1

‘Teach Me - Show Me’- End-user personalisation of a smart home and companion robot

Joe Saunders, Dag Syrdal, Kheng Lee Koay, Nathan Burke and Kerstin Dautenhahn, *Senior Member, IEEE*

***Abstract*—Care issues and costs associated with an increasing elderly population is becoming a major concern for many countries. The use of assistive robots in ‘smart-home’ environments has been suggested as a possible partial solution to these concerns. One of the many challenges faced is the personalisation of the robot to meet the changing needs of the elderly person over time. One approach is to allow the elderly person, or their carers or relatives, to teach the robot to both recognise activities in the smart home and to teach it to carry out behaviours in response to these activities. The overriding premise being that such teaching is both intuitive and ‘non-technical’. As part of a European project researching and evaluating these issues a commercially available autonomous robot has been deployed in a fully sensorised but otherwise ordinary suburban house. Occupants of the house are equipped with a non-technical teaching and learning system. This paper details the design approach to the teaching, learning, robot and smart home systems as an integrated unit and presents results from an evaluation of the teaching component and a preliminary evaluation of the learning component in a Human-Robot interaction experiment. Results from this evaluation indicated that participants overall found this approach to personalisation useful, easy to use, and felt that they would be capable of using it in a real-life situation both for themselves and for others. However there were also some salient individual differences within the sample.**

***Index Terms*—Robot personalisation, robot teaching, robot learning, activity recognition, robot companion.**

I. Introduction

ASSISTIVE robots in ‘smart-home’ environments have been suggested as a possible cost and care solution to demographics changes characterised by an increasing elderly population [1], [2]. The vision is that service robots are available in the home to help and assist elderly residents. Furthermore, the robot partner might also motivate and provide active support in terms of *re-ablement* - defined as “Support people ‘to do’ rather than ‘doing to / for people’ ” [3] - and *co-learning* - working together to achieve a particular goal. Thus, the assistive robot and the person form a partnership which is ever changing and evolving to meet the changing needs of the elderly person as they age, the robot effectively becoming a trusted companion to the person. We define this mechanism of providing support, assistance and active engagement over time as *personalisation*. This paper describes an approach to service robot personalisation based on end-user *robot teaching and learning* designed to be used by carers, relatives and elderly persons themselves. Personalisation has been shown in longitudinal studies to reinforce rapport, cooperation and engagement with a robot [4].

The authors are with the Adaptive Systems Research Group, University of Hertfordshire, College Lane, Hatfield, Herts., AL10 9AB, United Kingdom. E-mail: j.1.saunders,d.s.syrdal,k.l.Koay,n.burke,k.dautenhahn@herts.ac.uk

The work described in this paper uses a commercially available robot, the Care-O-bot3®, manufactured by Fraunhofer IPA [5]. The robot resides in a fully sensorised but otherwise completely standard British three bedroom semi-detached house near the University of Hertfordshire (we call this the *robot house*). This environment being more ecologically valid resembling a real living environment rather than a scientific laboratory, and is used to test and evaluate work in Human Robot Interaction (HRI) studies.

II. Problem Definition and Literature Review

A. Co-learning and Re-ablement

The idea of co-learning in this context refers to the situation whereby a human user and a robot work together to achieve a particular goal. Typically the robot can provide help and assistance, but in return also requires help and assistance. Usually the human teaches the robot how to solve a problem, however the robot can also assist by suggesting to the human that it has particular capabilities and techniques which may prove fruitful (or indeed that it already knows how to address this particular problem). This concept is extended by further considering that the robot will need to learn from the user about the user’s activities and subsequently be able to exploit this information in future teaching episodes This means that co-operation will typify the user’s interaction with the robot. The concept of re-ablement [6] exploits the co-learning capability in order not to disenfranchise the human partner. Thus, rather than passively accepting imposed solutions to a particular need, the user actively participates in formulating with the robot their own solutions and thus remains dominant of the technology and is empowered, physically, cognitively and socially. This idea is extended by ensuring that the robot engages in empathic and socially interactive behaviour. For example, the robot should not attempt to encourage immobility or passivity in the user, but to re-able the user by making motivating suggestions to persuade the user to be active or engage in an activity in the home. For example, it could prompt the user to carry out tasks, for example: writing a greeting card after reminding the user of a relative’s birthday, or bring relevant events to the user’s attention and suggest to the user an activity in order to avoid social isolation. Thus the user-robot relationship is one of mutually beneficial support, assistance and companionship.

B. Background

Achieving this level of personalisation presents many challenges for a companion robot. Simple scripting of interactions will not achieve the above aims due to the dynamics of the interaction and the key requirement of the robot to develop and learn.

1) Robot Teaching and Learning: All of the approaches in robot learning attempt to derive a policy based on one or more demonstrations from the user and subsequently execute that policy at the appropriate time. Other key challenges are how to refine the policy from further demonstrations, how to scaffold different policies together to form more complex robot behaviours and how to allow the robot to inform the user of its existing repertoire of policies. For a more detailed survey please refer to Argall et al., [7].

2) Learning by 'Following': This approach typically involves both robot and user sharing a close context. The robot often uses a vision system or some other sensory modality (e.g. infra-red sensors, electronic markers) to detect the presence of the user and then follow him/her. By closely following the user the robot is able to approximately experience the same perceptions as those experienced by the user. Thus the 'state' of the user, which is not normally perceivable by the robot, can be perceived indirectly. The 'following' approach has been used in work by Nicolescu and Mataric [8] where a mobile robot tracks a human teacher's movements by following the teacher and matching predicted postconditions against the robot's current proprioceptive state. It then builds a hierarchical behaviour-based network based on "Strips" style production rules [9]. This work attempts to provide a natural interface between robot and a teacher (who provides feedback cues) whilst automatically constructing an appropriate action-selection framework for the robot. During the learning process the robot can use both external environmental perceptions and any available internal proprioceptive feedback in order to correctly replicate the user's behaviour (for a more detailed discussion of these ideas please see Saunders et al., [10]). In the personalisation research reported in the current paper we exploit many of these techniques, however external sensory cues are provided to the robot exclusively via the smart home sensors.

3) Behavioural Cloning: Behavioural cloning is used primarily as a way of encoding human knowledge in a form that can be used by a computational system. The actions of a human subject, who will be typically operating a complex control system (such as an aircraft), are recorded and analysed. The actions and decisions are extracted and used to control the system without human presence. An example of behavioural cloning is Claude Sammut's "learning-to-fly" application [11], [12] where recordings of control parameters in a flight simulator flown by a number of human subjects were analysed using Quinlan's C4.5 induction algorithm [13]. The algorithm extracts a set of "if-then" control rules. Van Lent and Laird extended this work by providing a user interface which could be marked with goal transition information [14]. This allowed an action selection architecture to be constructed using "Strips" style production rules [9]. In the studies presented in the current paper we also provide the house resident with an interface for teaching robot behaviours based on previously learnt activities using Quinlan's C4.5 rule induction system. The resulting robot behavioural rules are also based on a production rule approach.

4) Learning by Demonstration: Learning by Demonstration normally refers to the direct interaction between a human teacher and a robot[1]. The interaction is direct because the teacher sends instructions to the robot directly through some external control mechanism (e.g. a joystick or screen based GUI). This direct approach avoids many of the complexities of the *Correspondence Problem* [15]. Early work by Levas and Selfridge [16] controlled a robot via tele-operation and then used the robot's proprioceptive feedback to construct a set of production rules. A long line of research into teaching service robots by observing humans in this manner has also been carried out by Dillman et al., [17]–[20]. Kaiser trained various robotic platforms in order to compute a control policy using function approximation techniques and recognised the important role of the human teacher in providing feedback. Similar observations have also been made by Thomaz and Breazeal [21].

5) Learning from Observation: Learning from Observation normally decreases the closeness of shared context between learner and user. Thus the robot operates by sharing context with the user but at a distance.This research relies on recognising human motions and thus faces a difficult vision problem. In order to obviate this problem complex vision techniques are sometimes employed. Often however the problem is simplified using coloured markers or some other tagging technique.Some of the earliest examples of learning using an observational approach is that of Kuniyoshi, Inaba and Inoue [22] and Ikeuchi and Suehiro [23] where hierarchical and symbolic representations of assembly tasks are learned from human demonstration. Johnson and Demiris [24] use learning from observation in their work where coupled inverse and forward models [25], [26] are used to allow a robot to imitate observed human actions and recognise new actions. In the smart home context described in this paper we do not directly use observational approaches but use the human feedback derived from the house sensor activations (including human location tracking).

C. Teaching and Learning in Smart Home Environments

Teaching, learning and adaptation in smart home environments tend to be less HRI specific and based more on automatic service discovery (where the home automatically learns the daily activities on the resident). Often called 'Cognitive Robotic Ecologies' they attempt to understand the requirements of the house residents based on perception, planning and learning from the house 'ecology' and derive robotic actions to subsequently service these requirements. These methods face difficult problems in identifying the information needed to make these judgements and to identify the appropriate teaching information to adapt such services.

Typical approaches to these issues include capturing and merging sensor information via machine learning techniques and then predicting resident behaviour [27]–[29], the majority of which use labelled training examples built from annotation

[1]"Learning by Demonstration" is often also used in a wider sense to denote all of the research areas that study robot teaching.

of resident activities. However, labelling can be both costly and time consuming.

III. Methodological Formulation

The main objective of our work is to allow the house resident to personalise the robot to meet their ever changing needs and to exploit the robot's existing competencies to achieve this where necessary.

In order to do this the approach that has been taken is one where all basic activities, be they robot behaviours or house sensory states, can be easily interpreted by the house resident. Furthermore, the underlying design ensures that any new behaviours or activities can be interpreted as basic activities and exploit any services that apply to these activities.

