recent example is the POSEIDON system, in which a user-centric intelligent environment development process is implemented during the design of the system (Augusto 2007).

Based on the current scholarly work, a user-centric architecture implies two things. Firstly, it concentrates on the interface design between the IT application and the individual users (Ceccacci, Germani, and Mengoni 2013; Ceccacci and Mengoni 2017; Portet et al. 2013). Secondly, it entails development of scenarios and their evaluation concerning the prospects of IT usage by inviting prospective user participation and controls (Amiribesheli and Bouchachia 2015; Ball and Callaghan 2012). The current smart home study highlights potentials and scenarios for IT application in residential buildings through smart home development.

A data-driven approach mainly concentrates on designing a system that works smoothly without user interruption (Jakovljevi, Njegu, and Donov 2016). These approaches may sometimes not work because of complex and irregular human behaviours (Aztiria et al. 2013). For overcoming such cases, there is a need for a system design where users can incorporate their comments or opinions into the system. Such incorporation will allow the system to take more accurate decisions and provide maximum utility to the user.

Today, new smart home designs are mainly driven by technology rather than user needs. In very limited cases, the user is engaged in the development of the system. Since many smart homes are designed for elderly people, developers may find it difficult to find potential users for testing during systems development. There is a lack of knowledge from the developers side with respect to engaging potential users during system development, which explains the lack of such involvement (Amiribesheli and Bouchachia 2015).

Time and stakeholders constraints, along with financial limitations, are some of the reasons for neglecting to integrate user feedback during smart home design (Glende, Podtschaske, and Friesdorf 2009). Knowledge that comes from user activity is used to improve the system during its development process. In a user-centred approach, the user is directly involved with the development process, and may feel the final product is more convenient and secure after taking part in the evaluation and validation process.

According to ISO (1999), the user-centred design aims at building a system that meets all user requirements and is highly usable. During a user-centred design process, the users are fully involved in the process of designing the system, through interviews and other feedback, providing suggestions until all user requirements are satisfied.

In some cases where elderly users are involved, devices known to the users are preferable, because unfamiliar ones can cause anxiety for the occupants (Amiribesheli and Bouchachia 2015). User involvement also improves the adaptation process, especially in a data-driven smart home where there is a great lack of user-centred smart home design (Rashidi and Cook 2009a; Ravishankar, Burleson, and Mahoney 2015).

Amiribesheli and Bouchachia (2015) proposed a user-centred scenario-based approach to develop smart homes for dementia patients. Their approach was created based on existing literature and collaboration with caregivers. They highlighted that stakeholders involved in user-centric systems should participate in every stage of the design process, and recommended collecting relevant information from stakeholders around the dementia patient as well as directly from the patient for better generalisation of the system (Amiribesheli and Bouchachia 2015).

Hussein et al. (2014) proposed a self-adaptive smart home prototype for disabled people. Two types of neural networks were used in the prototype: feed-forward and recurrent. The proposed system uses a recurrent neural network for acquiring human behaviour patterns, and then the habits and activities are learned to predicting human activity and recommend actions on behalf of the user. A feed-forward architecture is then applied to integrate safety and security system applications within the smart home. The prototype also allows users to reduce power waste by evaluating and adapting consumer behaviour patterns (Hussein et al. 2014).

Research has demonstrated that integrating continuous Ambient Intelligence (AmI) technologies, including sensor networks, pervasive computing and wearable devices in a user-centred design significantly improves the degree of user acceptance of intelligent systems. Casas et al. (2008) argued for the importance of user modelling during user-centric smart home development since different users have different needs. However, developing a unique system for individual needs is costly and impractical; thus, Casas and colleagues proposed a user modelling technique for creating an accurate, parameterized profile for the individual user to enable the system to change its parameters for new users or adjust them for existing users upon request. The system profiles users, taking into account cognitive and sensorial disabilities (Casas et al. 2008).

Hwang and Hoey (2012) presented the research gap found between current technology and end-users. To address this gap, a proposed person-specific knowledge base of user needs that connects the user with the medical professional, family member, product developer and all stakeholders is vital (Hwang and Hoey 2012). The work of Hwang and Hoey involved feedback from caregivers providing adult and elderly care, and information from complex smart homes that are able to sense surroundings and provide assistance. The main challenge was to develop an intervention (prompts) and sensing mechanism delivered at the appropriate time, since the system should understand the type of intervention necessary, as well as recognize changes in the users ability and adapt the intervention accordingly.

Haines et al. (2005) proposed that a user-centred approach improves the home system interface design and enables assistance to people with a wide range of characteristics and abilities. Additionally, the authors state that a prototype system can be designed and tested either in a laboratory setting or field trials to identify potential problems and solve them based on user feedback (Haines et al. 2005).

Ravishankar, Burleson, and Mahoney (2015) presented an approach for identifying technical and design issues during the designing, developing, and testing phase by using functional assessment systems. They conducted case studies to explore the deployment of the smart home systems interfaces and systems geared towards evaluating instrumental activities of daily living and activities of daily living. Several interesting challenges were identified, including connection failures between sensor and receiver. The male and female participants showed different responses to problems; where the female participants wanted to share problems with their families, the male participants denied any problems existed. After examining the pre- and post-interview results, the authors emphasized the importance of user experience related to independence and/or privacy needs and the necessity for adaptation or customization based on individual needs.

Other types of user-centric smart home approaches that are becoming popular are virtual smart home prototypes designed by user interaction through context-aware criteria (Krzyska 2006; Lertlakkhanakul, Choi, and Kim 2008). There are different approaches for designing such virtual smart home applications. 3D (Krzyska 2006; Lertlakkhanakul, Choi, and Kim 2008) virtual environments, for instance, can be created of full smart home facilities. The mouse pointer is dragged on an avatar (user) throughout the virtual environment to gather positioning data. In another virtual prototype design (Jozam, Bauke de Vries, and Timmermans 2012), the user performs some real-time interactions through visualization to develop a better understanding of the smart home. The users feedback is used by the designers to improve the smart environment. Free smart home simulators such as UbikSim (Serrano, Botia, and Cadenas 2009) and OpenSHS (Alshammari et al. 2017) were used by researchers to import smart devices into the environment, allowing simulation of user-specific events and generation of synthetic data. A summary of user-centred approaches for smart home design is given in Table 2.

Based on the above discussion, it seems that the user-centred approach is complicated and time-consuming due to the iterative refinement process. In practise, though, the approach has a lot of benefits. We also have seen there are some approaches that allow users to indicate their preferences, like the LFPUBS

Table 2. Summary of the user-centred approach for smart home design.

