Augmented Human Assistance (AHA)

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Abstract. Aging and sedentarism are two main challenges for social and health systems in modern societies. To face these challenges a new generation of ICT based solutions is being developed to promote active aging, prevent sedentarism and find new tools to support the large populations of patients that suffer chronic conditions as result of aging. Such solutions have the potential to transform healthcare by optimizing resource allocation, reducing costs, improving diagnoses and enabling novel therapies, thus increasing quality of life.
The primary goal of the "AHA: Augmented Human Assistance" project is to develop novel assistive technologies to promote exercise among the elderly and patients of motor disabilities. For exercise programs to be effective, it is essential that users and patients comply with the prescribed schedule and perform the exercises following established protocols. Until now this has been achieved by human monitoring in rehabilitation and therapy session, where the clinicians or therapists permanently accompany users or patient. In many cases, exercises are prescribed for home performance, in which case it is not possible to validate their execution. In this context, the AHA project is an integrative and cross-disciplinary approach of 4 Portuguese universities, the CMU, and 2 Portuguese industry partners, that combines innovation and fundamental research in the areas of human-computer interaction, robotics, serious games and physiological computing (see partner list in Appendix A). In the project, we capitalize on recent innovations and aim at enriching the capabilities and range of application of assistive devices via the combination of (1) assistive robotics; (2) technologies that use well-understood motivational techniques to induce people to do their exercises in the first place, and to do them correctly and completely; (3) tailored and relevant guidance in regard to health care and social support and activities; and (4) technologies to self-monitoring and sharing of progress with health-care providers,

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enabling clinicians to fine-tune the exercise regimen to suit the participant's actual progress.
We highlight the development of a set of exergames (serious games controlled by the movement of the user's body limbs) specifically designed for the needs of the target population according to best practices in sports and human kinetics sciences. The games can be adapted to the limitations of the users (e.g. to play in a sitting position) so a large fraction of the population can benefit from them. The games can be executed with biofeedback provided from wearable sensors, to produce more controlled exercise benefits. The games can be played in multi-user settings, either in cooperative or competitive mode, to promote the social relations among players. The games contain regional motives to trigger memories from the past and other gamification techniques that keep the users involved in the exercise program. The games are projected in the environment through augmented reality techniques that create a more immersive and engaging experience than conventional displays. Virtual coach techniques are able to monitor the correctness of the exercise and provide immediate guidance to the user, as well as providing reports for therapists. A socially assistive robot can play the role of the coach and provide an additional socio-cognitive dimension to the experience to complement the role of the therapist. A web service that records the users' performances and allows the authorized therapists to access and configure the exercise program provides a valuable management tool for caregivers and clinical staff. It can also provide a social network for players, increasing adherence to the therapies.
We have performed several end-user studies that validate the proposed approaches. Together, or in isolation, these solutions provide users, caregivers, health professionals and institutions, valuable tools for health promotion, disease monitoring and prevention.

Keywords: Active aging · Serious games · Assistive robotics
Augmented reality · Virtual coach

1 Introduction

The elderly population is increasing worldwide and in combination with sedentarism and a longer life expectancy represents one of the most important challenges our societies will face in the near future (WHO, 2012). Just the 'Health, demographic change and well-being' theme alone in the Horizon 2020 European Framework has an indicative budget of €8 billion associated European research and innovation work. Scientific evidence based on numerous studies show that elderly who are physically active have lower rates of chronic conditions such as cardiovascular diseases, diabetes, cancer, hypertension and obesity (WHO, 2012). Chronic patients experience an increased loss of independence, autonomy and low self-esteem, and consequently require of continuous rehabilitation and therapy. There is the need, therefore, not only to develop strategies to support healthy habits, prevent sedentarism and promote active aging, but to also support those with age related chronic conditions.

