A Framework for Personalized and Adaptive Socially Assistive Robotics

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***Abstract*— Assistive technology is playing a crucial role in supporting caregivers and patients with neurological disorders to carry out home care services. Nevertheless, the technological advances allowing for the automation of such services often lead to systems composed of several devices that make patients not always comfortable when interacting with them, so limiting their effective use. In order to improve the acceptance level of an assistive system, a robotic system is proposed to act as a smart sensor whose functionalities to control its behavior as well as to provide meaningful observations from the input data are modeled as services. The system is supported by a middleware able to automatically schedule a set of home care services that are personalized for each patient considering the personal daily routine, the cognitive status, and the personality profile. In addition, the proposed system is able to react to dynamic changes in the patient's state by modifying the robot behavior and adapting on the fly the set of proposed home care services.**

I. Introduction

People with mild cognitive impairment, as well as many old people, prefer to live in their own home, when possible. However, they are not always in the condition to autonomously take care of themselves, since, for example, they can eat in a not proper way, they can make mistakes while following the medical prescriptions, or even not to perform activities that could improve their physical state. The possibility to monitor the proper handling of their personal needs, referred to both the so-called Instrumental Activities of Daily Living (IADL) and the Activities of Daily Living (ADL), and to detect deviations from previous routine patterns, is a primary challenge in supporting this type of people and their caregivers. Even though assistive technology is mature enough to theoretically provide an accurate monitoring of a patient, its use in a concrete scenario is still far from being widely adopted because of the associated costs, and the low acceptance level from people not used to it.

Usually, the human activities recognition and monitor problem was tackled using environmental sensors (e.g., cameras and RFID), and "wearable" sensors (e.g., mobile phones, wrist watches). In the first case, the devices are positioned at certain points of interest distributed throughout the space, so requiring structural environmental setup, while the use of wearable sensors represents a more viable approach from an economic point of view that does not require a structural intervention in the environment. Both approaches have disadvantages. In particular, elderly patients are reluctant to continually wear multiple sensors on the body [1]. On the other hand, embedding sensors on a myriad of daily living objects has challenging operational costs and battery-life issues [2], and it requires an invasive and massive intervention in the house. Finally, video sensors are often viewed as too intrusive to be accepted in assisted living homes due to privacy concerns.

In addition, assistive technology products do not take into account the cognitive and personality characteristics of their end-users, such as their specific deficit, emotional and behavioral problems, the attitude towards technology, and their physical and social environment, which could affect their acceptance, use, and effectiveness. A valid assistive system with a high degree of user acceptance must be based on the knowledge of the potential users, as well as on contextual information, that provides essential parts of effective planning of the assistance process [3].

In this paper, we introduce the overall architecture of an assistive technology system, composed of a low-cost mobile robot, wearable sensors, and a middleware software infrastructure responsible for automatically providing a monitoring plan that is generated by considering patient's needs and preferences. The plan can be adapted according to detected changes both in the patient's conditions, and in the environment. The proposed system is being developed within the UPA4SAR project with the goal of providing an affordable and well-accepted monitoring system. The mobile robot is used as an active sensor for monitoring the user's activities, together with a wearable device, in order to minimize structural interventions and therefore to increase the spread and the acceptance of such applications. The robot, given its physical presence, represents an added value for a monitoring system since it can proactively provide additional services to the user, such as to communicate with relatives and caregivers in video-conferencing, and to provide cognitive support with reminders and notifications. These services play an important role to improve the system acceptance and usefulness perceived by the user. The possibility to schedule a set of personalized and adaptive monitoring tasks relies on the possibility to profile the patient's individual skills related to IADL, the cognitive status, and the personality. This collected information together with dynamic information gathered from ambient sensors is used to customize the monitoring tasks with respect to the current detected situation. We present an example where state of the art machine learning techniques are adopted for implementing different monitoring activities that could be dynamically selected considering the available contextual information and

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whose execution can be adapted to the specific user.

II. The Proposed Framework

The proposed framework for the generation and the execution of personalized assistive plans for home patients affected by neurological disorders is composed of different modules organized according to a layered architecture depicted in Figure 1. The aim of the design is to decouple low-level functions for managing devices, for data elaboration, and for basic robotics behaviors, from high-level functions adopted for reasoning on the assistive plans.

