Human-in-the-Loop Adaptation and Reuse of Robot Assistance Policies for Ambient Assisted Living

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https://doi.org/10.31256/Fn5Eb4A

***Abstract*—Personalisation and adaptation of *Ambient Assisted Living* (AAL) solutions is the subject of many existing works, which seek to embed and/or learn user preferences and needs. However, with a focus on lab-based evaluation, it has been easy to overlook the potential realities of what AAL might look like in the future: a range of heterogeneous platforms, devices, and robots will generate swathes of knowledge that must be shared, within and outside the home. As such, it is important to consider scalability and interoperability in every aspect of future AAL solutions. *Adaptivity as a Service* (AaaS) is proposed as a highly specialised service with a core function of personalising and adapting smart homes and AAL systems to the needs and wants of individuals.**

***Index Terms*—adaptivity, personalisation, Ambient Assisted Living (AAL), robotic care, Human-in-the-Loop (HITL), Digital Twin**

I. Introduction

It is expected of future AAL solutions to be *adaptive*. It has been recognised for over a decade that this adaptivity must be deeply ingrained in AAL systems at the "algorithmic, architectural, and human interface" levels [1]. They must adapt to the changing habits, evolving needs, and individual preferences of users.

A recent stakeholder participatory study on requirement gathering for future assisted living solutions found that long-term personalisation and adaptation is vital for elderly users: the system must understand the impact of the ageing process [2]. Furthermore, solutions must be goal-oriented in that they work towards delivering a desired user state. This suggests a high degree of autonomous adaptation, which is in contrast to previous works which have suggested solutions be adapted over time through iterative user surveying to ensure the solution still meets the needs of the user [3].

It has been common in the past to think of personalisation as something that is not integral to the architecture of the system, but rather as an added feature. As such, there a number of approaches which propose the use of a *Graphical User Interface* (GUI) to provide personalisation insofar as some parameters of the system are modifiable by the user (e.g. [4] [5]. However, this puts a significant burden on the user in terms of effort, effectively causing the user to adapt to the system, rather than vice versa.

This work was supported by the Engineering and Physical Sciences Research Council (grant EP/L016834/1), EPSRC Centre for Doctoral Training in Robotics and Autonomous Systems.

Other solutions may instead provide a set of predefined templates of a user profile. For instance, in an AAL system these could be "dependent, assisted, at risk, and active" [6]. Users can be manually assigned, or automatically classified, into these categories so the system can modify behaviour accordingly. However, these approaches are limited: (1) to models provided during the design phase; and (2) in that it is virtually impossible to cater for elderly individuals with a wide and diverse range of needs.

It is increasingly common to see approaches which adapt in real-time, such as the social robot 'GrowMu', which offers services to users based on their emotion and where the robot is in the environment [7]. The robot is trained (offline) to gravitate towards services which elicit a positive response. While useful, the approach is limited to service selection only, with little regard to adaption within those services.

In contrast, Adaptivity as a Service (AaaS) is inspired by established 'hybrid' approaches in Human Activity Recognition (e.g. [8]): hybrid models fuse knowledge- and data-driven sources to enable adaption to individual users and improve baseline performance and scalability. This typically means starting with initial 'seeds' (templates) of what a system can recognise or do (from provided knowledge), while subsequent data collection at run time enables a semi-supervised learning process to grow capability over time.

Where existing approaches focus primarily on providing one or a few dimensions of personalisation and adaptivity within AAL solutions, AaaS puts it at the core. AaaS is proposed as a highly specialised service that combines extensive user modelling, distributed learning, and knowledge transfer [9].

II. Proposal

AaaS addresses three types of long-term adaptation [9]:

1) Adapting context-awareness itself to account for predicted physical and mental decline, based on individual's known conditions and principles of ageing.
2) Adapting assistive functionality, including interaction modalities, to fit an individual's exact needs/wants.
3) Adapting quickly to new users, based on experience.

AaaS is 'distributed' in the sense that services are delivered in-home, through 'local' nodes, while data is aggregated and processed centrally, at a 'global' level. A (simplified) conceptual architectural overview of AaS is provided in Figure 1. As shown, AaaS sits between existing AAL components, acting

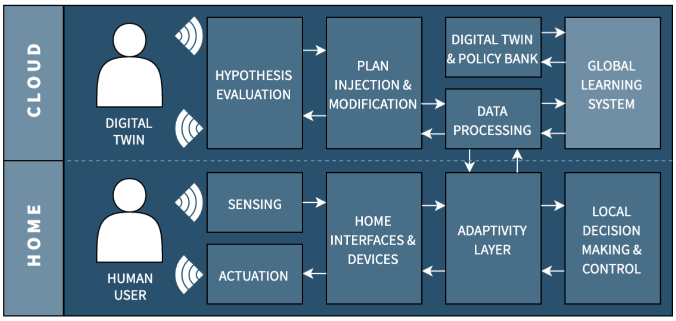

Fig. 1. Conceptual architecture overview of AaaS.

as an intermediary, similar to the concept of an 'adaptivity layer' proposed in [10]). The user is a single member in a population of individuals requiring personalised and adapted AAL. This population-centric view enables knowledge transfer and learning from common experience at the local level.