A. Extending the Idea of a Sensor

Consider a situation where the elderly resident has a robot that is capable of navigating autonomously around the house, can move to the user's location, is equipped with a raisable tray and has the ability to 'speak' text strings. She would like the robot to always be present in the kitchen when she is using the microwave in order to carry items back to the dining table. She might teach the robot to do this by providing simple directives such as:

```
If the microwave is on
then go to the kitchen and raise your tray
```

In this example the microwave sensor is a basic physical sensor, and the robot actions are navigation and tray actuation. Simple sensory information could also be enhanced with temporal constraints. For example:

```
If the microwave has been on
              for more than 5 minutes
Then go to the user location
    and say 'the microwave is still on'
```

Furthermore the simple sensory states could be replaced by states with higher levels of meaning. For example:

```
If 'food is being prepared'
then come to the kitchen
```

where the sensory state 'food is being prepared' is derived from activity recognition (for example recognising that the microwave or main oven or fridge were being used). Additionally these higher states could be temporally extended:

```
If 'food is being prepared'
            and this has been happening
                         for more than 30 minutes
then go to the user location
     and say 'I think you are making a meal,
                       do you need help?'
```

Similar grouping of basic robot actions should also be possible. Thus simple sets of robot actions such as

```
go to user location, lowering tray if tray empty
```

could simply be labelled:

```
come to me
```

By enabling constructs of this kind the robot behaviour personalisation is greatly enhanced. Consider a carer setting up a robot behaviour to remind the elderly resident that

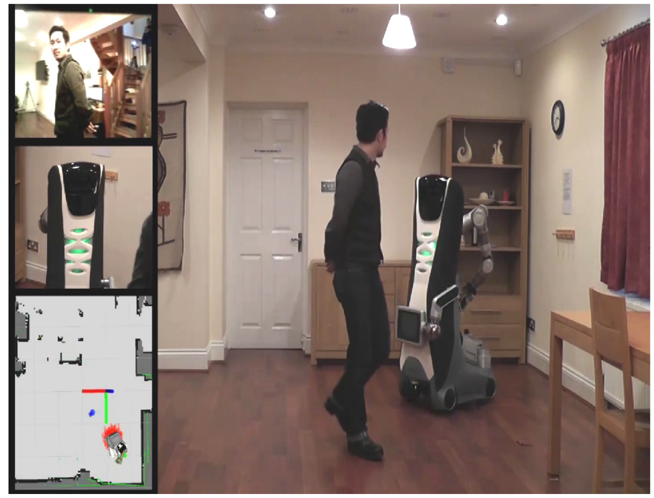


Fig. 1. The interior of the robot house 'living room' with the Care-O-Bot3 robot. The images on the left side of the picture show the view from the robot camera, the robot itself and the real-time mapping visualisation showing person and robot location

her daughter visits her in the afternoon on Tuesdays and Thursdays:

```
If it is Tuesday or Thursday and 1pm
then 'come to me'
    and say 'Irene is coming to visit you today'
```

In this work the definition of 'sensory state' is expanded to include both physical and semantic state and the definition of robot action expanded via the ability to 'scaffold' robot behaviours [30] to create more complex but semantically simpler behaviours. This has the dual effect of making the overall system easier to understand and of hiding the technical complexities of robotics and smart home systems from the user.

Two complimentary approaches to achieving this level of personalisation were designed and called "Teach Me/Show Me". These were implemented as a program running on a laptop computer (but could be modified for use on a tablet computer). The "Teach Me" system allows residents' to define and test robot behaviours based on both house sensory activities and basic robot actions. These new behaviours, once defined, can be used subsequently to create more complex behaviours. The "Show Me" system allows the resident to 'show' the robot new activities (such as 'preparing a meal') by simply carrying out that task. Once learned that activity becomes part of the available sensory activities exploitable by the Teach Me system.

A major advantage of this approach is that there is no prelabelling of activities. Labelling of sensory combinations of all types is effectively carried out by the resident themselves. The resident thus personalises their requirements and is thus enabled and enfranchised by being at the centre of the personalisation process.

B. System Architecture

We regard the house as one entity rather than as a collection of individual parts. In practise this means that the house sensor information is considered to be no different from robot sensor information, the sensory information derived from the occupants activities or from semantic sensors. This provides the bedrock for the main focus of our work enabling co-learning and re-ablement by not artificially treating the robot, user (or indeed the house) as separate entities but rather focus the generation of behavioural activity (which in our case is via the robot, but in an ambient home it could be via actuation of household devices) on the complete system.

1) Robot House Ontology: The robot house consists of sensors, locations, objects, people, the robot and (robot) behaviours. These were analysed to yield a house ontology which is instantiated in a 'mySQL' database. Episodic information, which consists of both images and sensory feedback during behaviour execution is also captured and can be accessed via GUI's allowing post-review of activities of the robot and the user (this work is described in [31]). Procedural memory, which is here defined as the robot actions together with pre and post behavioural conditions, is also held as tables in the database. However the rules themselves are encoded as SQL statements which refer back to the semantic information created by the sensor system.

2) Robot Capabilities: For this work we use the Care-O-bot3® (see Fig. 1) which has been especially designed for research in assistive environments. The Care-O-bot3 uses ROS navigation (a form of SLAM) [32] using its laser range-finders to update a map of the house in real-time and can thus navigate to any given location whilst avoiding obstacles and replanning routes. Similarly the robot is equipped with facilities for manipulating the arm, torso, 'eyes', robot LED's, tray and has a voice synthesiser to express given text. High level commands are sent via the ROS 'script server' mechanism and interpreted into low level commands by the robot software. Typical commands would be for example, 'raise tray', 'nod', 'look forward', 'move to location x', 'grab object on tray', 'put object x at location y', 'say hello' etc.

3) Robot House Sensors: All sensory information (both from physical and from semantic sensors) is held in a 'sensors' table and a 'sensor logging' table in the database. Each individual sensor is held as a row in the sensors table and each row provides the instantaneous value of the sensor as well as the time it changed and its previous value. Each row in the logging table contains the historical sensor value over time. The 'TeachMe' system uses only the current and previous sensor values, whereas the 'ShowMe' system exploits the historical sensor log. The robot house (see Fig. 1) contains around 50 'low level' sensors . These range from electrical (fridge door open, microwave on etc.), to furniture (cupboard door and drawers open etc.), to services (such as toilet flushing, taps running etc.) and pressure devices (sofa or bed occupied). Sensory information from the robot is also sent to the database or for high throughput, is acquired via ROS messaging [32]. In addition user locations are known to the robot via ceiling mounted cameras [33] and robot locations are available via ROS navigation [32] in a common framework. There are an unlimited number of semantic sensors dependent on what the resident teaches the robot.

4) Behaviour Encoding: Behaviours are automatically generated from the teaching facilities described in section III-C below. However each behaviour generated follows a template similar to Nillson's T-R formalism [34] of evaluating pre-conditions, followed by execution of robot actions and updating of post-conditions. Pre-conditions can be applied to any form of sensory information, both set by the environment or set at a 'semantic' level. An example of such a behaviour would be

```
IF   the oven has been on for 90 minutes
        // house sensor pre-condition
AND  the user has not already been reminded
        // semantic sensor pre-condition
THEN 'come to me'
        // scaffolded robot action
      say 'The oven has been on for
                         a long time'
        // basic robot action
      update the database to signal
       that the user has been reminded
        // set semantic sensor post-condition
```

The pre-conditions would be automatically encoded by the teaching system as SQL statements (two SQL statements representing pre-conditions would be generated for the example given above):

```
SELECT * FROM Sensors WHERE sensorId = 50
   AND value = 'On' AND
       lastUpdate+INTERVAL 5400 SECOND <= NOW()
SELECT * FROM Sensors WHERE sensorId = 701 AND
       value = 'notReminded'
```

If a row is returned from the execution of the SQL statement, then that pre-condition is deemed to be true, otherwise false. Typical robot actions, e.g. calling the navigation system to move the base, making the robot say something and updating a semantic sensor are shown below:

```
base,0,[4.329:0.837:51],999,wait
speak,0,The oven has been on for a long time
cond,701,reminded
```

These commands, depending on the command type (e.g. for the example above, 'base' moves the robot, 'speak' invokes the voice synthesiser and 'cond' sets the value of a semantic sensor), would then either be sent to the planner (see section III-B9), or sent directly to a lower level control module if planning was not required.

5) Sensors and Sensor Abstraction: All sensory information updates the database in real-time and all robot behaviours continually retrieve information from these sensors to assess whether their behavioural pre-conditions are met allowing behavioural scheduling and execution (explained in section III-B11). Behaviours will continue to execute if their pre-conditions remain true or unless they are pre-empted by a higher priority behaviour.

6) Semantic Sensors: In order to cope with ongoing events in the house which are not reflected by the physical house sensors a set of 'semantic sensors' can be created by the teaching system, e.g. a sensor with the label 'User has been reminded that the oven is on'. This latter sensor would be set to 'reminded' following the spoken oven reminder in the example in section III-B4 above. Similarly an activity context recognition system can update semantic sensors in real-time based on the 'Show Me' system described in section III-C2 below. Thus if the user has shown the system what activities constitute 'preparing a meal' then the 'preparing a meal' semantic sensor would be set to 'true' when these events occur.

7) Temporal Aspects of Sensors: Using sensors at a physical and semantic level provides the opportunity to apply temporal constraints. Consider for example a doorbell; this type of sensor is 'on' only for a short period of time, and thus rather than ask 'Is the doorbell ringing?' we would ask 'has the doorbell rung within the last 30 seconds?'. This is checked by exploiting the underlying capabilities of the SQL database by holding episodic values and we thus have the ability to query previous values at a previous point in time:

```
SELECT * FROM Sensors WHERE sensorId = 59
   AND lastActiveValue > 0 AND
         lastUpdate+INTERVAL 30 SECOND >= NOW()
```

The further capability of assessing how long a sensor has been active (or inactive) allows for greater behavioural expressivity. For example 'Has the user been sitting on the sofa for longer than 2 hours?', 'has the user opened the fridge in the last 3 hours?, 'has the user been reminded to call his friend Albert this week?'. These encoding facilities can therefore cope with a very wide range of situations and capture information related to current activity, past activity and socially desirable activity, the latter being primarily set through the creation of semantic sensors. More detailed information on temporal aspects of sensors is described in Saunders et al., [35].