References	User	Contributor	Interface	Design approaches
Amiribesheli and Bouchachia (2015)	Dementia patient	User, Carer, Dementia specialist	Microphone, visual display	Scenario based approaches.
Hwang and Hoey (2012)	Older adult	Older adult, Carer	2D,3D interface	To design a system to reduce gap between the different type of stakeholder.
Ravishankar, Burleson, and Mahoney (2015)	Older adult	Older adult, Interviewer	Face-to-face interview and feedback	User sanctification measurement prior and post activity feedback.
Hussein et al. (2014)	Disabled patient	User, responsible authority	Computer, tablet, microphone, TV	Integrating different types of neural networks to design self-adaptive smart homes.
Casas et al. (2008)	Elderly People with disabilities	User, Carer	Haptic interface, voice controller	To design a system that understands the capability of disabled people.

system (Aztiria et al. 2013). Rashidi and Cook (2009a) designed a user centric interface, CASU-U, that accepts user input to identify and modify automated events and their times. These user-centric approaches are important at some level in improving the adaptation process; however, LFPUBS and CASU-U do not offer user adaptation during development, but only after the system has been launched. Consider the case of Bob, mentioned in the previous section. Bob and his family can contribute to the smart home adaptation process. Bobs family or his carers can explain his behaviour and preferences to the smart home developer. Based on the information provided, the developer can install sensors and configure the system to suit Bobs needs. Likewise, the family does not immediately leave Bob alone in the smart house. In the user-centric approach, technology is adjusted to human activities; the familys concern about Bob living is gradually reduced, as trust in the smart home system increases.

Transfer Learning for Activity Recognition in Smart Home

In this section we provide an overview of recent research about transfer learning for activity recognition in sensor-based smart homes and address potential issues along their solutions. A generic and comprehensive review on transfer learning can be found in the survey works of Cook, Feuz, and Krishnan (2013) and Pan and Yang (2010).

As mentioned previously, current research on activity recognition in smart homes focuses on the introduction of new machine learning algorithms (Jakovljevi, Njegu, and Donov 2016). Even machine algorithms, though, cannot provide immediate results where there is a lack of training data. With transfer learning, a system can leverage experience from previous tasks to improve the performance of new tasks, solving the challenge of missing training data (Cook, Feuz, and Krishnan 2013).

Transfer learning has been categorized into several types depending on the applications, source and target domains, including differences in feature-space representation, marginal probability distribution, and conditional probability distribution among others (Cook, Feuz, and Krishnan 2013). Pan and Yang (2010) proposed four classifications based on the transferred type; instance-transfer, feature representation transfer, parameter re- escalation transfer and relational-knowledge transfer. For the specific domain of activity recognition, the difference between source and target is more prominent due to the inclusion of time, people, sensors, and space. In the smart home context, it is presumed that enough data is available in the source domain while the main observation is the target domain (Jakovljevi, Njegu, and Donov 2016).

Traditionally, machine learning is categorized into two classes, namely supervised and unsupervised learning. The classification depends on the availability of labelled data (Cook, Feuz, and Krishnan 2013). Based on the source and the target domain, labelled data availability has been divided into four types: informed supervised, uninformed supervised, informed unsupervised and uninformed unsupervised (Pan and Yang 2010) Figure 2. However, based on the label and data availability, the target domain could be classified into three categories: labelled, unlabelled and no data, as shown in Figure 3.

Labelled Target Domain

Labelled data can be available in the target domain regardless of the source domain defining the inductive learning (Pan and Yang 2010). Supervised transfer learning techniques can thus be considered for activity recognition, and in fact, this approach is popular for activity recognition in smart homes. If data availability in the target domain is adequate, the traditional supervised machine learning methods perform adequately in activity recognition. However, if there

	Supervised	**Unsupervised**
Informed	Labelled data available both source and target domain	Labelled data available only target domain
Uninformed	Labelled data available only source domain	Labelled data available neither source or target

Figure 2. Different types of machine learning.

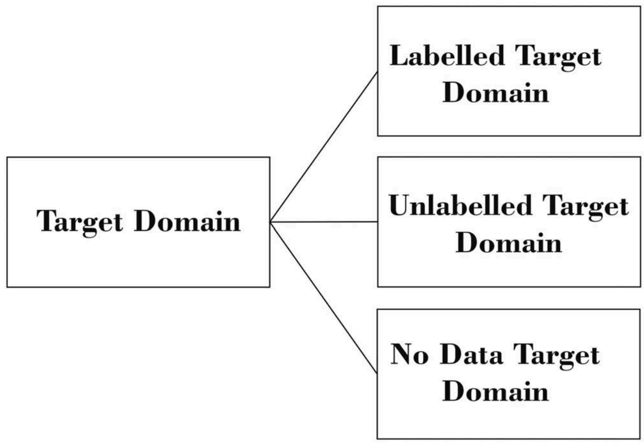

Figure 3. Different types of target domain.

is a limited amount of labelled data, the activity recognition is inefficient (Dillon Feuz and Cook 2014). In such cases, the transfer learning process can be elaborated at this point to improve activity recognition performance.

More precisely, in activity recognition, the primary challenge is to collect and annotate huge amounts of data for every single new physical setting to facilitate the customary activity discovery as well as the recognition algorithms. Rashidi and Cook (2010a) proposed a Home to Home Transfer Learning (HHTL) method to improve the performance of the target home in cases of limited datasets. The proposed method transfers learnt activity knowledge into new physical spaces. The method includes sensor grouping based on location and function and mapping similar types of sensors in the target domain. By using the proposed technique, several insights from prior spaces can be obtained that allow a better adaptation process.

While universal computer applications normally need information concerning the activities being undertaken, activity recognition models usually need a considerable amount of labelled training data for every setting (Bakar et al. 2016). Reusing the available labelled data in some new settings has been proposed as a solution in some cases. Dillon Feuz and Cook (2014) proposed three different ways to achieve transfer learning, namely feature-space remapping (FSR), the genetic algorithm for feature-space remapping (GAFSR), and the greedy search for feature- space remapping (GrFSR). These techniques facilitate feature-based mapping, and a single days labelled data are used for target domain validation and 30 days of labelled data for source domain validation.

Unlabelled Target Domain

Several studies have been conducted on activity recognition based on unlabelled data in the target domain. Like in other domains, smart home data is not well-annotated, since labelling is one of the most time-consuming tasks involved in activity recognition. For that reason, source domain data is utilised for labelling the target domain dataset. Hu and Yang (2011) introduced an approach that uses web knowledge as a bridge to build a map between the two domains. Transfer learning occurs in the area where the two domains have different sets of sensors and different activity labels, with the source domain having labelled sensor readings and the target domain unlabelled ones (Hu and Yang 2011).

