Synergy of Distributed Agents in a Smart Home to Promote Physical Activity in Elderly Users

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Abstract—This paper proposes a smart environment system aimed at promoting physical activity in elderly people, one of the three key dimensions of active and healthy aging. The system is based on the collaboration between a smart environment and two interaction devices – a social robot and an avatar. The system automatically detects sedentary behavior, promotes physical exercise through verbal interaction, and instructs and accompanies the user while performing the exercise. Pilot tests conducted with 30 users, 4 of which elderly, demonstrate: i) the system's synergistic relationship between the environment's sensors and interaction devices, ii) that the users find the system usable and acceptable, iii) how the proposed system's innovative technical features can be used to help elderly people remain physically active.

I. Introduction

The ratio of people aged 60+ to the working-age population has been rising steadily, especially in developed countries. According to the United Nations, it is likely that by 2030 the global elderly population will exceed 1.4 billion people [1]. Societal answers need to be provided, as current health and social support systems progress towards unsustainability. Ambient assisted living (AAL) technologies [2], including smart environments and social robots, have been developed to help elderly people live independently in their household for longer, while remaining cognitively, socially, and physically active.

We propose an architecture for assisted living in a smart home, which leverages the cooperation between a centralized planning system, a social robot, a camera network and a virtual avatar. We test the architecture in an illustrative use case of promotion of physical activity, as a contribution to tackle one of the three dimensions of active and healthy aging.

A. Related Work

Smart sensors distributed in the environment have been proposed for tasks such as human activity recognition from video [3] or human behavior inference [4]. As a counterpart, there is also an extensive body of research devoted to activity monitoring based on wearable sensors [5]. We opt for the former approach, basing our solution on environmental sensors, resulting in a truly unobtrusive system that is potentially better accepted by end users and more practical in their daily life.

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Significant research efforts have been devoted to developing social robots to assist elderly users in their daily lives, in projects such as Giraff and GiraffPlus [6], Robot-Era [7], CARESSES [8] and GrowMeUp [9]. These projects developed robots providing telepresence, support, and monitoring for independent living through, subjecting them to validation tests with end users.

Regular physical exercise has been shown to reduce allcause mortality [10], motivating researchers to develop systems for helping elderly users to adhere to such activities. The authors of [11] discuss the main challenges of developing these systems, arguing that they can also influence the users' psyche positively. [12] presents a system based on a robot, comparing it to the performance of virtual avatars, concluding that elderly users prefer the embodied robot as a coach. [13] presents another robot-based system, able to learn from a demonstrator, which also shows that elderly users can successfully perform exercise with a robot while remaining engaged in the activity.

These systems are either based on static sensors and appliances in the smart home, on a single social robot, or a single avatar. The key differentiating feature of the system proposed herein lies in a stronger environment-agent and inter-agent synergy. The introduction of distributed agents in a cooperative team leads us to a Multi-Agent Planning problem [14], which we aim to solve by using a hierarchical technique based on a centralized planning framework, extending previously-presented single-agent architectures.

II. THE EUROAGE ARCHITECTURE

The EuroAGE Architecture, depicted in Fig. 1, combines the abilities of multiple agents to reach a common goal. We employ a centralized approach, with a task scheduler responsible for making high-level decisions, and several distributed agents responsible for executing their assigned tasks. This paradigm is the best fit for our problem, as the need to coordinate a set of distributed agents calls for multi-agent planning, and the full connectivity within the smart home allows for a centralized approach. Centralized planning requires a unified view of the state of the system. However, different agents can perceive the same reality differently, e.g. a mobile robot and a camera network may have different estimates for the position of the robot in the world. Thus, every agent can contribute to the state of the system by sending state contributions, representing the agent's perspective of the state of the system. The centralized system must then fuse all contributions to update the system state, obtaining a unified state as illustrated in Listing 1.

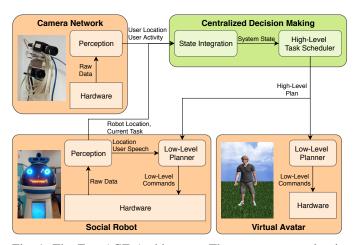


Fig. 1: The EuroAGE Architecture. The camera network, virtual avatar and social robot are integrated into the architecture, leveraging their abilities (only the main data paths are shown).

```
avatar_0/task:
source_id: avatar_0,
timestamp: 1529922157.729546,
value: idle
robot_0/task:
source_id: robot_0,
timestamp: 1529922114.844235,
value: idle
user_0/activity:
source_id: CamNet,
timestamp: 1529922321.844235,
value: idle
```

Listing 1: Example of the unified system state. In this case, both agents are idle and the user has been detected as idle as well. This will trigger the assignment of new tasks to both.