8) External Sensors and External Actions: The sensor system provides a standardised way of encoding information and therefore provides possibilities for associating semantic sensors with other, typically external, events. For example, by polling an external weather service it would be possible to set a 'weather' sensor. This could then be checked by a behaviour which might suggest to the user that this was a good day for a walk, or to do some gardening. In this way the idea of *re-ablement* can be operationalised. External actions could also be run, for example calling a text messaging (SMS) service. For example, a behaviour that checks whether the bed pressure sensor had been active for more than 12 hours and that there had been no activity in the kitchen might then send a text message to the user's caregivers suggesting that the person might need assistance to get out of bed.

9) Planning: Our general approach is to plan only when needed and when necessary. Thus the overall behaviour of the system is driven primarily by the environmental conditions via house or semantic sensors values queried via behavioural pre-conditions. Behaviours are explicitly scheduled. However there are instances where, due to multiple choices being available for robot action (e.g. in a multi-room environment navigation may take multiple paths), or when there is conflict between available resources when planning is necessary. We consider that creating planning domains to be too complex for end-user involvement and therefore we pre-code these where necessary. Although such planning complexity could be coded as multiple behaviours within the existing execution framework, this would lead to an overly complex set of behavioural rules. By separating these pre-coded planning domains for particular tasks, and calling them only as necessary within behaviours that require them, the overall complexity is reduced.

10) Planning Domain: We use an open source state-of-the-art HTN (Hierarchical Task Network) planner (SHOP2 [36]) to cope with these situations. We follow the approach described by Hartanto [37] and Off and Zhang [38], in that each planning domain is individually coded in the lisp-like syntax of SHOP2 and called when the high level action is required. For example, asking the robot to fetch a cup, SHOP2 will plan the appropriate actions on the robot to get the cup (i.e. if the cup were in the kitchen and the robot was in the kitchen the robot would not need to drive to the kitchen, however if the robot were elsewhere then some form of navigation would be necessary). SHOP2 returns the planning actions as robot actions. After each action execution we recall the planning component just in case the environment has changed between actions.

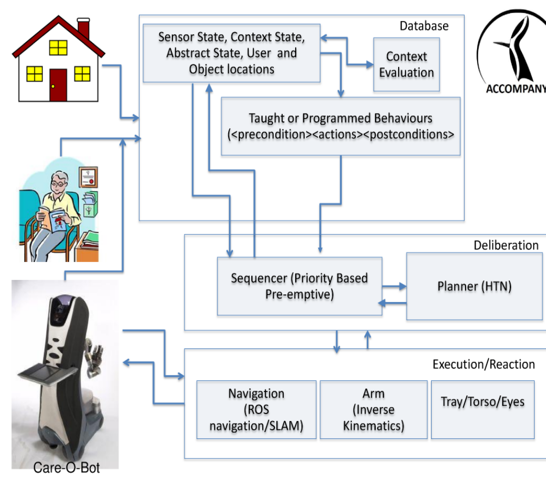


Fig. 2. The diagram shows the layers in operation in the robot house. Sensory information from the robot, house and people together with semantic sensors update the database in real-time. Taught behaviours use these sensors to access behavioural pre-conditions and may subsequently set semantic sensors during execution. All behavioural pre-conditions are continually evaluated by the scheduling system and become available for execution if all pre-conditions are met. Actions that require planning call a HTN planner. Lower level functions, such as navigation and arm manipulation work at a reactive level.

11) Pre-emptive Scheduling: Behaviours can be created in two ways: via a technical interface [39], used when the system is first installed, by technical personnel. Or by the end user using the 'TeachMe' facility described in this paper. The 'technical' interface allows a priority to be given to each behaviour whereas the 'TeachMe' system sets all created behaviours to have the same priority. On execution the scheduling system continually checks all of the preconditions of all of the behaviours (in a manner similar to Nilsson [40]). Should all of the pre-conditions of a behaviour be satisfied the behaviour becomes available for execution, with the highest priority behaviour being executed first. Priority ties result in a random choice of behaviour for execution. Note that due to continual checking of all behavioural pre-conditions, behaviours may become valid or invalid for execution as the currently executing behaviour operates. In this manner the set of environment and semantic sensors drive behaviour execution. Some behaviours can also be set as non-interruptible, for example if a behaviour was reporting on a critical house event

- such as the bathroom taps running for a long time. Fig. 2 provides a pictorial overview of the architecture.

C. Teaching and Learning Interfaces

The teaching interface allows users to create robot behaviours, the learning interface allows users to create higher level semantic sensors for use by the teaching system. For example, the user might create a sensor called 'relaxing in the afternoon' using the learning system and subsequently exploit it in a robot behaviour such as "If I am 'relaxing in the afternoon' for longer than 3 hours remind me to take some exercise".

1) Teaching Interface - 'Teach Me': In order to create behaviours the user as a minimum would need to specify *what needs to happen* (the actions of the robot) and *when those actions should take place* (setting pre-conditions based on the values of physical or semantic sensors). Having specified 'what' and 'when' the system automatically generates many of the sub-behaviours required to operationalise the system. It does this by using templates. The cost of this simplification is a loss of generality; however it is compensated for by ease of use, the latter being one of our priorities in order to develop systems that can be used by non-experts in real-life scenarios.

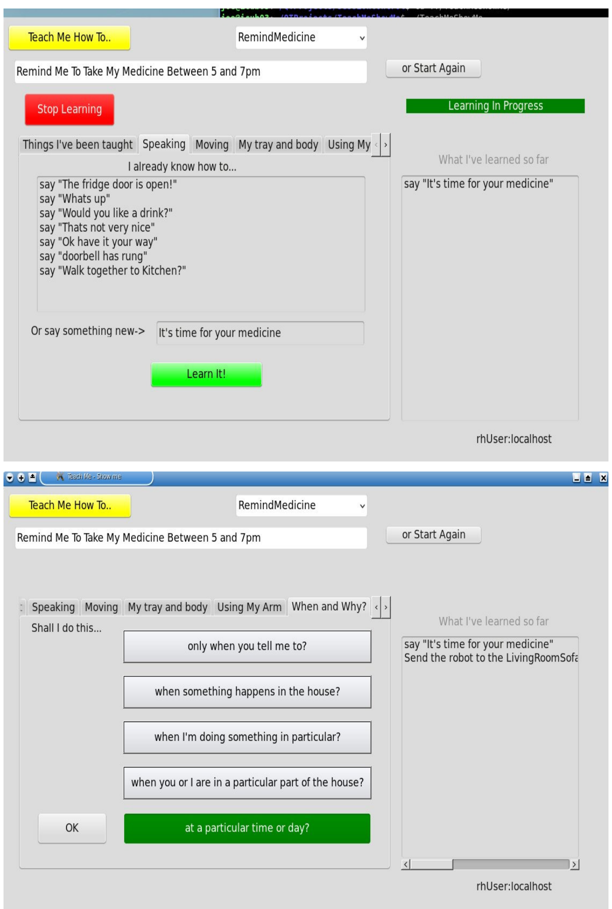


Fig. 3. Shown are screenshots of the teaching interface (note that not all screens are shown - see main text and Fig. 4). In the top figure the user has entered the words that the robot is meant to say. The second screen allows choice of differing activities, such as polling sensors or setting diary events.

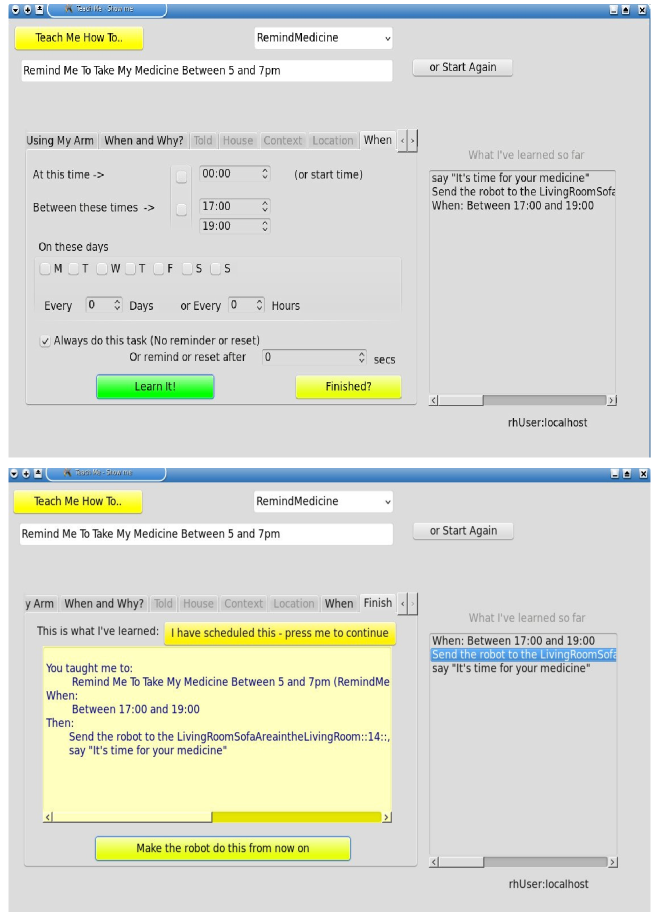


Fig. 4. Shown are final 2 screenshots of the teaching interface (see Fig. 3 for the first 2 screens). The top image shows the diary option selected in this case and the condition 'after 5pm' is entered. The bottom screen shows the final behaviour created (in fact this may generate multiple behaviours on the robot execution system).