The transfer learning approach proposed by Rashidi and Cook (2009b), the discontinuous misplaced sequential method (DMSM), discovers variations of the required pattern from the target domain. Then, the activity mapping method (AMM) is utilised and the results applied for mapping the source to the target. Another approach proposed by the same authors (Rashidi and Cook 2010b), multi-home transfer learning (MHTL) helps recognize human activities from multiple physical smart environments and exploit this knowledge for a new or target home. This is achieved by a data mining method for finding the target activities from the target dataset by representing the source and target space in the same form. Then, a semi-expectation maximization (EM) framework is used to map each source to the target domain, finally fusing the multiple source dataset and labelling the target (Rashidi and Cook 2010b).

No Data Target Domain

There are no data available in the target domain and is considered a new approach in the transfer learning area. To date, published surveys (Cook, Feuz, and Krishnan 2013; Pan and Yang 2010) do not discuss this approach. All other approaches are categorized based on data labelling; the lack of data labelling in this approach makes it difficult to categorize. The lack of available data in the target domain is a common issue for activity recognition in a smart home, because when a brand-new home is launched, no data or information is available for the occupant.

To tackle this problem, Chiang and Hsu (2012) introduced a solution to build an intelligent smart home system in a laboratory, collect the required data, and then transfer it to a new home. During this process, the authors used sensor profiling methods for both the source and target domains, with additional background knowledge from the sensor network. The weakness of the method is that sensor profiles, like sensors, need manual profiling, making them appropriate only for certain datasets (Chiang and Hsu 2012).

Table 3 indicates three types of smart homes (target domain). Any smart home used as a target domain can fall into one of the categories. For example, the no-data category could be the perfect match for Bobs scenario. To improve the adaptation process, Bobs home can be considered a target home, and another, similar home type can be used as the source domain.

Table 3. Summary of transfer learning for activity recognition in a data-driven smart home.

Paper	Target Domain Data	Multiple Sources	Differences	Type of Knowledge Transfer
Dillon Feuz and Cook (2014)	Labelled	No	Location, Layout	Instance-based and feature-representation
Rashidi and Cook (2010a)	Labelled and Unlabelled	No	Layout, sensor network	Feature-representation
Hu and Yang (2011)	Unlabelled	No	Lab Space, Location	Instance-based and feature-representation
Rashidi and Cook (2009b)	Unlabelled	No	People	Feature-representation
Rashidi and Cook (2010b)	Labelled and Unlabelled	No	Layout, sensor network	Feature-representation
Chiang and Hsu (2012)	No data	No	Lab Space, Location	Feature-representation

Discussion about the New Smart Home Adaptation and Recommendation

It is clear that data-driven activity recognition is emerging rapidly, driven by smart homes. Recent advances in transfer learning methods have opened new directions for smart home research. The enormous amount of data that is generated daily by sensor-based smart homes can be helpful for developing other smart homes. This avenue of data reuse to develop future smart homes needs further investigation.

Very little scholarly work has focused on the new smart home adaptation process. Only one approach proposed by Chiang and Hsu (2012) illustrates a possible new smart home adaptation process. The method accommodates a user in the new smart home, where an intelligent system is built for a smart home in a laboratory environment. The data is collected, and afterwards, a transfer learning approach is used to pass the data to the new smart home (Chiang and Hsu 2012). Chiang, Lu, and Hsu (2017) proved that without any 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 challenging for a new home adaptation. On the other side, knowledge-driven smart homes do not require data, but need instead a contextual knowledge usually acquired by standard knowledge engineering approaches (Bouchard, Giroux, and Bouzouane 2006). Based on the acquired knowledge, different approaches can be applied for representing the activity recognition models, such as logic-based approaches, logical formalisms (Augusto 2001b), event calculus (Cicekli and Yildirim 2000) and lattice theory (Bouchard, Giroux, and Bouzouane 2006). Another approach, ontology activity modelling, is similar to the logical approach and uses a description logic based on mark-up language (Chen, Nugent, and Wang 2012).

These knowledge-driven approaches can help diminish the cold-start problem. However, in contrast with data-driven approaches, these methods cannot handle uncertainty. They use inference and reasoning based generic knowledge rather than uncertain sensor data. There are some other reasoning techniques, such as fuzzy logic and probabilistic reasoning, but they are still not integrated with modelling techniques (Helaoui, Riboni, and Stuckenschmidt 2013).

To the best of our knowledge, there is no available method for tackling the cold-start problem for a data-driven activity recognition smart home. Our main aim is to reuse the previously acquired smart homes data for improving the accuracy of activity recognition in other smart homes via transfer learning. The transfer learning method is rarely used in an absolutely new smart home adaptation where old smart home data is used to train the new home to recognize user activity. However, even in such cases, the accuracy rate is very low if no data is available in the new smart home (Chiang, Lu, and Hsu 2017). So, a pure transfer learning process will struggle to satisfactorily address the cold-start problem without human input. For example, going back to Bobs scenario, we will need to input Bobs daily activity information to the system before he starts living in the house.

Data simulation tools are very popular, especially for evaluating newly designed models with synthetic data before implementing them in a smart home (Krzyska 2006; Lertlakkhanakul, Choi, and Kim 2008; Serrano, Botia, and Cadenas 2009). In the context of solving the cold-start problem, an approach proposed by Azkune et al. (2015) is notable. The proposed hybrid methodology uses data from real user daily activity surveys as inputs to the simulation tools. The key idea is to distribute the survey among target users with the aim of knowing how the users perform their daily activities in the smart home. The survey data is then processed by synthetic data generator tools for an arbitrary number of days to generate a labelled activity dataset. However, this approach does not provide any synthetic data evaluation. Thus, the created dataset is used only for modelling and recognizing the user activity in a smart home. In case the dataset is not applicable to the user, the process does not suggest any alternatives. On the contrary, our proposed method is fully user-centric. In this novel approach, every step is completed by user feedback. The process continues to the next step only after the user is satisfied; otherwise the previous step is repeated. The user is involved in the smart home simulation stage, allowing device familiarization before they interact with them in the actual home. This in an advantage of the method, especially since unfamiliar devices (sensors, interfaces) can cause anxiety in some users, e.g. people with dementia (Amiribesheli and Bouchachia 2015). Unlike other approaches, the simulator in this method not only generates data for evaluating the model or illustrating the response of the object in the virtual environment, but also creates a simulated dataset with a level of detail close to that generated by a real smart home. This simulated dataset is created using the transfer learning approach and user feedback.