AaaS addresses the three types of adaption with a two-pronged approach to Human-in-the-Loop operation: (1) implicit consideration of the user in decision making, and (2) continuous learning of desired system behaviour relative to user profile for the updating of beliefs.

III. A Hybrid Model

It is expected that AaaS employ hybrid models to: (1) model users, and (2) enable personalisation. A *Digital Twin* (DT) is therefore proposed to provide a digital counterpart for each user, which is then evolved through a *Human-in-the-Loop* (HITL) process that enables learning while implicitly expanding the knowledge represented by the DT.

a) Digital Twin: The digital twin is a user model initially comprised only of explicitly provided information (e.g. from the user or their carers). Based on this information, a set of initial *Assistive Policies* (APs) are selected and assigned to the DT. Selection is based on learning from experience with similar users. Policy reuse is fundamental in improving the initial user experience and acceptance, providing a higher degree of familiarity in the first instance.

Each AP is a general plan of an assistive functionality, originally created from expert knowledge. All of these APs together form a bank of policies covering a range of scenarios. APs describe: (1) a plan of actions that can be carried out in a robot-enabled home environment; and (2) the variability in these plans. APs are not hardware-specific, and instead rely on translation from the high-level to the command-level.

Through the policy personalisation process explained below, APs evolve over time as they are fine-tuned to a given user. In terms of forecasting, this has the following implications: (1) short-term, AaaS can evaluate whether proposed actions by a local planner (e.g. from the smart home / AAL system) are sensical for the given user through hypothesis testing; and (2) long-term, it allows forecasting of user behaviour and health, which allows for monitoring of specific conditions with/without the condition being specified in the DT.

b) Policy Personalisation: Realising a hybrid approach, APs originally provided from knowledge engineering should be evolved and branched out into a set of source APs from a *Reinforcement Learning* (RL) and policy reuse process. Knowledge can be extracted about the impact of certain traits (e.g. the presence of a specific *Mild Cognitive Impairment* [MCI]) based on the aggregation of real-world experiences with relevant users.

APs are evolved to suit the *wants*, and *needs*, of each user. The optimal state of users' APs are used to enhance their DT, and for policy reuse more broadly. This enables, for example, the automated selection of an AP set for new users, based on experience from similar users within the population of DTs.

IV. Conclusion & Future Work

Here, the fundamental principles of AaaS and its novel distributed HITL approach have been outlined in relation to existing challenges in AAL personalisation. Within AaaS, individual homes can benefit from and contribute to a wider network of adaptivity specialisation. Future research will need to focus on the best approaches to meet key goals of AaaS. Ultimately, the Digital Twin will serve as a rich source of data that accompanies a user for life, which systems that deal with personalisation independently may fail to replicate.

While the vision for AaaS is rather broad, research will focus on feasibility by addressing underpinning scientific issues, enabled by our Robotic Assisted Living Testbed (RALT)[1]: a 60m^2, fully-furnished simulated apartment comprising a bedroom, bathroom, and combined kitchen/dining/living area.

Work will therefore focus on: (1) encoding/representation of personalisation and adaptivity policies/plans; (2) translating these for heterogeneous AAL platforms and devices; (3) merging and processing feedback to best reflect learning from similar users; and (4) management of "unhealthy" feedback, where users have moulded policy to their unhealthy wants.

The next phase will focus on adapting robot-enabled assistance for some example scenarios. The target for adaptation in the experiments is users with varying level of capability in performing cognitive and physical tasks during a scenario, and so the latent variable is user skill. The agent is the smart home, as an ensemble of *Internet of Things* and robotic devices. A scenario may represent, for example, a use case in which an immobile user wishes to have a cup of coffee and the adaptive service must learn how to meet this goal using the devices at hand, in a way that suits the user. As such, the AP for each scenario can be formulated as an RL problem, with the state and actions of the system modelled in an MDP. The transition function depends on user actions (e.g. requests, feedback, active sensing), while rewards are allocated based on successfully achieving the goal. The end product is that users can effectively build their own solutions through interactions with the system.

[1]Virtual tour available at https://ralt.hw.ac.uk/

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