To illustrate this idea let us consider a user who wants to be reminded to take their medicine at 5pm. If we were to create this task, individual behaviours would need to be created to associate each precondition with the appropriate sensor, including the semantic sensors, effectively creating two behaviours, one to carry out the task and one to reset conditions, as follows:

i) The first behaviour would need to check that the time was after 5pm and that the user had not been already reminded i.e. a 'user not yet reminded' semantic sensor would be true. If both of these conditions are true then the robot carries out a procedure of moving to the user and saying 'It's time for your medicine' then re-setting the semantic sensor to false to indicate that the user has been reminded.

ii) At some point later, a second behaviour would need to be created, which in this example would be: if after midnight, reset the 'user not yet reminded' sensor to true so that it can fire the next day.

Thus two behaviours need to be created, and careful alignment of reminder rules need to be inserted.

However, the sort of behaviours (see table I) that we envisage users setting up themselves tend to follow a set of common templates e.g. diary like functions, or direct actions based on sensory conditions in the house. We can therefore exploit these templates to generate the appropriate conditional logic. The template in the example above is based on 'diary' like conditions and the automatic setting and creation of support behaviours (such as the resetting behaviour above). In this manner much of the cognitive load is removed from the user and left to the behaviour generation system. Co-learning is operationalised by allowing the robot to provide details of its existing sets of skills that can then be exploited by the user. Re-ablement is supported simply in the act of teaching the robot.

The standard template for 'diary like' robot actions is as follows:

```
Entered by user via GUI:

  reminderTime = t (e.g. 5pm)
  textItem e.g. 'Have you taken your medicine?'
  repeatAfter = n (e.g. 60 seconds)
  <other robot actions> e.g. "Move to user"

Created automically:

  Cond-Reminder = TRUE
  Cond-Remind-again = FALSE
```

Then create the following robot behaviours automatically:

```
1) ReminderX-reset: % resets conditions

    IF NOW between midnight and t
    AND
    Cond-Reminder = FALSE
      SET Cond-Reminder = TRUE
      SET Cond-Remind-again = FALSE

2) ReminderX:   % the actual diary reminded

   IF NOW >= t
   AND
   Cond-Reminder = TRUE
     EXECUTE <other robot actions>
     SAY <text item>
     SET Cond-Reminder = FALSE
     SET Cond-Remind-again = TRUE
```

An example of the user teaching GUI is shown in Figs. 3 and 4 and displays the actions a non-technical person would use to create the example behaviour above. The steps consists of 'what' the robot should do followed by 'when' the robot should do it:

i. The user chooses to send the robot to the current user location and then presses a 'learn it' button. This puts the command into the robot memory (screenshot not shown).
ii. Then the user makes the robot say 'It's time for your medicine'. This is not in the robot's current set of skills and so is entered as a text input by the user (screenshot shown at top of Fig. 3). This is followed by a press of the 'learn it' button.
iii. Now the two actions are in the robot's memory and the user completes the 'what' phase and starts on the 'when' phase.
iv. The user is offered a number of choices including reacting to events in the house, or user or robot locations or a diary function (second screen in figure 3).
v. The user chooses a diary function and enters 17:00 in the 'at this time' box (first screenshot shown in Fig. 4).
vi. Again this is followed by pressing the 'learn it' button.
vii. Having completed both 'what' and 'when' phases the user is shown the complete behaviour for review and can modify it if necessary (screenshot shown at bottom of Fig. 4).
viii. Once happy the user presses a 'make me do this from now on' button and the complete behaviour becomes part of the robot behavioural repertoire.

2) Learning Interface - 'Show Me': The 'Show Me' approach is contingent on the house occupant indicating to the robot that activities are underway. For example, the person might indicate that they are now 'preparing food'. Activities typically have a nested and sometimes hierarchical nature. For example, 'preparing food' might also include 'making a hot or cold drink' or 'using the toaster'. The start and end times and durations of the main task and the sub-tasks are completely variable. However, when any of the sub-tasks are active (e.g. using toaster) the main task must also be active (i.e. preparing food).

Consider that the person has indicated to the robot that they are 'preparing food' and at some point they also indicated that they are now 'using the toaster'. If the robot learns the set of sensory activities associated with these tasks it should be able to recognize them when they occur again in the future. Thus the robot would recognize when the toaster is active and infer not only that 'using the toaster' is true but also that 'preparing food' is true.

Given that these activities can be recognized by the robot (via the house sensory system), it would then be possible to exploit these in the teaching system outlined above and the person would now be able to teach the robot based on the higher level semantics associated with the task. For example, the user might teach "When I am 'Preparing food', the robot should come to the kitchen and raise its tray".

The learning system provides symbolic entries by automatically creating semantic sensors labelled with the descriptive term (e.g. 'preparing food') provided by the user. These can then be exploited to create new behaviours on the robot.

The challenges for a learning system are therefore to be able to recognise that learnt situations can be active in parallel, have an implicit nested hierarchy and that higher levels in the hierarchy (typically) represent higher level of semantic knowledge. These need to be represented as lexical symbols in the memory architecture which the teacher can then exploit.

3) Approach to Learning: In order to learn typical activities in the house the robot needs to recognize when these situations re-occur. This recognition would be primarily based on the current sensory state of the house, however, in more complex circumstances both the historical sensory state and a predicted future sensory state may also be necessary (for example, in historical terms, to recognize that the postman called this afternoon, or in the predicted sense, that the house occupant is likely soon to go to bed). In the work presented in this paper we only consider the current sensory state. Work on a predicted sensory state (for example using sequential data mining algorithms) is part of our ongoing studies.

We also have to consider that the certainty of situations cannot always be represented by a simple true/false dichotomy. For example, if I am in the kitchen it is likely I am preparing food, but it is not a certainty. The confidence of the task assessment by the robot has to be considered.

Our approach falls under the banner of Ambient Activity Recognition in that house resident activities are modelled by analysing a sequence of ambient sensor events. The various approaches to this research area typically apply supervised machine learning techniques such as decision trees/rule induction [41]) (as is used in the studies presented in this document), HMM's and dynamic Bayesian networks [42], template matching techniques such as k-NN [43] or dynamic windowing techniques [28]. Sensor data is typically pre-labelled by an external observer (although some techniques also search for common patterns in daily activities [27]). Our approach differs from a strict supervised learning approach in that the house resident is responsible for 'labelling' the data and does this by simply providing the label and then carrying out the activity whilst the system records and automatically assigns the label to the sensory data accordingly. Furthermore, the newly acquired activity can be subsequently used for direct robot teaching. Activity recognition is based on streaming vectorised sensor data - an approach which allows multiple activity patterns to be recognized in parallel.

The current memory system as a whole is based on rule sets held as behaviours, these are human readable and taught by the human using the teaching system. Ideally a learning system should also be human readable to allow them to be understood by the user. We therefore decided to employ a rule induction approach to learning based on Quinlan's C4.5 Rule induction algorithm (the latest version is C5.0) [13] which allows generation of rule sets in human readable form.

4) Verification of Approach: In order to verify the plausibility of our approach we exploited some existing end user behaviour data available from previous studies in the University of Hertfordshire robot house by Duque et al., [44].

In these previous studies 14 participants were asked to carry out a series of typical daily activities within the house. Each participant took part in two sessions of approximately 45min duration each. In the first (training) session the experimenter suggested to the participant particular tasks that should be carried out. In the second (test) session the experimenter asked the participant to carry out any of the tasks (or none) at their own discretion. During the experiment all house sensory data was recorded and all sessions videotaped. Subsequently the video tapes were annotated by both Duque [44] and an external observer (with subsequent appropriate inter-observer correlation carried out) and marked with the task and subtask start and end times. These were then matched against the recorded sensory data. Duque et al's. [44], aim in these experiments was to *manually* create a rule-set, derived from the training sessions, which could be applied to the test data and accurately predict the activity that was being carried out by the participant. This rule set was constructed and applied to the test data resulting in recognition accuracy (based on precision,

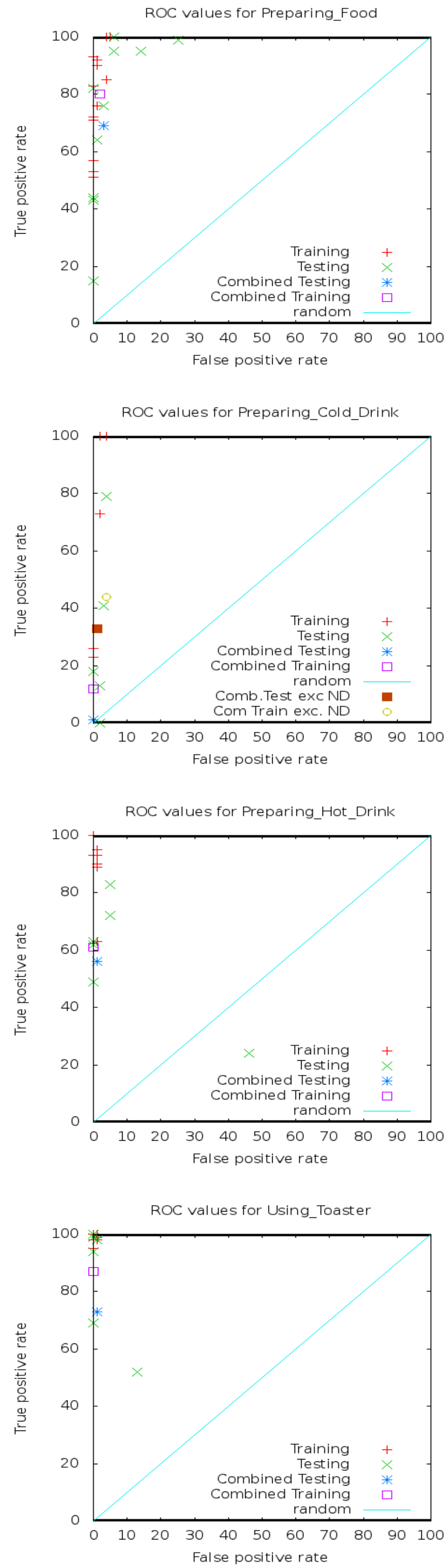


Fig. 5. The ROC curves showing the results of the applying the induction system on both the training and testing data for four categories of classification. Points near the top left hand corner of the curve indicate good classification results. Random classification is shown as the diagonal line from bottom left to top right. Entries towards the bottom right corner indicate poor classification.

recall and accuracy) of over 80%. In the work presented in this paper we tested the plausibility of our approach by replacing the designer generated rules with rules *automatically derived* using the C5.0 algorithm. We then assessed the performance of this approach.