The lower layer is the *Daily Assistive Workflow Generator* (DAWG) [4], [5], a middleware responsible for the generation of a personalized set of assistive tasks, named a Daily Assistive Workflow (DAW), and for its reconfiguration when changes are detected by the Smart Environment. A DAW represents the flow of the activities that the robot, or even other devices, must perform to monitor the patient, and to interact with him/her. The DAWG is composed of different modules: the first processes the *daily routine* of the patient extracting the activities to be monitored, that are considered as goals to be fulfilled. Starting from the set of goals (according to the *goal model*), the encoded *user profile*, and the high-level *observations* deriving from the interaction of sensors with the environment and the elaboration of such data, the DAWG selects the assistive actions able to fulfill the goals, named an *Abstract Assistive Action*s. They are represented as parametric actions that have to be configured according to the patient's cognitive and personality profile. The configuration consists of selecting a specific action to execute, named a *Daily Assistive Action* (DAA) that is a concrete instance of an abstract assistive action. The separation between abstract and concrete actions is adopted to manage personalization and adaptation of the DAW, decoupling the general description of a certain action from its actual implementation concerning the way it is performed. In details, an Abstract Assistive Action specifies the high-level interface of a certain functionality, including its input parameters, preconditions, and possible outputs. Conversely, a Daily Assistive Action represents the actual implementation of the action executed by using the suitable Sensors and Actuators nodes provided by the Smart Environment. For each Abstract Action, a list of several Daily Assistive Actions may realize the same functionality. Moreover, effective planning of the activities will also have to consider contingent situations that may affect the patient's particular conditions, and so his/her possible habits, e.g. an activity involving the control that the patient has taken his medication may no longer be necessary if the patient had an unexpected medical necessity.

The middle layer is composed of DAAs. The goal of such actions is to effectively provide either different algorithms for analyzing input data to monitor the user state and behaviors (i.e., using different input data and modalities to obtain such information), and so updating the observations and the user profile, but also to implement different navigation and interaction strategies to be used by the robot. This approach is in the direction of integrating robot functionalities (DAAs) as services that can be requested for the seamless integration of robots, as well as other IoT devices, into a web or cloud computing environment [6], or Robot as a Service (RaaS) [7]. In this Service Oriented Architecture view of the assistive domain, RaaS are endowed with such functionalities, or services, to control their behavior as well as to provide meaningful observations from the input data [8]. Moreover, a robot could use different services to provide the same functionality, and a service could be shared and used by different robots. Some of these services will be requested by the execution of the Daily Assistive Workflow, while others are autonomously running or activated by events.

To obtain a better adaptation to the user, the project proposes to equip the user cognitive profile with a psychological personality profile, and to adapt the robotic behavior not only with respect to the choice of the single activity to be undertaken (selected by the DAW), but also with respect to the way in which the same activity is performed. Indeed, in order to be effectively deployed, also the robot should be able to regulate its social interaction parameters (e.g., the interaction distances, proxemics, the speed of movements, and the same modality of interaction) based on personality factors as well as of the cognitive state of the user. Hence, the user profiling plays a fundamental role both to generate a DAW tailored for each patient, but also to modulate the execution of Daily Assistive Actions. In fact, according to the personality of a patient, some actions can be performed with a different interaction modality, such as direct interaction with the robot if the user is in a state of inactivity and calm, or remote interaction with the robot staying at a certain distance, if the user is in a state of agitation.

The upper layer is represented by the *Smart Environment* composed of sensors and actuators that play the twofold role of gathering information on the patient's state, and of performing assistive actions. Low-level functionalities make direct use of sensors and actuators installed into the Smart Environment, which are respectively managed by the DAA. Figure 1 shows how low-level nodes are combined to compose high-level functionalities.

III. A First Framework Prototype

In this section, we present some modules of the proposed general frameworks that have been already developed in the first phase of the UPA4SAR project. The Robot Operating System (ROS) is employed to ensure modularity and scalability of the architecture.