The strength of such a data-driven approach is illustrated by the enormous amount of data produced by a smart home every day. A newly developed smart home does not have access to such detailed data from the beginning: new homes will need a considerable amount of time to gather a sufficient amount of data to model the activities of their inhabitants. During this learning period, the occupants do not have full use of the smart homes capabilities (automation, monitoring, etc.). Our proposed method introduces a new type of smart home, one rich in customized data from the beginning.

A survey is used to collect data from the user, capturing how he/she performs daily activities. The survey allows determination of how to perform some fixed activities in terms of the objects used as well as the amount of time required. As activities in the smart home are monitored according to the objects used, sensor activation or de-activation of an object has a great impact on activities. Thus, it is important to know the users sequences of object use, and the user survey will help identify patterns. A simulation is designed based on the survey answers and the user is invited to observe if it meets expectations.

In one scenario, user Bob wants to live independently in a smart home. After taking the survey, Bob is invited to interact with the simulation. In this way, Bob is familiarized with the new house and its facilities before he starts living in it, and Bobs activities are designed according to his answers. If he is satisfied with the activity processes the next step is initiated; otherwise, the step is repeated. The final simulation model will be generated after Bob is completely satisfied.

However, the simulated data might be insufficient to model all activities. To improve the reliability and acceptance of the data it will be mapped to the old smart home dataset using the transfer learning method. Afterwards, the house will be modelled with the dataset for activity recognition to allow the user to start living in the house. After some days, user feedback will be collected and used to personalize the existing user dataset.

System Architecture

Figure 4 provides some insight into how the system integrates the four approaches discussed: survey, transfer learning, activity recognition, and user preferences gathering. The combination of these approaches improves the adaptation process of the user to the new smart home. For an even better understanding of how the system works, a system data flow is provided in Figure 5.

Understanding the users daily activities is the major objective of this survey. Activities like making coffee, sleeping, watching television, etc., are targeted for monitoring. Afterwards, as seen in Figure 5, the developer (B) designs the survey (1) for the target user (A). In the survey the user is asked to list the days of the week on which certain activities take place. The user is then asked to

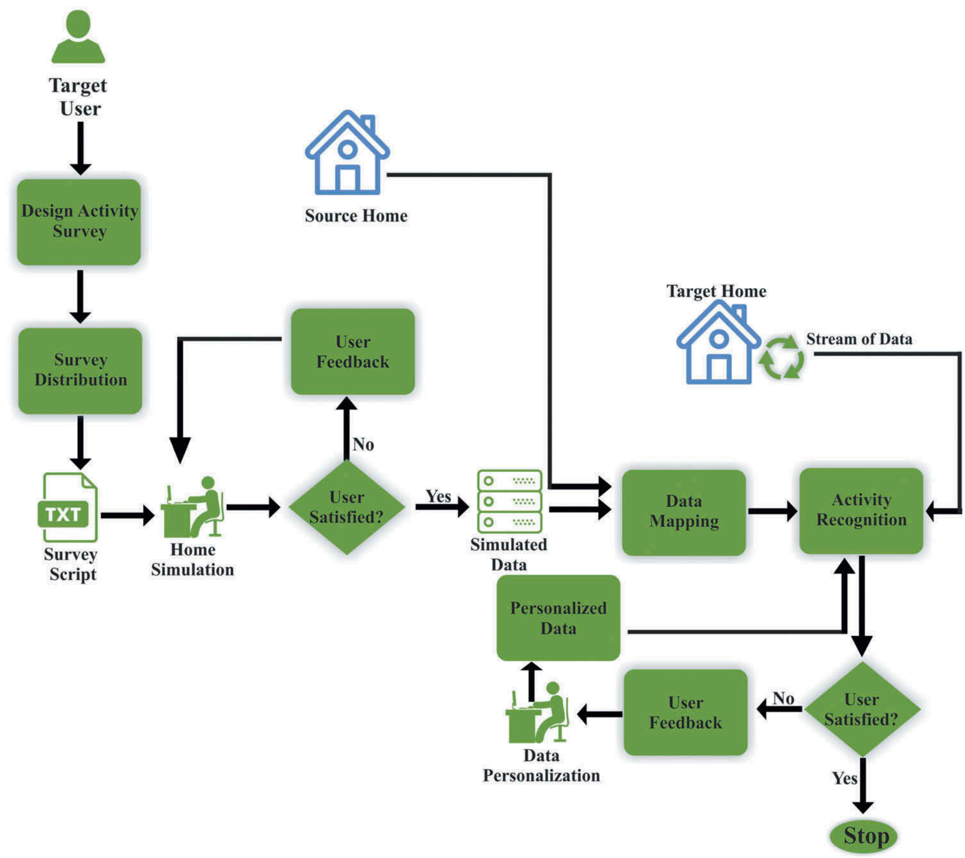

Figure 4. System architecture.

mention the number of times each activity occurs in a day, at what time, and for how long the activity lasts. Additional details, such as the number of objects used for the activity, the ways in which the activity can be performed, how the objects are used, and the overall sequence of activities, are also collected. For instance, for the activity of coffee preparation, the user may state that he/she makes coffee every day, twice on Mondays, that the activity occurs between 7:00 AM and 7:30 AM in the mornings and 2:00 PM and 2:30 PM in the afternoons, and that the process takes between 5–7 minutes. They report using five objects to make coffee: a microwave, milk, coffee, mug and a fridge. The activity was performed using two methods: in the first method, the user opened the fridge, took out the milk, picked a mug, poured some milk and put the mug in the microwave, while the second involved picking a mug, opening the fridge, picking the milk, pouring it into the mug and putting the mug in the microwave. As seen in Figure 5, after collecting data (2) from the user (A), developer (B) creates (3) the survey script (C).