The resulting system state includes the necessary information for the assignment of tasks by a centralized task scheduler, e.g. allocating agent_0 to the task exercise_service. Tasks are translated by the agents into agent-specific low-level commands, such as velocity commands, speech output, visual output, etc., which they use to fulfil their assignment. This two-tier architecture allows for the extension of the system beyond physical exercise promotion, as well as making it able to deal with a greater number and variety of agents. Tighter inter-agent coordination happens on a per-task basis.

A. Physical Activity Promotion Use Case

As a demonstration of the functionality of the architecture, we have implemented the exercise use case. This makes use of three agents, depicted in Fig. 1: a camera network, a social robot, and a virtual avatar, respectively executing three functions: i) detection of user inactivity; ii) user prompting; iii) physical exercise instruction. As the camera system detects that the user is idle for above a pre-set amount of time, as illustrated in Listing 1, the centralized planning system allocates specific tasks to both the avatar and robot and triggers their execution by these agents. In these cases, the robot prompts the user to perform the exercise, collecting

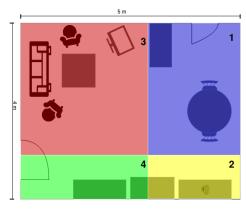


Fig. 2: Smart environment layout: (1) dinning room, (2) kitchen, (3) living room, (4) hallway.

Listing 2: Example of a routine dictionary. Each exercise contains an ID, the number of demonstration and regular repetitions, the performance speed, and the final rest time.

the necessary parameters from the user and passing them to the avatar. The avatar uses this information to adapt itself to the user's preferences, then replies to the robot with the appropriate sequence of exercises (routine) to execute, depicted in Listing 2. Then both agents act in coordination, with the avatar demonstrating what to do and the robot describing the exercises and trying to motivate the user with synchronous movements.

B. User Tracking Through the Camera Network

Each element of the four-camera network observes one of the rooms of Fig. 2. The video streams are analysed by a Convolutional Neural Network (CNN) model, YOLO 9000 [15]. Given that processing all images from all camera feeds simultaneously through the CNN is computationally unfeasible, a mechanism for the selection of the most informative camera was implemented. When detecting any object, the CNN outputs a bounding box and a label accompanied by a confidence level $c \in [0,1]$. Since the goal is to track users, the system selects the camera with the highest confidence of human detection for processing, a choice which is periodically re-evaluated by sampling one image of each camera.

The user is localized by an homography mapping that relates the floor and image planes. The homography matrix \mathbf{H} is easily estimated by using the locations of a set of marks $\mathbf{p_i} = \begin{bmatrix} x_i & y_i & 1 \end{bmatrix}^T$ on the floor and their respective images



(a) Experimental setup: 2 of the cameras (A), the social robot (B), and the virtual avatar (C).



(b) An elderly user performing exercise side by side with the robot.



(c) An elderly user performing exercise as instructed by the avatar.

Fig. 3: Pictures of the system in our experimental area and of elderly users performing exercise.

 $\mathbf{p_i'} = \begin{bmatrix} x_i' & y_i' & 1 \end{bmatrix}^T$, as they are related by $\mathbf{p_i'} = \mathbf{Hp_i}$. The coordinates of the user are then determined by computing x', y' with respect to the lowest point of the bounding box that contains the person. Due to the limited resolution of the cameras in the network (640x480) and the accumulated error in calibration and person segmentation, the position of users can be known to within ~20cm which, given it represents a ~5% error with respect to the room's dimensions (Fig. 2), is an acceptable level of precision. This allows for the detection of user inactivity by comparing a set of 10 recent positions of the user within the smart environment, and then informing the central planner as previously described.

C. User Prompting with the Social Robot

We employ the GrowMu social robot [9], depicted in Fig. 3a, which communicates verbally and non-verbally, by changing its facial expression or moving its base. When inactivity is detected, the robot navigates to the user and asks if they would like to perform some physical exercise in its company. If the user agrees, the robot leads him/her to the screen displaying the avatar agent, and asks whether they prefer a male or female trainer, and about intense or soft exercises. The user's responses are sent to the avatar, which adapts accordingly and replies with the exercise routine to be executed. Then, the robot performs the exercise together with the user, synchronizing with the avatar at each repetition and translating its movements into basic base movements that it can execute, using linear velocity commands defined by

$$v(t) = \alpha \sin(\frac{2\pi}{T}t),\tag{1}$$

where v is the linear velocity, T is the duration of each repetition and α is a manually-tuned constant. These are applied to linear and rotational velocity to mimic the movements of the avatar on the screen, rhythmically matching its concentric and eccentric phases, providing audible and visible feedback.