A. User Modeling

Problems related to functional limitations, behavioral and cognitive limitations, reduced capabilities, etc., that are specific to each individual, could strongly influence the user acceptance as well as the effectiveness of assistive technologies. Such knowledge is typically in the hands of clinicians that are provided with a variety of cognitive and behavioral evaluation instruments that aggregate a large amount of information that, potentially, could be extremely important

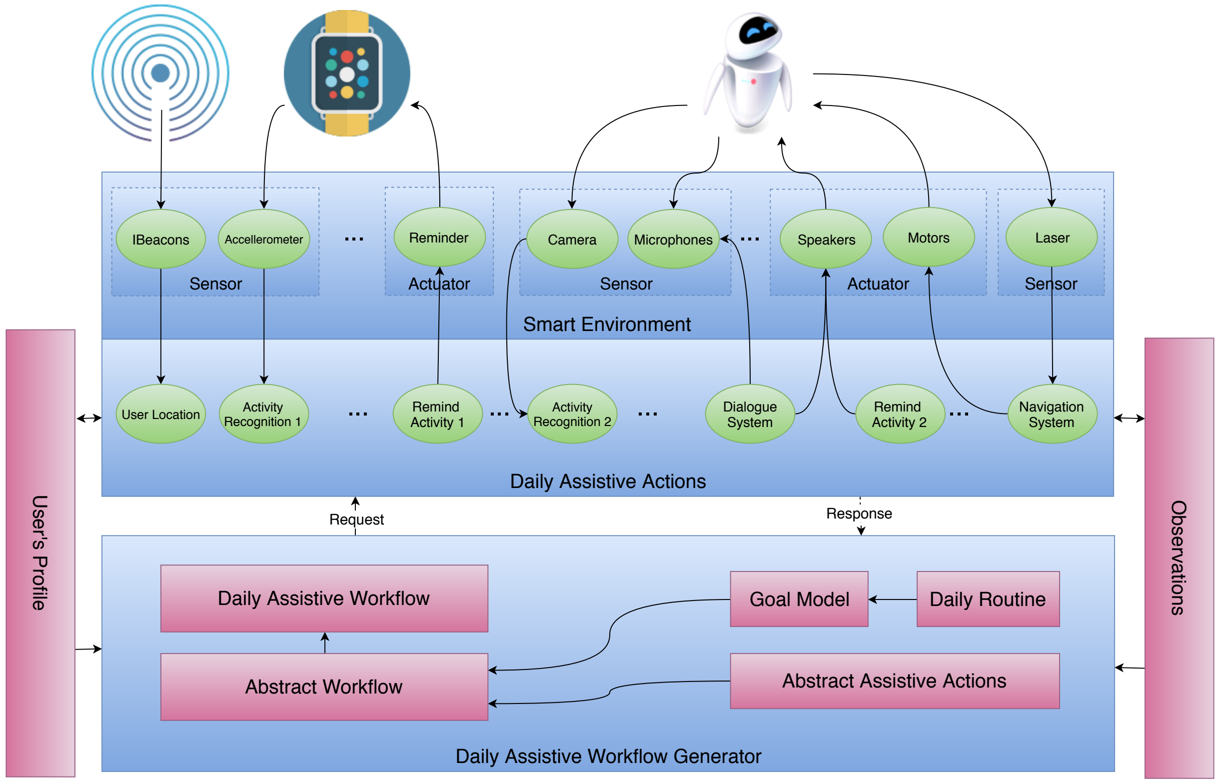

Fig. 1. The proposed architecture for a smart home assistive system

in order to provide personalized ICT technologies for a large class of the population with psychiatric and cognitive disabilities. Since the assessment of cognitive impairments is typically carried out using of a wide range of clinical tests, starting from the analysis of such tests, the project's goal is to develop such computational models of the user's profiles to provide the possibility of obtaining a personalized interaction with the robot in the assistive context.