Research interest in service robotics for active aging and health care has grown in the last few decades with potential applications on healthy, elderly or patients. The effectiveness of the use of robotic devices in elderly care (Bemelmans et al., 2012; Broekens et al., 2009), rehabilitation (Matarić et al., 2007), autism diagnosis and therapy (Scassellati, 2007) and weight loss applications (Kidd & Cynthia 2008), for example, have been empirically demonstrated in a number of works and raise great expectations on the use of robots as personal assistants. The Nursebot platform demonstrated the ability to contact a resident, remind them of an appointment, accompany them to that appointment, as well as provide information of interest to that person (Pineau et al., 2003). In touch Health deployed their robot in a Neurology Intensive Care Unit and a study suggested improvement in critical care nursing team satisfaction (Rincon et al., 2012). The Kompaï R&D robot has been tested for elderly assistance using a diary application for monitoring the medication and give information about daily events (Rincon et al., 2012). The autom robot is a weight-loss social robot (Kidd et al., 2012) that asks you about what you've eaten and how much you've exercised, proving helpful suggestions and feedback that's different every day and customized just for you, utilizing facial expressions and a simple touchscreen interface. In this context, the advances in information, robotic and assistive technologies have the potential to increase quality of life and change health care delivery models, reducing costs, and improving monitorization. The “AHA: Augmented Human Assistance” project is a novel, integrative and cross-disciplinar approach of 4 portuguese universities, CMU and 2 portuguese industry partners that combines innovation and fundamental research in the areas of human computer interaction, robotics, serious games and physiological computing. AHA’s goal is to develop a new generation of ICT based solutions that have the potential to transform healthcare by optimizing resource allocation, reducing costs, improving diagnoses and enabling novel therapies, thus increasing quality of life. The project proposes the development and deployment of a novel Robotic Assistance Platform designed to support healthy lifestyle, sustain active aging, and support those with motor deficits.

2 Human State Estimation

Biomedical signal analysis is nowadays a method of the greatest importance for data interpretation in medicine and biology, providing vital information about the condition and affective/emotional states of subjects. The demand for a correct and prompt diagnosis leads to a mandatory identification of insufficiency signs in the clinical context (Kayyali et al., 2008). Consequently, to analyze and follow up a subject’s condition it is very important to monitor and visualize the acquired signals and extract relevant information from them. In clinical cases, such as sleep disorders and neuromuscular diseases, a constant monitoring of the patient’s condition is necessary (Pinto et al., 2010). In patients with neuromuscular diseases, heart rate variability, respiration, muscular and electrodermal activity signals are extremely important, since they indicate when a muscular crisis is occurring.

Cameras have been used to detect and estimate the pose of human subjects (Lim et al., 2013) and body parts (Girshick et al., 2011)], detect faces (Xiao et al., 2004) and their expressions (Yang et al., 2008) and, at a close range, detect eye movement and gaze direction (Morimoto et al., 2005). Recently, with the massification of RGBD sensors in the gaming business, new levels of precision and reliability are being achieved in such measurements (Guha and Ward, 2012). The main advantage of model-based approaches is that it can reliably handle occlusions, noise, scale and rotation very well in contrast to the model-free approach (Zhang et al., 2007). The main advantages of Model-free methods are their simplicity and speed. Hidden Markov Models have been successfully used in gesture recognition (Saponaro et al., 2013). Goffredo et al. (2008) introduced view-independent markerless gait analysis based on the anthropometric propositions of human limbs and the characteristics of gait.

3 Motor Training and Rehabilitation

The use of gaming approaches to motivate players to engage in physical activity is popularly known as exergaming. Research on commercially available products has shown that they can produce moderate to vigorous physical activity (Garn et al., 2012), and that it results in physical, social, and cognitive benefits (Staiano et al., 2011). Unfortunately, these commercial tools are developed to target healthy young adults and they are not suited to elderly or motor (re)training. Most rehabilitation treatments involve repetitive exercises that are initially taught in a clinic and then continued at home. Compliance with the regimen is critical for successful rehabilitation – both in terms of adherence to the schedule of exercise and performing them correctly. A large percentage of people comply only partially, if at all, leading to minimal improvement or, at worst, further injury. There exist a class of computer-based systems called Virtual Coaches (VC) (Ding et al., 2010) that are aimed at mitigating the above mentioned limitations using state-of-the-art technology to capture considerably more detailed data regarding patient performance than previous experimental interventions. The benefits brought by VC are multifold: (1) VC can incorporate scheduled exercises following prescriptions of healthcare providers; (2) VC can monitor the performance of the user and provide appropriate feedback and encouragement for training compliance; (3) patients can exercise independently at their homes after hospital discharge; and (4) care providers can monitor remotely the progress of the user and upload new training protocols. Those approaches have been used in the past with success for rehabilitation, exercise, proper use of assistive technology and accomplishing instrumental activities of daily living (Siewiorek et al., 2012; Smailagic et al., 2013).