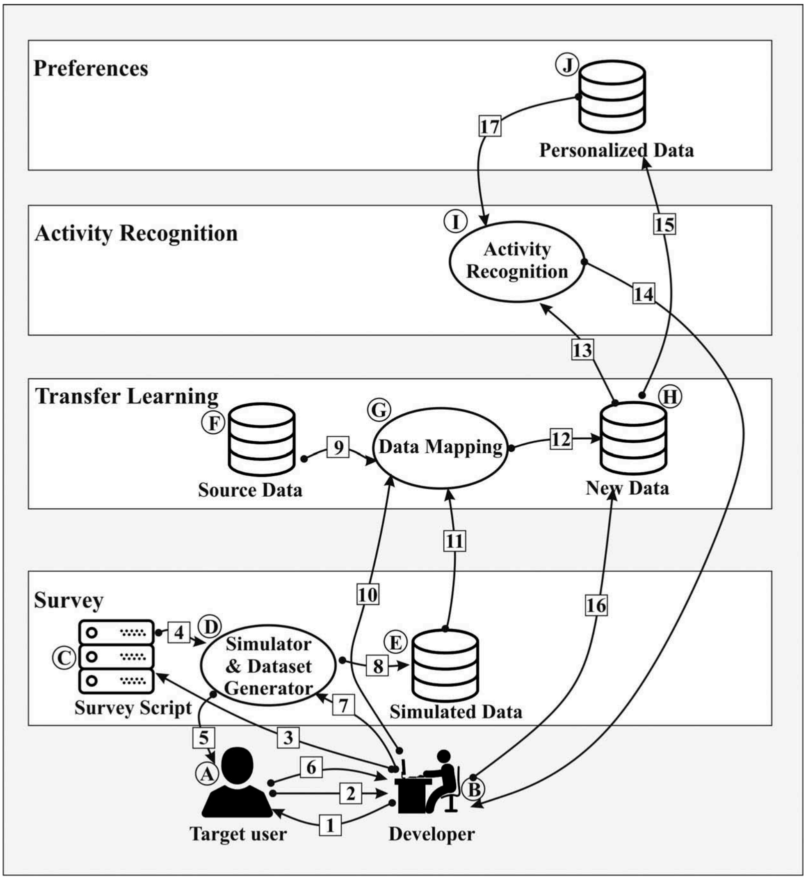

Figure 5. System data flow diagram.

The next step is to design the virtual environment or the smart home and insert (4) the survey script (C) to the simulator (D) to design the activity scenario. UbikSim software was used as a simulation tool for designing the house. This software was chosen because it is open source and thus can be customized according to user requirements, but other tools, such as OpenSHS, may be appropriate for future use.

The Middlesex university smart home as rendered in UbikSim can be seen in Figure 6. The next step includes sensor labelling with the same labels as the target home, so that when the dataset is implemented in the real home, no discrepancies between the sensor outputs will occur. Once this is done, the virtual house is ready to simulate activities according to the survey answers obtained from the user. There are two possible approaches to smart home simulation: model-based and interactive. The model-based approach relies on statistical models to generate data, while the interactive approach relies on real-time capture of fine-grained activities using avatars controlled by a human and a participant (user). The aim of our proposed

Figure 6. Simulation of the Middlesex university smart home using UbikSim.

method is to design the virtual home and create an activity scenario with the user (avatar) while capturing real-time data. Thus, the interactive approach is more appropriate in this scenario. The simulation tools allow the developer to simulate all days, or specific contexts like mornings, evenings, or another specific time, e.g. designing weekday activities for when the user returns from work. All simulated data are stored in a dataset; an example dataset generated using UbikSim where a virtual user randomly visiting the rooms, can be seen in Figure 7.

idMeasure	idUser	idDevice	oldValue	newValue	time
450	2	36	0	1	29/11/2017 14:00
455	2	36	0	1	29/11/2017 14:02
458	2	101	0	1	29/11/2017 14:03
459	2	101	0	1	29/11/2017 14:03
462	2	101	0	1	29/11/2017 14:11
463	2	101	0	1	29/11/2017 14:11
474	2	36	0	1	29/11/2017 14:11
493	2	36	0	1	29/11/2017 14:12
518	2	101	0	1	29/11/2017 14:30
519	2	101	0	1	29/11/2017 14:30
522	2	101	0	1	29/11/2017 14:35
523	2	101	0	1	29/11/2017 14:35
526	2	9	0	1	29/11/2017 14:35
527	2	9	1	0	29/11/2017 14:35
531	2	9	0	1	29/11/2017 14:35
532	2	9	1	0	29/11/2017 14:35
533	2	9	0	1	29/11/2017 14:35
534	2	36	0	1	29/11/2017 14:35

Figure 7. A synthetic output dataset generated by UbikSim simulation of the Middlesex university smart home.

The proposed method is user-centred, so the user is a major part of the development process. After simulation, user feedback is used to improve the system and help the user be familiar with and understand the house and its technology. This familiarization allows the user to be comfortable with the new devices (sensor, actuator etc.) when they first move into the house. User feedback (Figure 5, 5) is also necessary regarding the simulation driven by the survey. The simulation will be then re-configured or updated according to the user feedback (6–7). These steps are repeated until the user is finally satisfied. Simulated data (E) are generated (8) after the user accepts the simulation.

To increase acceptance of the stimulated dataset and make it more realistic, the developer (Figure 5b) will map (G) source data (F) and simulated data (E) using a transfer learning approach (9–11) for generating (12) new data (H). The new dataset is the main strength of the approach, since it can help solve the cold-start problem and speed the new house adaptation process for the user. Afterwards, the activity recognition (Figure 5i) algorithm is modelled (13) with the new data (H). The user starts living in the new home, and after a few days, user feedback (14) will be collected and the data personalized (15) accordingly. This data personalization might prove to be a challenging process since it can be done in various ways. For an example, we can go back to the Bob scenario. Bob likes to watch TV every night, so the target activity is watching TV. If we use LFPUBS as the activity recognition algorithm, LFPUBS concludes the activity involves taking the following actions: open door (door sensor on/off), enter the room (room motion sensor on/off), turn on room light (the light on/off), sitting on the sofa (sofa pressure sensor on/off) and TV turned on. So, the most frequent pattern for watching TV activity might be DoorOn → Door Off → Room On → Room Off → Light On → Light Off → Pressure On → Pressure Off → TV On. After collecting feedback, though, it becomes clear that Bob wants the light On when he watches TV. Based on his preference, the pattern can be modified to Door On → Door Off → Room On → Room Off → Light On → Pressure On → Pressure Off → TV On;. This is an example of how data can be personalized (16) by user collaboration. . After user feedback, the personalized data (Figure 5j) is sent again (17) for activity recognition. This data personalization process is repeated until the user is satisfied.

Conclusion

In this paper, we examined the current approaches for sensor-based data-driven activity recognition and user-centric transfer learning for smart homes. This review was intended to identify possible ways of improving the data-driven smart home adaptation process.