In details, in this project, we considered characteristics that are related to the user personality since they affect the way public spaces are shared and the perception of socially acceptable movements [9]. The NEO Personality Inventory [10] measures five dimensions of the personality according to the Big Five Model: Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness. Cognitive and functional characteristics that are related to the Alzheimer disease are modeled by considering the ACE-R [11] and Clinical Dementia Rating (CDR) [12]. The ACE-R is a rapid screening battery assessing several cognitive domains including attention/orientation, memory, fluency, language, and visuospatial. Finally, CDR is used to characterize six domains of cognitive and functional performance applicable to Alzheimer disease such as Memory, Orientation, Judgment and Problem Solving, Community Affairs, Home and Hobbies, and Personal Care.

B. Sensors and Actuators

The smart environment relies on a series of sensors and actuators. More specifically, we considered two types of robots. A Pepper robot, developed by Softbank, that is able to navigate using sonars, lasers and bumpers. It has two frontal cameras and one RGB-D camera for object recognition, face recognition and people recognition. It can interact with the user using the speech recognition and speech synthesis by 4 directional microphones and two loudspeakers but also using a tablet. It can also locate the user position and identify the user emotions using microphones. The second considered robot is Turtlebot 2, that is a low-cost mobile base configured with a tablet on the top of it and a Microsoft Kinect 2 (RGB-D camera). The base of the robot is a Kobuki, endowed with bumpers and infrared sensors to navigate and automatic docking for charging the battery pack. iBeacons are used for the indoor positioning system. Such devices are capable of transmitting a signal at low cost and energy, using Bluetooth Low Energy (BLE) technology. We used the strength of the signal, the RSSI (Receive Signal Strength Indicator), to define proximity relations in order to pinpoint the position of the door of the rooms. Therefore, iBeacons are displaced near room doors, and the signals are captured through an Android smartphone. Finally, we used a Polar M-600 smartwatch that mounts accelerometer, gyroscope, optical heart rate measurement with 6 LEDs. The optical heart rate can alert us in dangerous situations, giving in real time the heart condition and the state of health of the patients.

Specifically, each Sensor Node publishes collected information over the time on its corresponding Sensor Topic, whilst a generic Actuator Node subscribes to a specific Actuator Topic to handle its parametric execution.

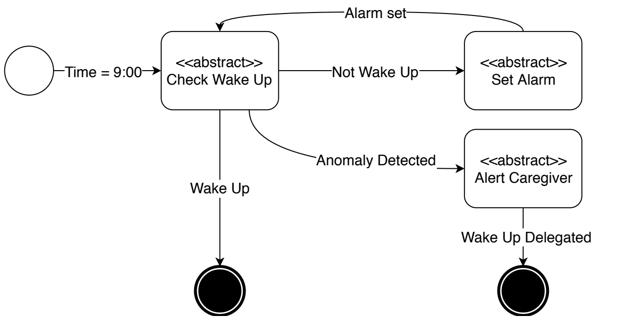

Fig. 2. Example of an abstract workflow generated for the *Wake-Up* activity

Fig. 3. Monitoring the user activity by indirect observation (left), or by making a request (right)

C. Daily Assistive Workflow Generator

The Daily Assistive Workflow Generator (DAWG) is the component responsible for the generation of monitoring assistive plans. In order to perform this task, the DAWG takes into account the user's profile described in Sec. III-A along with the daily routine, the current observations and the entire set of Abstract Assistive Actions, and Daily Assistive Actions. The daily routine is represented by a set of activities that the user has to perform throughout the day, each of them labeled with a time constraint. The daily routine is then encoded into a set of goals, one for each activity, that the system has to achieve with respect to the time constraints. The workflow generation process consists of two main steps. The first step is responsible for the generation of the abstract daily assistive workflow, representing the set of actions to be scheduled to monitor the daily routine of the patient, organized as a set of goals to be fulfilled. Figure 2 shows an example of an abstract workflow for the *Wake-Up* activity, representing the set of abstract actions necessary to monitor the Wake-Up activity. Each Abstract Assistive Action has to be instantiated by a concrete Daily Assistive Action in order to be executed. Therefore, an abstract workflow represents a high-level template for the sequence of actions required to achieve a certain goal.