D. Physical Exercise Guided by a Virtual Avatar

The avatar is supported by OpenAR, an in-house software platform¹. When the user accepts the suggestion of physical exercise, OpenAR sets up and displays the created virtual

1http://orion.isr.uc.pt/OpenAR/

environment, on which the avatar is greeting the user. After the user specifies the parameters to the robot, these are communicated to the avatar. Depending on the parameters received, the avatar displays a character compatible with the user's preferences, and loads the specific routine, which is then propagated to the robot. The routine comprises a set of exercises to be performed, with an associated number of repetitions, speed and rest time (see an example in Listing 2). Each exercise is described as a set of animations, which are sequences of the avatar joint configurations. These are used to show the user the precise movements to execute for each exercise, serving as the formal part of the exercise guidance.

III. EXPERIMENTAL EVALUATION

A. Goals and Metrics

We aim to demonstrate that the system is able to act in a coordinated way, achieving all the necessary functionalities in an usable manner². An evaluation was performed without any Wizard of Oz approaches; the system operated autonomously. A total of 30 users participated in the study, of which 80.0% were male. Users were aged 37.3 ± 18.0 years, with 4 of the users being aged 60+, allowing us to extract insight from target end users. Around 50% of the users reported that they performed physical exercise regularly.

In order to assess the system's success, we have employed the following metrics, collected manually during the trials:

 M_1 : Time taken by the system to detect an inactive user;

 M_2 : Number of times the user misunderstood the robot;

 M_3 : Number of times the robot asked the user to repeat an utterance, or that an utterance had to be manually input;

 M_4 : Number of times the robot misclassified an answer;

 M_5 : Number of times a researcher had to intervene in the test. It is important to note that the trials in which the researchers intervened were not discarded from the evaluation. Subjective assessments were obtained using the European Portuguese version [16] of the System Usability Scale [17].

B. Results and Discussion

Table I presents the results obtained for the metrics defined in Section III-A. Through M_1 , we observe that idle users

²A video demonstrating the operation of the system can be found at https://cloud.isr.uc.pt/index.php/s/wgQ5Od0fBLMxnSQ.

TABLE I: A summary of metrics 1 through 5. μ stands for average, and σ for standard deviation.

Metric	μ	σ
M_1	24.966	3.499
M_2	0.533	1.024
M_3	1.667	1.075
M_4	0.333	0.537
M_5	1.067	1.482
SUS Score	81.083	10.241

were detected in an average of 25 s. Since inactive users were always detected, and that this value is close to the reference of 22 s, we can conclude this functionality is working correctly.

Metrics M_2 through M_4 show that, on average, the robot and user misunderstood each other 1.7 times during each test. This can be considered a low number, since the interaction included a potential set of six questions and answers for prompting the user and gathering parameters.

 M_5 and the SUS scores (Fig. 4), provide an overview of the system's performance. In 30 trials, 23 (76.7%) occurred with minimal intervention, indicating a high level of autonomy. As depicted in Fig. 4, the users find the system usable, resulting in high scores in all aspects of usability, with low variability and an average of 81%. Items 3 and 10 of the SUS obtained the highest scores, indicating that the users found the system easy to use and learn, an important trait of elderly-focused systems. Thus we conclude that, for this use case, our architecture works as intended and is usable by end users.

Having achieved these results, the system can now be used to promote physical exercise in elderly users, potentially yielding the health benefits mentioned in Section I.

IV. CONCLUSION

We have presented the EuroAGE Architecture for multiagent coordination in a household environment, which we instantiated using a camera network, a social robot and a virtual avatar. The system was used on a physical exercise scenario and tested with 30 users, showing that the proposed system works as intended and that users find it usable and useful. In the future, it would be interesting to further develop the system by enabling it to evaluate in real-time the user's performance and better inform and adapt the exercise to them.

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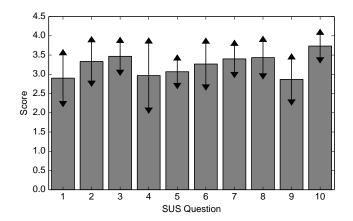


Fig. 4: Results obtained using the System Usability Scale. The maximum score is 4, bar height corresponds to the question's average score, and the arrows denote the $\pm \sigma$ area.

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