The training data for the 14 participants was used to train a learner using C5.0 with boosting over 10 trials. The learner was then applied to the test data and the resulting performance analysed for four activity states displayed on ROC curves (see Fig. 5).

Each data point in the ROC curves indicate a participant's training or testing session. Also shown are the combined results after aggregation of data of all of the 14 participants into one data set. Clusters that occur in the top left quadrant of the ROC curves indicate a strong level of learning and recognition performance.

The results of the ROC analysis indicated that such a learning approach can allow the robot to recognize human activities in the robot house. However, in a 'real' situation we are faced with having no observer of human actions and no annotator of those actions to derive a classification set. In order to provide a solution to this issue we allowed the *house occupant to become the observer/annotator* by informing the robot when tasks are starting and finishing. To carry this out an end-user training GUI was developed which we called 'Show Me' (see Fig. 6). The GUI allowed users to state what they are currently doing (up to three hierarchical levels) and subsequently test whether the system correctly recognises these actions .

5) Learning and Execution Mechanism: Data for the induction algorithm is held as a table of single row sensor vectors each labelled with the user defined text provided by the GUI. The sensor vectors are used by C5.0 to produce its rule sets. These rule sets are then applied in real-time to incoming sensory data from the house. The effectiveness of the rule set is expressed by C5.0 as a percentage. If this percentage exceeds 50% the labelled semantic sensor is set to true, otherwise false. A pictorial representation of the process is shown in Fig. 7.

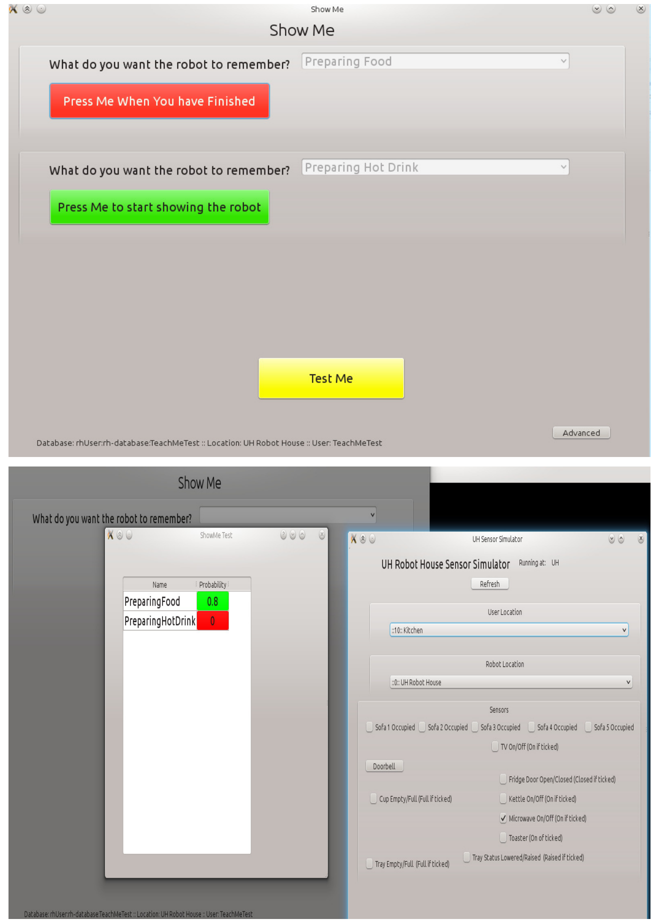


Fig. 6. The 'Show Me' learning GUI. Here the user has entered 'Preparing Food' and when ready presses the 'press me to start showing the robot' button. They then carry out actions associated with preparing food (e.g. starting the microwave oven). If a sub-task is required (in this case 'Preparing a Hot Drink'), the user can continue to enter new tasks up to a maximum of 3 levels deep. Once each task completes, the user presses the red 'Press me when you have finished' button. Testing can be carried out by pressing the 'Test Me' button. This operates in real-time and allows the user, whilst repeating the task, to check if the system correctly identifies it. A probability % is also given based on the predicted accuracy of the real-time classifier using the learned rules. The colour of the classifier symbol turns green if the probability exceeds 50%. Note that the system automatically creates lexical symbols which are then available within the robot teaching interface. In the testing example (shown being tested with the house simulator), the microwave is on, therefore the system infers that 'Preparing Food' is 80% certain. However as the kettle is off 'Preparing Hot Drink' is very unlikely (0%).

IV. Evaluation of the Teaching and Learning Systems

A. Procedure for the Teaching System - 'Teach Me'

The evaluation of the template based teaching system involved 20 participants recruited from the general population. Each participant was introduced to the experimenter, a technician and the experiment psychologist. The technician was present only to ensure the safety of the participant (this is a safety requirement of the ethics agreement required for using this particular robot) and played no other part in the experiment. The technician was stationed in a part of the room outside the main interaction area and took an entirely passive role.

The psychologist asked the participant to complete several forms: a consent form, a demographics form, a questionnaire assessing computer and robot experience and the Ten Item Personality Inventory(TIPI) [45].

The experimenter then took over and the psychologist retired to a different room. The experimenter then explained the purpose of the experiment, the nature of the sensorised house and the capabilities of the robot (in this experiment the robot capabilities were restricted to moving to differing locations and speaking, although the tray and arm/gripper were visible).

The robot had previously been taught to approach the experimenter and participant and to introduce itself by saying "welcome to the robot house". This gave the experimenter a chance to explain the robot capabilities and for the participant to see the robot in action for the first time.

Examples of three sets of behaviours, each with increasing complexity, were shown to participants (the behaviours are shown in table I). The behaviour relating to 'answering the doorbell' in set 1 was used by the experimenter to show the

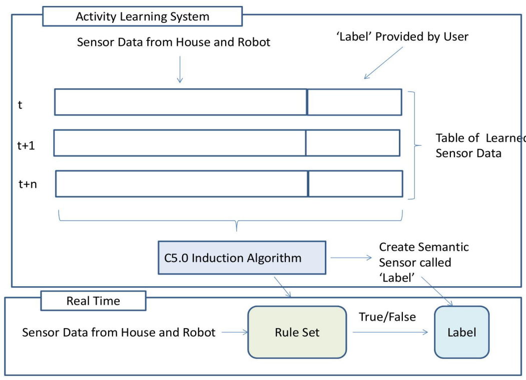


Fig. 7. The 'Show Me' system first asks the user to provide a label for the activity. The user then clicks the green 'start' button and actually carries out that activity. During the activity vectorised sensor data is captured to a file in real-time. The user indicates that this task has finished by pressing the red 'stop' button and the recorded file is subsequently processed by the C5.0 algorithm resulting a a rule set. The system also creates a semantic sensor labelled with the name given by the user. To test the system the user presses the 'test' button and repeats the task. Real-time sensory data from the house and robot is queried by the rule set generated by C5.0 which results in the labelled semantic sensor being set either true or false.

TABLE I
TAUGHT ROBOT BEHAVIOURS INCREASING IN BEHAVIOURAL COMPLEXITY.

Taught Behaviours - Set 1
Whenever you open the microwave oven, make the robot come to the kitchen and wait outside.
If the TV is on, and you are sitting on the sofa, make the robot join you at the sofa.
If the doorbell rings and the TV is on, make the robot say "There's someone at the door" and then go to the Hallway.

Taught Behaviours - Set 2
Make the robot come to the table and remind you to always call your friend "Mary" on Thursday at 2pm.
On Mondays, Wednesdays and Fridays make the robot stand in the hall and remind you that your lunch is being delivered at 12:30pm.
If you are sitting on the sofa for more than 30 minutes, make the robot come to the sofa and tell you to take some exercise. Make the robot do this again after another 30m if you are still sitting there.
Make the robot come to the table and remind you to take your medicine at 12pm and 4pm every day, yellow pills at 12, pink at 4pm.

Taught Behaviours - Set 3
Make the robot come to the sofa and tell you to 'move about a bit', if, in the afternoon, you have sat on the sofa for longer than 1 hour continuously.
If it is after 9pm, and you have left the sofa for over 5 minutes and the TV in on, make the robot go to the hall entrance and say "turn off the TV".
If the microwave has been open or on for more than 1 minute, make the robot come to the table and tell you that the microwave is open or on. Make the robot remind you every minute until the microwave is turned off and door is closed.

participant how to use the teaching GUI.

Participants were then asked to choose one behaviour from each set of behaviours and use the teaching GUI to teach the robot these behaviours.

During the teaching process the experimenter stayed with the participant and helped them when asked. Given that none of the participants had ever interacted with a robot before, and that the teaching GUI was entirely new to them, we felt that

TABLE II
THE TABLE SHOWS THE QUESTIONS POSED TO PARTICIPANTS SPECIFICALLY RELATING TO USABILITY. ALL ANSWERS WERE BASED ON A 5-POINT LIKERT SCALE

Modified Brooke's Usability Scale
I think that I would like to use the robot teaching system like this often.
I found using the robot teaching system too complex.
I thought the robot teaching system was easy to use.
I thought the robot teaching system was easy to use
I think that I would need the support of a technical person who is always nearby to be able to use this robot teaching system .
I found the various functions in the robot teaching system were well integrated.
I thought there was too much inconsistency in the robot teaching system.
I would imagine that most people would very quickly learn to use the robot teaching system.
I found the robot teaching system very cumbersome to use.
I felt very confident using the robot teaching system.
I needed to learn a lot of things before I could get going with the robot teaching system .

this was a necessary requirement. Furthermore, part of the post experimental questionnaire asked them to indicate whether they thought they could continue to use the teaching system without the help of the experimenter. The participant's use of the teaching system was also videotaped for later analysis.