The second step is responsible for the instantiation of a specific Abstract Assistive Workflow. This process starts as soon as a certain time constraint triggers a new goal. For instance, with respect to the workflow shown in Figure 2, the instantiation process will be activated at 9:00 am by triggering the corresponding goal *Wake Up* at that time. When a goal is triggered, the system retrieves the abstract workflow associated with the current activity to be monitored and turns it into a concrete workflow. The instantiation process follows the structure of the corresponding abstract workflow. Its general structure is represented as a graph $G(V, E)$ in which each vertex $v \in V$ represents an abstract action to be instantiated and each edge $e \in E$ represents a transition labeled with a condition. Starting from the first vertex, each abstract action is instantiated by selecting the most suitable one among the available concrete Daily Assistive Actions. For instance, in Figure 2, the abstract assistive action *Check Wake Up* may be implemented by different concrete actions offering the same functionality with different modalities. If we consider the environmental setting depicted in Figure 1, *Check Wake Up* can be actually realized by the Activity Recognition module provided by the Smartwatch, as well as by the Robot via Camera. Moreover, even the Robot's Dialogue System can be suitable for this task. The main characteristics we consider to differentiate a concrete action from each other are its reliability and the interaction modality. These non-functional parameters are then matched against the user profile to determine a ranking over possible concrete implementations to select the one that represents the best trade-off between user needs and reliability. Once an abstract action is instantiated, the selected concrete implementation can be executed by the corresponding device, e.g., the robot. In addition, the concrete action can be executed in different modes (e.g., interaction modes), i.e. with different values of some non-functional parameters. Here, the execution of a certain action produces as output new observations deriving from sensors installed into the environment. These observations are used to determine whether a certain state is reached. Hence, the system is able to determine the transition to the next vertex in the graph after the execution of each concrete assistive action. When a final condition is reached, the workflow execution is completed and the system waits until a new goal is triggered.

D. Daily Assistive Actions

The set of Daily Assistive Actions considered in the project includes, for example, the IADL recognition [13], emotion recognition, disengagement recognition [14], human search, approach and interaction with the user, speech recognition and speech synthesis. Between these tasks, we already implemented some instances of the IADL recognition that is activity recognition via wearable data and activity recognition via camera using pose/skeleton recognition. Moreover, the robot Dialogue System could be used to directly ask confirmations to the user or the caregiver. Here, we briefly introduce these three implementations of the abstract action *monitoring*.

1) Dialogue System: For the robot to approach the user and to perform a user-tailored interaction, it has to find him/her, and subsequently position itself properly with respect to the activity requirement. When the robot is instructed to approach or start monitoring the subject, the wander module - implemented with a ROS node - executes a walking routine in order to find the person in the room: it will move forward for a few seconds, then it will steer the robot first to its right and then to its left, for a number of seconds each turn, that has to differ to avoid getting stuck in a dead end. The obstacle avoidance relies respectively on the Softbank NAOqi-API for the Pepper robot and on bumpers placed at the base of the Turtlebot2, and if an impediment is found, the robot will turn to direct elsewhere. The robot will navigate in the room until the user is found.

Once the user has been detected, it is necessary to recognize his/her pose so that the robot can move to the correct approach/monitoring position. Pepper and the Turtlebot2 recognize the human skeleton with an RGB-D camera. The pose/skeleton recognition algorithm considers only the single depth image of each frame to predict the human skeleton joints. The predicted joints are translated on the average point between the points of the torso, left and right shoulder, left and right hand. Then they are normalized with the standard score, computing the mean and the standard deviation on the entire sequence of the instance. The normalization reduces the dependencies with the length of the limb and the height of the person.

Thanks to these skills, the robot can search a human by wandering in the rooms, considering the user position given by the iBeacons to narrow down the search area. Once the user position and his/her pose are recognized, the robot approaches the person with a direction and a speed that depends on the user profile. The robot will then ask directly the user a confirmation for the hypothesized activity by using the tablet, speech interaction or both (see Figure 3 (right)).

This action is considered to have a strong reliability since it directly asks for a confirmation to the user, but, conversely, it is considered invasive since it implies a direct interaction with the user and consequently a distraction from his/her current activity.