Initially, we explained the data-driven activity process for a sensor-based smart home by specifying the process into three steps. Next, we explored recent contributions to user-centred approaches in smart home development. Transfer learning approaches from a sensor-based activity recognition perspective were discussed and classified. Finally, we reviewed recent research regarding new smart home adaptation and provided suggestions to improve the process.

During the review, we identified key concerns and raised the important issue of user contribution to smart home system development. More precisely, the data-driven smart home does not involve users from the beginning of the design process. Feedback provided by the users and other stakeholders from the beginning of the development process can make the home application friendlier to the user, improving the probability of successful adaptation. In this paradigm there are few chances for users to refuse the product after the development process is completed. Another possible direction for research is to use the transfer learning approach for a smart home where the target domain contains no data. This approach could also help boost the new smart home adaptation process.

Finally, the study identified future areas of research for designing data-driven smart home systems that recognize user activities and provide the required service promptly once the user starts living in the new smart home. To attain this goal, there is a need for full user engagement and other stakeholders' (family members) input to identify the users daily activities and to start providing the expected services. If this goal is achieved, the user can rely on the smart home sooner and continue enjoying independent life.

Disclosure

The authors declare that they have no competing interests.

Author's contributions

All authors corrected the manuscript. All authors read and approved the final manuscript.

ORCID

S M Murad Ali http://orcid.org/0000-0002-8327-8918
Juan Carlos Augusto http://orcid.org/0000-0002-0321-9150
David Windridge http://orcid.org/0000-0001-5507-8516

References

Akhavian, R., and A. Behzadan. 2015. "Wearable sensor-based activity recognition for data-driven simulation of construction workers' activities." In *Winter Simulation Conference*, Huntington Beach, CA, USA, 3333–44.

Alshammari, N., T. Alshammari, M. Sedky, J. Champion, and C. Bauer. 2017. "OpenSHS: Open Smart Home Simulator.". *Sensors* 17:5. doi:10.3390/s17050968.

Al-Shaqi, R., M. Mourshed, and Y. Rezgui. 2016. "Progress in ambient assisted systems for independent living by the elderly" . *SpringerPlus* 5 (1):624. doi:10.1186/s40064-016-2272-8.

Amiribesheli, M., and A. Bouchachia. 2015. "Smart homes design for people with dementia." In *International Conference on Intelligent Environments*, Prague, Czech Republic, 156–59.

Arifoglu, D., and A. Bouchachia. 2017. "Activity recognition and abnormal behaviour detection with recurrent neural networks.". *Procedia Computer Science* 110:86–93. doi:10.1016/j.procs.2017.06.121.

Augusto, J. C. 2001a. "The logical approach to temporal reasoning". *Artificial Intelligence Review* 16 (4):301–33. doi:10.1023/A:1012551818243.

Augusto, J. C. 2001b. "The logical approach to temporal reasoning". *Artificial Intelligence Review* 16 (4):301–33. doi:10.1023/A:1012551818243.

Augusto, J. C. 2007. "Ambient Intelligence: The Confluence of Ubiquitous/Pervasive Computing and Artificial Intelligence.". In *Intelligent computing everywhere*, ed. A. J. Schuster, 213–34. London: Springer London.

Augusto, J. C., and C. D. Nugent. 2006. "Smart Homes Can Be Smarter.". In *Designing smart homes, the role of artificial intelligence,* ed. J. C. Augusto, and C. D. Nugent, vol 4008, 1–15. Berlin, Heidelberg: Springer Berlin Heidelberg.

Azimi, I., A. M. Rahmani, P. Liljeberg, and H. Tenhunen. 2017. "Internet of things for remote elderly monitoring: A study from user-centered perspective". *Journal of Ambient Intelligence and Humanized Computing* 8 (2):273–89. doi:10.1007/s12652-016-0387-y.

Azkune, G., A. Almeida, D. L.-D. Ipiña, and L. Chen. 2015. "Combining users activity survey and simulators to evaluate human activity recognition systems" . *Sensors* 15 (4):8192–213. doi:10.3390/s150408192.

Aztiria, A., and J. C. Augusto. 2013. "Context-aware discovery of human frequent behaviours through sensor information interpretation.". In *Human behavior recognition technologies: Intelligent applications for monitoring and security*, ed. H. W. Guesgen and S. Marsland, IGI Global vol. 2, 14–32. ISBN 9781466636828

Aztiria, A., J. C. Augusto, R. Basagoiti, A. Izaguirre, and D. J. Cook. 2013. "Learning frequent behaviors of the users in intelligent environments.". In *IEEE transactions on systems, man, and cybernetics: systems*, ed. C. L. Philip Chen, vol. 431265–1278. doi: 10.1109/TSMC.2013.2252892

Bakar, U. A. B. U. A., H. Ghayvat, S. F. Hasanm, and S. C. Mukhopadhyay. 2016. "Activity and anomaly detection in smart home: A survey.". In *Next Generation Sensors and Systems*, Smart Sensors, Measurement and Instrumentation, ed. Mukhopadhyay, vol 16, 191–220. Cham: Springer.

Ball, M., and V. Callaghan. 2012. Managing Control, Convenience and Autonomy - A Study of Agent Autonomy in Intelligent Environments. In *Vol. 12 of ambient intelligence and smart environments,* ed. T. Bosse , 159–96. Amsterdam, The Netherlands: IOS Press.

Bao, L., and S. Intille. 2004. "Activity recognition from user-annotated acceleration data.". In *Pervasive Computing. Pervasive 2004. Lecture Notes in Computer Science*, ed. A. Ferscha A and F. Mattern, vol 3001. Berlin, Heidelberg: Springer.

Bouchard, B., S. Giroux, and A. Bouzouane. 2006. A smart home agent for plan recognition of cognitively-impaired patients. *Journal of Computers* 1 (5):53–62. doi:10.4304/jcp.1.5.53-62.

Bourobou, S., T. Mickala, and Y. Yoo. 2015. User activity recognition in smart homes using pattern clustering applied to temporal ANN algorithm. *Sensors* 15 (5):11953–71. doi:10.3390/s150511953.

Brdiczka, O., J. L. Crowley, and P. Reignier. 2009. Learning situation models in a smart home. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 39 (1):56–63. doi:10.1109/TSMCB.2008.923526.

Bux, A., P. Angelov, and Z. Habib. 2017. *Vision based human activity recognition: A review*. In Advances in Computational Intelligence Systems, Springer, Cham, 341–371.

Casas, R., R. B. Marn, A. Robinet, A. R. Delgado, A. R. Yarza, J. Mcginn, R. Picking, and V. Grout. 2008. “User modelling in ambient intelligence for elderly and disabled people.” In *International Conference on Computers for Handicapped Persons*, Linz, Austria, 114–22.