Having taught the robot a new behaviour the experimenter then invited the participant to test it. If the behaviour operated successfully then the participant moved on to teaching the next behaviour in the subsequent set. Alternatively they could modify the existing behaviour and re-test. Having taught all three behaviours (one from each set) the experimenter retired to another room and the psychologist returned and asked the participant to fill in a post evaluation questionnaire based on Brooke's usability scale [46] that had been adapted to the HRI domain from its typical form in HCI (see table II). A subsequent questionnaire (see table VI) was also completed which focused on the usefulness of the robot and teaching system specifically. We felt that this separation of duties between the experimenter and psychologist was necessary to avoid putting any pressure on the participant when they were completing the evaluation questionnaire.

After completion of the questionnaires the participant was invited to ask questions if they wished about the experience, the house the robot etc. In fact, all of the participants were very interested to know how the house and robot worked.

B. Results of the 'Teach Me' Evaluation

1) Demographics: There were 20 participants in the study, 16 female and 4 male. The mean age in the sample was 44 years, with a median age of 49 years. The age range was from 20 to 67 years. The computer usage of the participants can be found in Table III, which suggest that majority of participants used computers for work/studies as well as for social reasons. There was a split in the sample however, in that about half of the participants used computers for recreational reasons, such as games. None of the participants programmed computers. The mean number of hours spent on computers in the sample

TABLE III
COMPUTER USAGE IN THE SAMPLE

Activity	Yes	No
Work or Study	18	2
Socialising	19	1
Recreation	8	12
Programming	0	20

TABLE IV
PERSONALITY IN THE SAMPLE

	Mean	SD
Extraversion	4.38	1.48
Agreeable	5.35	1.14
Conscientious	5.83	1.15
Emotional Stability	4.85	1.36
Openness	5.17	1.10

was 35 hours (SE=2.98) with a median number of hours of 33. Only one of the participant had had any experience with robots. Table IV shows the responses to the TIPI in the sample.

2) Responses to the 'Teach Me' SUS: The mean participant response to the the System Usability Scale regarding the teaching interface was 79.75 (SE=2.29), and the median response was 76.25. These scores were significantly higher than the "neutral score" of 68 ($t(19) = 5.12, p < .01$).

While considering the relationship between the usability scores to the 'neutral' score it is important to note that the collaborative carer/primary user usage and training scenarios intended for the 'TeachMe/Show Me' system is very different from the more industrial settings where the SUS is more commonly applied. As such, the score should be taken as representative of the experienced usability within the interaction context itself rather than merely a representation of the interface [47].

A multiple regression analysis was conducted in order to investigate demographic predictors of SUS responses to this task. After removing non-significant predictors, the final model had an adjusted r^2 of .28, and predicted SUS scores significantly ($F(2, 17) = 4.70, p < .05$). The model is described in Table V and suggests that both higher age and higher scores on the Conscientiousness personality trait were associated with lower scores on the SUS for this task.

3) Responses to the 'Teach Me' Ad-Hoc Questions: Participant responses to the ad-hoc Likert items can be found in table VI. All participant responded '*Very Useful*' or '*Useful*' when asked if they thought it useful useful to teach a robot. In addition all participants answered '*Definitely Yes*' or '*Yes*' when asked if they thought that they would be able to teach the robot, if they would do so for a relative, and that they would find it useful to customise the tasks of a robot beyond a set of standard tasks. The participants did not, however, agree as

TABLE V
PREDICTORS OF SUS SCORES

Predictor	β	SE	t(19)	p
Intercept	0.00	0.00	0.00	1.00
Age	-.49	.20	-2.48	$< .05$
Conscientiousness	-.40	.20	-2.23	$< .05$

TABLE VI
FREQUENCIES OF RESPONSES TO THE 'TEACH ME' AD-HOC LIKERT ITEMS

Do you think it is useful teach a robot?				
Very Useful	Useful	Neither	Not Useful	Not at all
18	2	0	0	0
Do you think that *you* would be able to teach the robot?				
Def. Yes	Yes	Neither	No	Def. No
10	10	0	0	0
Would you be willing to teach the robot for someone else e.g. if you were a relative or carer of the other person?				
Def. Yes	Yes	Neither	No	Def. No
14	6	0	0	0
Do you think that robot should already have been completely setup by someone else?				
Def. Yes	Yes	Neither	No	Def. No
1	3	4	11	1
Do you think that the robot should be able to carry out standard tasks but it would be useful to be able to customize it?				
Def. Yes	Yes	Neither	No	Def. No
13	7	0	0	0
Is it useful knowing what the robot can already do?				
Def. Yes	Yes	Neither	No	Def. No
12	8	0	0	0
How would you feel about having a robot suggesting that you take more exercise?				
Very Comf.	Comfortable	Neutral	Uncomf.	Very Uncomf.
9	8	2	1	0
How would you feel about having a robot suggesting that you play a game together e.g. a video game or chess/draughts?				
Very Comf.	Comfortable	Neutral	Uncomf.	Very Uncomf.
6	11	2	1	0
How would you feel about having a robot warning you that there was a problem in the house e.g. fridge left open or hot/cold taps running or TV left on?				
Very Comf.	Comfortable	Neutral	Uncomf.	Very Uncomf.
18	2	0	0	0
How would you feel about having a robot informing someone else that there was a problem in the house e.g. by texting them, if the problem had not been resolved?				
Very Comf.	Comfortable	Neutral	Uncomf.	Very Uncomf.
12	5	2	1	0

strongly on whether or not the robot should be completely set up by someone else, with a wider range of responses from the participants.

Participants also responded that they were overall '*Very Comfortable*' or '*Comfortable*' with a robot informing them that there was a problem in their house, and 17 out of the 20 participants answered that they were at least '*Comfortable*' with the robot informing a third party about an unresolved problem, but there was less agreement regarding having a robot suggest that they play a game or exercise.

As these were ordinal Likert-items, linear regression analyses were not performed, instead a series of exploratory Spearman's correlations were carried out.

For wanting the robot already set up, there was a correlation approaching significant between this and the *Emotional Stability* personality trait ($\rho(20) = .40, p = .08$) indicating that participants with higher scores along this dimension were less likely to want the robot fully set up by someone else. There was also a trend approaching significance for this item and *Age* ($\rho(20) = -.37, p = .10$), in which older participants were more likely to want the robot already set-up.

There were no significant relationships between comfort with the robot suggesting that one take more exercise and the demographic measures.

There was a significant relationship between *Age* and Comfort regarding the robot contacting a third party in case of a problem ($\rho(20) = -.53, p < .05$), where older participants were more comfortable with this.

4) Teaching Behaviours - 'Teach Me' - Summary of Results: The results from the SUS suggest that participants found the interface easy to use. Moreover, all participants indicated that they felt able to use a system like this to teach the robot, and willing to use such a system to set-up behaviours for an elderly relative or person in their care. These are encouraging results which suggest that further development of the robot teaching system is warranted.

In terms of individual differences, there are some salient relationships. The relationship between *Age* and SUS scores are not unexpected. The older members of the sample found the system more difficult to use than the younger participants. Related to this is the impact of age on the ad-hoc item regarding wanting the robot to be already set up by someone else. Here, older participants were more likely to want the robot being fully set-up than younger participants.

Taken together, this suggest that the current stage of this teaching system may be better suited for use by carers and relatives of elderly people to set up the robot's behaviours for them, but that it needs to be further developed in order to be more suitable for the use of elderly people themselves.

The relationship between items covering the possibility of the robot contacting third-parties in case of problems, and *Age* is also interesting (and we envisaged that this would be a key item that may be taught to the robot). While one explanation for this result may be that older participants were closer to having to consider these scenarios in their own lives than their younger counterparts, a more likely explanation may be that the older portion of the sample were more likely to have had more experiences with caring for elderly parents or other relatives and so might identify more strongly with the third party that is to be contacted. Some of the informal responses from participants during the debrief of the study did reference such experiences.

C. The Learning System - 'Show Me'

A preliminary evaluation of the learning system involved 3 persons, all female aged 58 to 66, who were "informal" carers. They typically looked after an elderly relative. All of the informal carers had previously been exposed to the 'Teach Me' system and were therefore familiar with the teaching process reported above.

1) Procedure: The experimenter explained the purpose of the study and ensured that they understood the instructions. The experimenter then chose one of the activities in Table VII and explained to the participant how to use the 'Show Me' GUI to allow the robot to learn about this activity - typically by actually carrying out that activity whilst the 'start showing me' button was active. They could then test whether this activity was recognised by pressing the 'test' button, repeating the activity and ensuring that the recognition bar turned green (i.e. over 50% probable). If lower than 50% the activity was repeated.

TABLE VII
SET OF ACTIVITIES USED FOR THE 'SHOW ME' EVALUATION

Create an activity called **'Watching TV'**.
Create an activity called **'Relaxing on the Sofa'**.
Create an activity called **'Preparing a hot drink'**.
Create an activity called **'Preparing a Ready Meal'** using the microwave
Create an activity called **'Kitchen Activities'** which is active when 'Preparing a hot drink' or 'Preparing a ready meal' or when any other kitchen activity is being carried out

TABLE VIII
SET OF BEHAVIOURS TAUGHT AS PART OF THE 'SHOW ME' EVALUATION

Teach the robot that if it is 7.30 and you are **'Watching TV'** then remind you that your favourite program is about to start.
If you have been **'Relaxing on the sofa'** for more than 30mins make the robot come to the sofa and tell you to 'move about a bit'
If there are **'Kitchen Activities'** make the robot come to the kitchen and offer to carry the drink or meal to the dining table

The participant was then asked to choose one of the other activities shown in Table VII and use the 'Show Me' GUI to allow the robot to learn about the activity. They then tested this activity to ensure that the robot correctly identified it.