2) Activity Recognition via camera: Differently from the previous action, the robot could also try to recognize the user activity by observing directly the user behavior. In this case, the robot will stop at a longer distance from the user (that again depends on the user preferences). Once the robot approaches the user a ROS node, that implements the Activity Recognition algorithm proposed in [13], detects the activity performed sampling a window of 140 frames of human skeleton data with 30 fps. This algorithm is based on a deep learning model trained on a dataset. It has two deep layers, a CNN layer [15] that considers the spatial dependencies of the skeleton joints and an LSTM layer [16] that extracts the temporal dependencies of the frames in the video sequence. The model predicts the activity taking in input the skeleton data (see Figure 3 (left)). The activity recognized are brushing teeth, chopping, drinking water, opening pill container, relaxing on the couch, rising mouth with water, stirring, talking on the couch, talking on the phone, wearing contact lenses, working on the computer, writing on a whiteboard.

The Activity Recognition via camera action is less reliable than the previous one, but also less invasive, since it would not distract the user from his/her current activity. However, also the use of the camera is sometimes considered invasive.

3) Activity Recognition via wearable: Finally, another possibility is to monitor the user behavior by directly considering data coming from a wearable device. The Activity Recognition via wearable service is a ROS node which is in charge of gathering data from an accelerometer to predict low-level activities. The recognized activities are standing up, getting up, walking, running, going up, jumping, going down, lying down, sitting down. Each instance contains the accelerations along each of the three Cartesian axes with a frequency of 50 Hz. The accelerometer information is given in input to a deep learning model formed by two LSTM layers.

With respect to the direct observation, Activity Recognition via wearable action is considered less invasive, since it does not use a camera or interrupt the user. However, the recognition ability is related only to human posture, so in order to recognize different high-level behaviors, such for example, watching tv, this information has to be integrated with other information, such as the location of the user. Hence, it is not as reliable as the direct observation.

IV. Conclusions

Adaptation and user modeling play a key role when it comes to design smart assistive systems to help elderly people live a longer and more independent life at home. A recent survey on self-adaptation for cyber-physical systems [17] highlights that robotics and health-care systems constitute about 10% of domains application requiring adaptation. Static and dynamic user's profiles have been already considered for Ambient Assisted Living and Robotics systems to provide adaptive reminders and modulate robotic behaviors accordingly.

Several systems have been designed for home-care assistance providing a different degree of personalization, but no adaptation on the fly that has been a major research issues in ambient intelligence scenarios [18]. For example, GiraffPlus [19] is an Ambient Assisted Living (AAL) system which deploys a network of sensors to collect elderly daily behavioral and physiological measurements. The system uses both static and a dynamic user profile to provide adaptive reminders through a telepresence robot. Other works encode the daily routine as a set of temporal constraints to determine the user's plan throughout the day [20].

An effective assistive robotic system for home care assistance should be affordable and well accepted by end users. In order to meet these requirements, our aim is to further explore user's adaptation by considering a dynamic environmental setting where each functionality can be realized in several ways and concrete implementations are selected according to the user's profile.

In this paper, we present a framework, under development within the project UPA4SAR, that allows generating personalized and adaptive assistive plans for home patients affected by neurological disorders, that are executed by the smart environment devices that are part of the framework. Hence, the framework integrates business processes with real-world objects, humans and digital services [21]. The generated plans are executed by the set of sensors and actuators that equip the environment the patient is located in.

The proposed framework is designed according to a layered architecture that allows decoupling the actual execution of an assistive plan, from its planning and adaptation. The planning and adaptation depend on the cognitive and personality profile of the patient, in addition to dynamic information on his/her state as detected by the smart environment. This separation allows to guarantee the system functioning according to both the available information about the patient's profile and the specific assistive actions available in a specific setting of the Smart Environment. The rationale of this choice is to provide a modular and extensible framework where assistive actions to be performed can be added, removed and customized according to the specific setting of the Smart Environment, and the high-level reasoning that allows for the personalization and the adaptation of the daily assistive plan that is performed according to the collected profiling information [22]. The proposed framework is in line with the view of RaaS business models, especially in the field of health-care whereas different applications and services for managing the user data are required for decoupling robots from the available functionalities and taking advantages of cloud-based computing platforms to provide computational power.

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