Ceccacci, S., M. Germani, and M. Mengoni. 2013. “A method to design a smart home interface.” In *Smart Product Engineering: Proceedings of the 23rd CIRP Design Conference, Bochum, Germany, March 11th - 13th, 2013*, 915–25. Berlin, Heidelberg: Springer Berlin Heidelberg.

Ceccacci, S., and M. Mengoni. 2017. “Designing smart home interfaces: traditional vs virtual prototyping.” In *Proceedings of the 10th International Conference on PErvasive Technologies Related to Assistive Environments*, Island of Rhodes, Greece, PETRA ’17, 67–74. New York, NY, USA: ACM.

Chen, L., C. D. Nugent, and H. Wang. 2012. A knowledge-driven approach to activity recognition in smart homes. *IEEE Transactions on Knowledge and Data Engineering* 24 (6):961–74. doi:10.1109/TKDE.2011.51.

Chen, S., T. Liu, F. Gao, J. Jianting, X. Zhanbo, B. Qian, W. Hongyu, and X. Guan. 2017. Butler, not servant: a human-centric smart home energy management system. *IEEE Communications Magazine* 55 (2):27–33. doi:10.1109/MCOM.2017.1600699CM.

Chiang, Y.-T., and J. Y.-J. Hsu. 2012. “Knowledge transfer in activity recognition using sensor profile.” In *Ubiquitous Intelligence & Computing and 9th International Conference on Autonomic & Trusted Computing (UIC/ATC), 2012 9th International Conference on*, Fukuoka, Japan, 180–87. 10.1094/PDIS-11-11-0999-PDN

Chiang, Y.-T., L. Ching-Hu, and J. Yung-Jen Hsu. 2017. A feature-based knowledge transfer framework for cross-environment activity recognition toward smart home applications. *IEEE Transactions on Human-Machine Systems*. doi:10.1109/THMS.2016.2641679.

Cicekli, N. K., and Y. Yildirim. 2000. “Formalizing workflows using the event calculus.” In *Database and Expert Systems Applications: 11th International Conference, DEXA 2000 London, UK, September 4–8,2000 Proceedings*, edited by Mohamed Ibrahim, Josef Küng, and Norman Revell, 222–31. Berlin, Heidelberg: Springer Berlin Heidelberg.

Cook, D., K. D. Feuz, and N. C. Krishnan. 2013. Transfer learning for activity recognition: A survey. *Knowledge and Information Systems* 36 (3):537–56. doi:10.1007/s10115-013-0665-3.

Cook, D., and S. Das. 2004. *Smart environments: technology, protocols and applications (wiley series on parallel and distributed computing)*. Hoboken,New Jersey: Wiley-Interscience.

Cook, D. J. 2009. Multi-agent Smart Environments. *Journal of Ambient Intelligence and Smart Environments* 1 (1):51–55.

Dillon Feuz, K., and D. J. Cook. 2014. Heterogeneous transfer learning for activity recognition using heuristic search techniques. *International Journal of Pervasive Computing and Communications* 10 (4):393–418. doi:10.1108/IJPCC-03-2014-0020.

Giannakouris, Konstantinos. 2008. Ageing characterises the demographic perspectives of the European societies. *Statistics in Focus* 72:2008.

Glende, S., B. Podtschaske, and W. Friesdorf. 2009. “Senior User Integration: Ein ganzheitliches Konzept zur Kooperation von Herstellern und älteren Nutzern während der Produktentwicklung.” In *Conference: Ambient Assisted Living–AAL–2. Deutscher AAL-Kongress mit Ausstellung/Technologien–Anwendungen–Management*, Berlin,German, Vol. 2728.

Guralnik, V., and K. Z. Haigh. 2002. "Learning models of human behaviour with sequential patterns." In *Proceedings of the AAAI-02 workshop "Automation as Caregiver"*, Edmonton, Alberta, Canada, 24–30.

Haines, V., M. Maguire, C. Cooper, V. Mitchell, F. Lenton, H. Keval, and C. A. Nicolle. 2005. *User centred design in smart homes: Research to support the equipment and services aggregation trials*. Loughborough: Loughborough University Institutional Repository.

Hammerla, N. Y., S. Halloran, and P. Thomas 2016. "Deep, convolutional, and recurrent models for human activity recognition using wearables." In *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence*, New York, USA, 1533–40.

Hanson, M. 2016. "I'd rather die than be a burden on my daughter like many older people." Lastchecked = December 15, 2016, https://www.theguardian.com/commentisfree/2016/dec/15/old-people-dementia-deathsocial-care-costs.html.

Helaoui, R., D. Riboni, and H. Stuckenschmidt. 2013. "A probabilistic ontological framework for the recognition of multilevel human activities." In *Proceedings of the ACM international joint conference on Pervasive and ubiquitous computing*, Zurich, Switzerland, 345–54.

Hu, D. H., and Q. Yang. 2011. "Transfer learning for activity recognition via sensor mapping." In *IJCAI Proceedings-International Joint Conference on Artificial Intelligence*, Barcelona, Catalonia, Spain, Vol. 221962.

Huch, M., A. Kameas, J. Maitland, P. J. McCullagh, J. Roberts, A. Sixsmith, R. Wichert, and J. C. Augusto. 2012. *Handbook of ambient assisted living: technology for healthcare, rehabilitation and well-being - volume 11 of ambient intelligence and smart environments*. Amsterdam, The Netherlands: IOS Press.

Hussein, A., M. Adda, M. Atieh, and W. Fahs. 2014. Smart home design for disabled people based on neural networks. *Procedia Computer Science* 37:117–26. doi:10.1016/j.procs.2014.08.020.

Hwang, A. S., and J. Hoey. 2012. "Smart home, the next generation: closing the gap between users and technology." In *AAAI Fall Symposium: Artificial Intelligence for Gerontechnology*, Menlo Park, California. doi:10.1094/PDIS-11-11-0999-PDN

ISO. 1999. "Human-centred design processes for interactive systems, International Organization for Standardization."

Jakovljevi, M. M., A. Njegu, and N. Donov. 2016. "Data-driven human activity recognition in smart environments." In *International Scientific Conference on ICT and E-Business Related Research*, Belgrade, Singidunum University, Serbia, 94–99.

Jebara, T. 2004. Generative Versus Discriminative Learning. In *Machine learning: discriminative and generative*, ed. M. Ismail, 17–60. Boston, MA: Springer US.