Having successfully tested that the robot had learned about this activity, the participant was then asked to choose the corresponding teaching task in Table VIII. For example, if the robot had learned about 'watching TV', then the behaviour involving 'watching TV' would be chosen. The participant then taught the robot the chosen behaviour and subsequently tested that it worked. For example, for 'watching TV', that the robot would approach the participant (who was now sitting on the sofa watching TV) and inform them about an upcoming TV program. Following this the participant was asked to complete the System Usability questionnaire and completed two additional questionnaires on ad-hoc usability and provide, if they wished, an overall comment on the system.

2) Results of the 'Show Me' Evaluation: Note that the number of participants in the 'Show Me' evaluation was very low and therefore not statistically valid. We hope however that they are indicative of possible promising research in this area.

The SUS scores for the 'Show Me' interface ranged from 67.5 to 80. The mean score was 75.83 and the median score was 80. This was larger than the expected average of 68. Ad-hoc likert item results are shown in table IX and some user comments are shown in table X.

Clearly such a small sample may only be indicative, however the results from the SUS suggested that participants found the interface relatively easy to use. The three participants all found the 'Show Me' feature useful, and felt confident in their ability to use a feature like this to teach a robot about their own activities or to use on behalf of someone else. They also felt that this should not be something that was already set up prior to use.

TABLE IX
FREQUENCIES OF RESPONSES TO THE 'TEACH ME' AD-HOC LIKERT ITEMS

Do you think it is useful to teach robot activities?				
V. Useful	Useful	Neither	Not Useful	Not at all
3	0	0	0	0
Do you think that *you* would be able to teach robot activities?				
Def. Yes	Yes	Neither	No	Def. No
2	1	0	0	0
Would you be willing to teach activities for someone else carer of the other person?				
Def. Yes	Yes	Neither	No	Def. No
2	1	0	0	0
Should activities already have been setup by someone else?				
Def. Yes	Yes	Neither	No	Def. No
0	0	0	3	0

TABLE X
COMMENTS MADE ON THE 'SHOW ME' INTERFACE

I think it is a great idea to personalise the robot for an individual's needs. But also think this can be used alongside prepared repetitive tasks. I think also very important for the robot to learn activities rather than or as well as one off tasks. When teaching activities need to show robot in simple exaggerated steps so that it does not confuse activities
Not completely set up but a range of everyday types of activities which can be personalised

V. CONCLUSION

We have described a robot personalisation system designed to be used by persons operating in assistive environments in smart homes, typically carers, relatives or the elderly person themselves. The teaching component exploits sets of standard templates in order to generate robot behaviours. This approach avoids the complexity of robot behaviour generation for a large set of tasks which we believe would be required by such persons, clearly however more complex tasks would still need technical personnel involvement. The teaching interface was evaluated with end users and indicated that participants considered that such a system would be both useful and useable by them for aiding persons to stay in their homes for longer periods. We have also described and presented a limited evaluation of a user driven activity learning system which allows the robot and smart home to recognise user activities. This activity recognition system compliments the teaching system by allowing a higher level of semantic behaviour creation to be achieved.

The results of both of these studies indicate that such facilities would be readily accepted for use by carers, relatives and the elderly themselves. However, with increasing age, the willingness to learn new ways to operate, by personalising a robot's behaviours, decreases.

In these studies the robot was operating primarily as a cognitive prosthetic and our future work in this area will attempt to extend from memory prosthetics to also include teaching fetch and carry tasks. However, as a memory prothestic, a question that could be asked is 'why use a robot?' and not simply another device such as a mobile phone? We would argue that the use of a robot differs in a number of ways to that of a mobile phone. Firstly, the robot will find the person to inform them (a mobile phone may be somewhere else and ignored). Secondly, there is some evidence [48]–[51] that the robot, by having a physical presence, is perceived as more authoritative, i.e. a person is more likely to follow a robot's instructions or suggestions rather than, say, a phone.

The exploration, via the 'Show Me' system, of creating higher level semantics, is we believe a novel and promising way to ease the teaching burden. For example, being able to instruct a robot by using everyday terms, such as 'when it's time for bed do...' or 'if I'm making dinner do ....'. We have only partially explored such opportunities and issues which surround 'showing' a robot typical activities and this work is at an early stage. A number of improvements and enhancements to such facilities would be to use both inductive and predictive mechanisms to increase the reliability of the robot recognising user activities. Prediction algorithms already exist which use past sensory data to predict possible next actions [52]. A further extension of this work would be to use those predictions to then predict again - effectively creating a predictive forward model for the robot. This forward model then being subject to the inductive algorithm, which would now use both historical and predicted sensor vectors to make a decision on user activity.

This area of research also presents some ongoing design challenges that are currently being pursued from two largely distinct viewpoints. The first viewpoint focuses on people-centred initiatives and improving acceptance by tackling human-robot interaction issues by giving control on personalization and product customisation features. The second viewpoint studies technologically-driven initiatives by building impersonal systems that are able to autonomously adapt their operations to fit changing requirements, but ignore human-robot interaction. In order to inform the development of a new generation of smart robotic spaces, solutions to the combination of these different research strands is, we believe, a fundamental requirement [53].

Finally, we have demonstrated in this work that personalisation of an autonomous robot is possible in a domestic environment. Further analysis of the exploitation and commercialisation of these findings may also be a positive next step.

ACKNOWLEDGMENT

The work described in this paper was partially funded by the European project ACCOMPANY (Acceptable robotics COMPanions for AgeiNg Years). Grant agreement no.: 287624.

REFERENCES

[1] B. Przywara, "Projecting future health care expenditure at European level: drivers, methodology and main results," in *European Economy*. European Commision, Economic and Financial Affairs, 2010.

[2] Eurostats, "Population projections. online database." http://epp.eurostat.ec.europa.eu/statistics_explained, 2013.

[3] Welsh Social Services Improvement Agency, "Demonstrating improvement through reablement," http://www.ssiacymru.org.uk/reablement, Last referenced 23rd November 2012.

[4] M. K. Lee, J. Forlizzi, S. Kiesler, P. Rybski, J. Antanitis, and S. Savetsila, "Personalization in HRI: A longitudinal field experiment," in *Proc. Int. Conf. Human-Robot Interaction*, 2012, pp. 319–326.

[5] U. Reiser, C. Connette, J. Fischer, J. Kubacki, A. Bubeck, F. Weisshardt, T. Jacobs, C. Parlitz, M. Hagele, and A. Verl, "Care-o-bot® creating a product vision for service robot applications by integrating design and technology," in *Int.Conf. on Intelligent Robots and Systems*. IEEE, 2009, pp. 1992–1998.

[6] G. Pilkington, "Homecare re-ablement," *London, Department of Health*, 2008.

[7] B. D. Argall, S. Chernova, M. Veloso, and B. Browning, "A survey of robot learning from demonstration," *Robot. Auton. Syst.*, vol. 57, no. 5, pp. 469–483, May 2009.

[8] M. Nicolescu and M. J. Mataric, "Learning and interacting in human-robot domains," *Trans. on Systems, Man, and Cybernetics*, vol. 31, no. 5, pp. 419–430, 2001.

[9] R. E. Fikes and N. J. Nilsson, "Strips: a new approach to the application of theorem proving to problem solving," *Artificial Intelligence*, vol. 2, pp. 189–208, 1971.

[10] J. Saunders, N. Otero, and C. L. Nehaniv, "Issues in human/robot task structuring and teaching," in *Int. Symp. on Robot and Human Interactive Communication*. IEEE, 2007, pp. 708–713.

[11] C. Sammut, S. Hurst, D. Kedzier, and D. Michie, "Learning to fly," in *Proc. Ninth Int. Conf. on Machine Learning*. Morgan Kaufmann, 1992, pp. 385–393.

[12] ——, "Learning to fly," in *Imitation in Animals and Artifacts*, K. Dautenhahn and C. L. Nehaniv, Eds. MIT Press, 2002, pp. 171–190.

[13] J. R. Quinlan, *C4.5: Programs for Machine Learning*. San Mateo, CA: Morgan Kaufmann, 1993.

[14] M. van Lent and J. E. Laird, "Learning procedural knowledge through observation," in *Proc. 1st Int. Conf. Knowledge Capture (K-CAP 2001), Victoria, Canada*. ACM Press, 2001, pp. 179–186.

[15] C. L. Nehaniv and K. Dautenhahn, "The Correspondence Problem," in *Imitation in Animals and Artifacts*, K. Dautenhahn and C. L. Nehaniv, Eds. MIT Press, 2002, pp. 41–61.

[16] A. Levas and M. Selfridge, "A user-friendly high-level robot teaching system," in *Int. Conf. on Robotics and Automation*, vol. 1. IEEE, 1984, pp. 413–416.

[17] M. Kaiser, V. Klingspor, J. del R. Millán, M. Accame, F. Wallner, and R. Dillmann, "Using machine learning techniques in real-world mobile robots," *IEEE Expert: Intelligent Systems and Their Applications*, vol. 10, no. 2, pp. 37–45, 1995.

[18] M. Kaiser and R. Dillman, "Building elementary robot skills from human demonstration," in *Proc. Int. Conf. on Robotics and Automation*, vol. 3. IEEE, 1996, pp. 2700–2705.

[19] H. Friedrich and R. Dillman, "Robot programming based on a single demonstration," in *Proc. 3rd European Workshop on Learning Robots at ECML95*, ser. Lecture Notes in Computer Science, vol. 912. Crete: Springer, 1995.

[20] R. Dillmann, "Teaching and learning of robot tasks via observation of human performance," *Robotics and Autonomous Systems*, vol. 47, pp. 109–116, 2004.

[21] A. L. Thomaz and C. Breazeal, "Teachable robots: Understanding human teaching behavior to build more effective robot learners," *Artificial Intelligence*, vol. 172, pp. 716–737, April 2008.

[22] Y. Kuniyoshi, M. Inaba, and H. Inoue, "Learning by watching: Extracting reusable task knowledge from visual observations of human performance," *IEEE Trans. on Robotics and Automation*, vol. 10, pp. 799–822, November 1994.

[23] K. Ikeuchi and T. Suehiro, "Towards an assembly plan from observation," in *Proc. Int. Conf. on Robotics and Automation*. IEEE, 1992, pp. 2171–2177.

[24] M. Johnson and Y. Demiris, "Hierarchies of coupled inverse and forward models for abstraction in robot action planning, recognition and imitation," in *Proc. Int. Symp. on Animals and Artifacts*, SSAISB. The Society for the Study of Artificial Intelligence and the Simulation of Behaviour, April 2005, pp. 69–76.

[25] K. S. Narendra and J. Balakrishnan, "Adaptive control using multiple models," *IEEE Transactions on Automatic Control*, vol. 42, no. 2, pp. 171–187, February 1997.

[26] D. M. Wolpert and M. Kawato, "Multiple paired forward and inverse models for motor control," *Neural Networks*, vol. 11, pp. 1317–1329, 1998.

[27] T. Gu, Z. Wu, X. Tao, H. Pung, and J. Lu, "epsICAR: An emerging patterns based approach to sequential, interleaved and concurrent activity recognition," in *Proc. of the International Conference on Pervasive Computing and Communications*, 2009, pp. 1–9.

[28] N. C. Krishnan and D. J. Cook, "Activity recognition on streaming sensor data," *Pervasive and Mobile Computing*, vol. 10, Part B, no. 0, pp. 138 – 154, 2014.

[29] J. Ye, S. Dobson, and S. McKeever, "Situation identifcation techniques in pervasive computing: A review," *Pervasive and Mobile Computing*, vol. 8, no. 1, pp. 36–66, 2009.

[30] J. Saunders, C. L. Nehaniv, and K. Dautenhahn, "Teaching robots by moulding behavior and scaffolding the environment," in *Proc. Conf. on Human-Robot Interaction*. ACM Press, March 2006, pp. 118–125.

[31] W. C. Ho, K. Dautenhahn, N. Burke, J. Saunders, and J. Saez-Pons, "Episodic memory visualization in robot companions providing a memory prosthesis for elderly users," in *Proc. Conf. Advancement Assistive Technology in Europe*, 2013.

[32] M. Quigley, K. Conley, B. Gerkey, J.Faust, T.Foote, J. Leibs, R.Wheeler, and A. Y. Ng, "ROS: an open-source robot operating system," in *ICRA Workshop on Open Source Software*, 2009.

[33] N. Hu, G. Englebienne, and B. J. A. Kröse, "Bayesian fusion of ceiling mounted camera and laser range finder on a mobile robot for people detection and localization," in *Proceedings of IROS workshop: Human Behavior Understanding Vol. 7559. Lecture Notes in Computer Science (pp. 41-51)*, 2012.

[34] N. J. Nilsson, "Teleo-reactive programs for agent control," *Journal of Artificial Intelligence Research*, p. 158, 1994.

[35] J. Saunders, M. Salem, and K. Dautenhahn, "Temporal issues in teaching robot behaviours in a knowledge-based sensorised home," in *Proc. 2nd International Workshop on Adaptive Robotic Ecologies, Dublin, Ireland, (ARE13)*, 2013.

[36] D. Nau, Y. Cao, A. Lotem, and H. Muñoz-Avila, "SHOP: Simple Hierarchical Ordered Planner," in *Proc. IJCAI-99*, 1999, pp. 968–973.

[37] R. Hartanto, *A Hybrid Deliberative Layer for Robotic Agents: Fusing DL Reasoning with HTN Planning in Autonomous Robots*. Springer Berlin Heidelberg, 2011.

[38] D. Off and J. Zhang, "Multimodal integration processes in plan-based service robot control," *Tsinghua Science and Technology*, vol. 16, no. 1, pp. 1–6, 2011.

[39] J. Saunders, N. Burke, K. L. Koay, and K. Dautenhahn, "A user friendly robot architecture for re-ablement and co-learning in a sensorised homes," in *Proc. 12th European Conf. Advancement Assistive Technology in Europe, (AAATE13)*, 2013.

[40] N. J. Nilsson, "Teleo-reactive programs and the triple-tower architecture," *Electronic Transactions on Artificial Intelligence*, vol. 5, pp. 99–110, 2001.

[41] C. Chen, B. Das, and D. Cook, "A data mining framework for activity recognition in smart environments," in *Proc. International Conference on Intelligent Environments*, 2010.

[42] J. Lester, T. Choudhury, N. Kern, G. Borriello, and B. Hannaford, "A hybrid discrimative/generative approach for modelling human activities," in *Proc. of the 19th International Joint Conference on Artificial Intelligence (IJCAI '05)*, 2005, pp. 766–772.

[43] J. Saunders, C. L. Nehaniv, and K. Dautenhahn, "Using self-imitation to direct learning," in *Special Session on Learning Through Imitation, Proc. IEEE Ro-man 2006, 15th IEEE International Workshop on Robot and Human Interactive Communication*. IEEE Press, September 2006, pp. 244–250.

[44] I. Duque, K. Dautenhahn, K. L. Koay, I. Willcock, and B. Christianson, "Knowledge-driven user activity recognition for a smart house. development and validation of a generic and low-cost, resource-efficient system," in *In ACHI 2013, The Sixth International Conference on Advances in Computer-Human Interactions*, 2013, pp. 141–146.

[45] S. D. Gosling, P. J. Rentfrow, and W. B. Swann Jr, "A very brief measure of the big-five personality domains," *Journal of Research in personality*, vol. 37, no. 6, pp. 504–528, 2003.

[46] J. Brooke, "SUS-A quick and dirty usability scale," *Usability evaluation in industry*, vol. 189, p. 194, 1996.

[47] ——, "SUS: a retrospective," *Jnl. Usability Studies*, vol. 8, no. 2, pp. 29–40, 2013.

[48] J. Wainer, D. J. Feil-Seifer, D. A. Shell, and M. J. Mataric, "Embodiment and humanrobot interaction: a task based perspective," in *Proc. IEEE Int. Conf. on HumanRobot Interaction*, 2007, pp. 872–877.

[49] H. Kose-Bagci, E. Ferrari, K. Dautenhahn, D. S. Syrdal, and C. L. Nehaniv, "Effects of embodiment and gestures on social interaction in drumming games with a humanoid robot," *Jnl. Adv. Robotics*, vol. 23, pp. 1951–1996, 2009.

[50] W. Bainbridge, J. Hart, E. Kim, and B. Scassellati, "The benefits of interactions with physically present robots over video-displayed agents," *Int. Jnl. Social Robotics*, vol. 3, no. 1, pp. 41–52, 201.

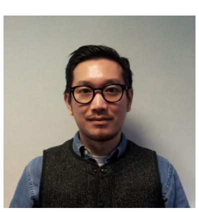
[51] M. Salem, G. Lakatos, F. Amirabdollahian, and K. Dautenhahn, "Would you trust a (faulty) robot? effects of error, task type and personality on human-robot cooperation and trust," in *Proc. IEEE Int. Conf. on HumanRobot Interaction*, 2015.

[52] K. Gopalratnam and D. J. Cook, "Active lezi: An incremental parsing algorithm for sequential prediction," in *In Sixteenth International Florida Artificial Intelligence Research Society Conference*, 2003, pp. 38–42.
[53] M. Dragone, J. Saunders, and K. Dautenhahn, "On the integration of adaptive and interactive smart and robotic spaces," *Journal of Behavioral Robotics*, vol. In press, 2015.

Joe Saunders is a Senior Research Fellow in the Adaptive Systems Research Group of the University of Hertfordshire, UK. He received his PhD from the University of Hertfordshire, UK, in 2007. He has carried out research in a number of European projects concerned with robot adaptation and learning at both a physical and linguistic level and has operated as lead researcher in these areas. He is especially interested in applying theoretical studies to practical real-world environments.

Dag Sverre Syrdal received his BSc. in Psychology from Queen's University of Belfast, and his MSc. in Research Methods from the University of Hertfordshire. He has worked in the Adaptive Systems Research Group since 2006 and has designed and run human-robot interaction studies within several EU projects. His research interests include individual differences in human-interaction, evaluation methodologies, and social aspects of human-robot interaction.

Nathan Burke received his BSc. in Computer Science from Texas State University and his MSc in Artificial Intelligence from the University of Hertfordshire. He is currently working on a PhD in Artificial Intelligence at the University of Hertfordshire. His research interests include machine learning, robot teaching methods, and assistive robotics.



Kheng Lee Koay received his B.Sc. degree in Robotics and Automated Systems and Ph.D. from the University of Plymouth, U.K. in 1997 and 2003 respectively. He is currently a Senior Research Fellow in the Adaptive Systems Research Group at the University of Hertfordshire, U.K. His research interests include Mobile Robotics, Robotic Home Companions and Human-Robot Interaction, in particular, aspects of human-centred socially acceptable interactions, design and evaluation methodologies.

Kerstin Dautenhahn is full Professor in the School of Computer Science at University of Hertfordshire in U.K. where she coordinates the Adaptive Systems Research Group. She received her Ph.D. degree from University of Bielefeld, Bielefeld, Germany, in 1993. She has published more than 300 research articles on social robotics, human-robot interaction, assistive technology and Artificial Life. Prof. Dautenhahn has edited several books and frequently gives invited keynote lectures at international meetings. She has been Principal Investigator of a number of European and nationally funded projects. Prof. Dautenhahn is Founding Editor in Chief of the journal "Interaction Studies: Social Behaviour and Communication in Biological and Artificial Systems", as well as Associate Editor of several other international journals. She is Senior Member of IEEE.