Jozam, M. H., E. A. Bauke de Vries, and H. Timmermans. 2012. "Prototype evaluation of a user centered design system for smart homes." In *Proceedings of the Conference on Design and Decision Support Systems in Architecture and Urban Planning*, 27–29, Eindhoven, Netherlands. doi: 10.1094/PDIS-11-11-0999-PDN

Krzyska, C. 2006. "Smart house simulation tool." Master's thesis, Technical University of Denmark, DTU, Lyngby, Denmark.

Lei, Z., S. Yue, Y. Chen, and S. Yuanchun. 2010. "SHSim: An OSGI-based smart home simulator." In *IEEE International Conference on Ubi-media Computing*, Jinhua, China, 87–90.

Leitner, G. 2015. The Future Home is Wise, Not Smart.", In *The future home is wise, not smart, e*d. R. Harper. Springer International Publishing Switzerland: Springer, Cham doi: 10.1007/978-3-319-23093-1.

Lertlakkhanakul, J., J. W. Choi, and M. Y. Kim. 2008. Building data model and simulation platform for spatial interaction management in smart home. *Automation in Construction* 17 (8):948–57. doi:10.1016/j.autcon.2008.03.004.

Liu, L., Y. Peng, M. Liu, and Z. Huang. 2015. Sensor-based human activity recognition system with a multilayered model using time series shapelets. *Knowledge-Based Systems* 90:138–52. doi:10.1016/j.knosys.2015.09.024.

Lutolf, R. 1992. "Smart home concept and the integration of energy meters into a home based system." In *International Conference on Metering Apparatus and Tariffs for Electricity Supply*, Glasgow, UK, 277–78.

Mckeever, S., Y. Juan, L. Coyle, C. Bleakley, and S. Dobson. 2010. Activity recognition using temporal evidence theory. *Journal of Ambient Intelligence and Smart Environment* 2 (3):253–69.

Mehr, H. D., H. Polat, and A. Cetin. 2016. *Resident activity recognition in smart homes by using artificial neural networks*. In International Smart Grid Congress and Fair, Istanbul, Turkey, 1–5.

Moeslund, T. B., A. Hilton, and K. Volker. 2006. A survey of advances in vision-based human motion capture and analysis. *Computer Vision and Image Understanding* 104 (2):90–126. doi:10.1016/j.cviu.2006.08.002.

Ni, Q., A. Beln, G. Hern, and I. P. De La Cruz. 2015. The elderlys independent living in smart homes: A characterization of activities and sensing infrastructure survey to facilitate services development. *Sensors* 15 (5):11312–62. doi:10.3390/s150511312.

Oguego, C. L., J. C. Augusto, A. Muoz, and M. Springett. 2018. Using argumentation to manage users preferences. *Future Generation Computer Systems* 81 (1):235–43. doi:10.1016/j.future.2017.09.040.

Pal, M., and P. M. Mather. 2001. "Decision tree based classification of remotely sensed data." In *Proceedings of the 22nd Asian Conference of Remote Sensing*, Singapore, November.

Pan, S. J., and Q. Yang. 2010. A survey on transfer learning. *IEEE Transactions on Knowledge and Data Engineering* 22 (10):1345–59. doi:10.1109/TKDE.2009.191.

Portet, F., M. Vacher, C. Golanski, C. Roux, and B. Meillon. 2013. Design and Evaluation of a Smart Home Voice Interface for the Elderly: Acceptability and Objection Aspects. *Personal Ubiquitous Comput* 17 (1):127–44. doi:10.1007/s00779-011-0470-5.

Rao, S. P., and D. J. Cook. 2004. Predicting inhabitant action using action and task models with application to smart homes. *International Journal on Artificial Intelligence Tools* 13:81–100. doi:10.1142/S0218213004001533.

Rashidi, P., and D. J. Cook. 2009a. "Keeping the resident in the loop: Adapting the smart home to the user.". *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* 39 (5):949–59. doi:10.1109/TSMCA.2009.2025137.

Rashidi, P., and D. J. Cook. 2009b. Transferring learned activities in smart environments. *Intelligent Environments* Vol 2, 185–92.

Rashidi, P., and D. J. Cook. 2010a. "Activity recognition based on home to home transfer learning." In *Workshops at the Twenty-Fourth AAAI Conference on Artificial Intelligence*, Atlanta, Georgia, USA.

Rashidi, P., and D. J. Cook. 2010b. Multi home transfer learning for resident activity discovery and recognition. *KDD Knowledge Discovery from Sensor Data* vol. 12, 56–63.

Ravishankar, V. K., W. Burleson, and D. Mahoney. 2015. Smart home strategies for user-centered functional assessment of older adults. *International Journal of Automation and Smart Technology* 5 (4):233–42. doi:10.5875/ausmt.v5i4.952.

Röcker, C. 2013. "User-centered design of intelligent environments: Requirements for designing successful ambient assisted living systems." In *Central European Conference on Information and Intelligent Systems*, 4. Varadin, Croatia.

Sarkar, A. M., Y.-K. L. Jehad, and S. Lee. 2010. A smoothed naive bayes-based classifier for activity recognition. *IETE Technical Review* 27 (2):107–19. doi:10.4103/0256-4602.60164.

Satpathy, L. 2006. "Smart Housing: Technology to Aid Aging in Place: New Opportunities and Challenges." Ph.D. thesis, Mississippi State University.

Serrano, E., J. A. Botia, and J. M. Cadenas. 2009. Ubik: A multi-agent based simulator for ubiquitous computing applications. *Journal of Physical Agents* 3 (2):39–43.

Skocir, P., P. Krivic, M. Tomeljak, M. Kusek, and G. Jezic. 2016. Activity detection in smart home environment. *Procedia Computer Science* 96:672–81. doi:10.1016/j.procs.2016.08.249.

Stankovski, V., and J. Trnkoczy. 2006. Application of Decision Trees to Smart Homes. In *Designing smart homes: the role of artificial intelligence*, ed. J. C. Augusto and C. D. Nugent, 132–45. Berlin, Heidelberg: Springer Berlin Heidelberg.

UN. 2015. *United Nations department of economic and social affairs, world population ageing*. New York, USA: United Nations Publications.

Weiss, K., T. M. Khoshgoftaar, and D. Wang. 2016. A survey of transfer learning. *Journal of Big Data* 3 (1):9. doi:10.1186/s40537-016-0043-6.

Yilmaz, A., O. Javed, and M. Shah. 2006. Object tracking: A survey. *Acm Computing Surveys (CSUR)* 38 (4):13. doi:10.1145/1177352.1177355.