One of the latest approaches in the field of rehabilitation is the use of Virtual Reality (VR). A number of studies have shown that this technology has a positive impact on functional motor recovery (Laver et al., 2012). VR based rehabilitation systems can support the requirements for effective motor (re)training (Cameirão et al., 2008). VR based approaches allow for a combination of features including: low cost; personalization of training; unsupervised training; goal-oriented actions; adaptability to a broad range of patients; quantifiable outcome measures; extended feedback; and motivation thanks to the use of game elements (Lucca, 2009).

4 Plan and Methods

The consortium of AHA includes research institutions and industry with expertise in complementary areas of human motricity, robotics, human computer interaction, data processing, bio-sensing technologies, and virtual and augmented reality solutions. Moreover, the cross-disciplinary nature of the project requires the consortium members to be organized in joint international teams across institutions.

Collaborations are organized in specific work packages that address complex real-world research and technological challenges and have to deliver concrete building blocks for the Robotic Assistance Platform (see Figure 1). Each work package has a leading partner that will coordinate the activities and tasks of that work package. In this project there will be an active involvement of the industrial partners not only as advisors, providing know-how in business and innovation, but also as active contributors in the realization of the technological and scientific work.

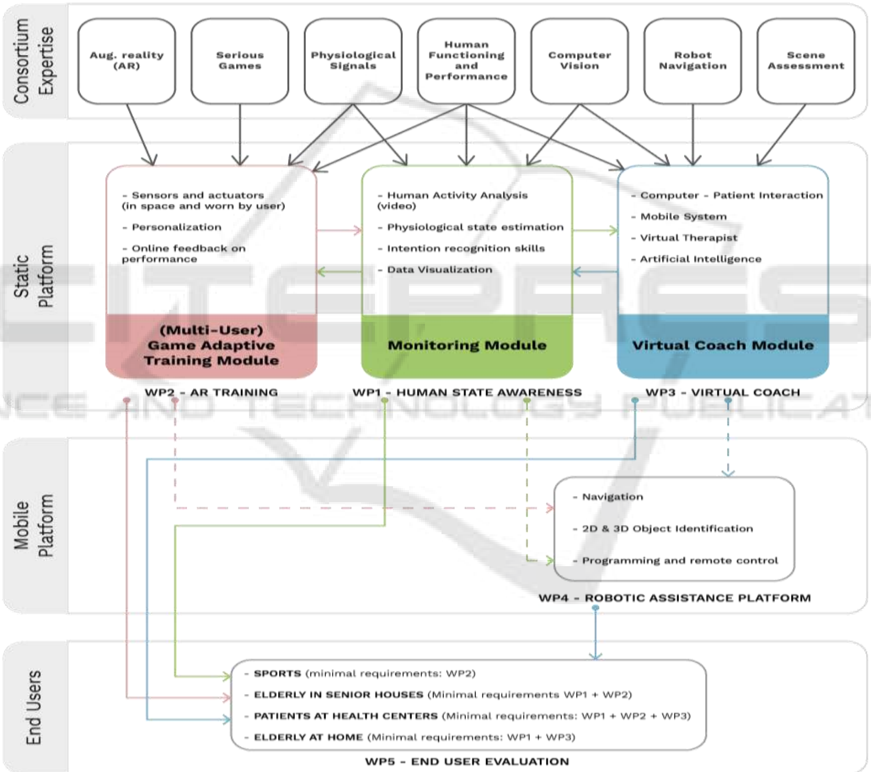


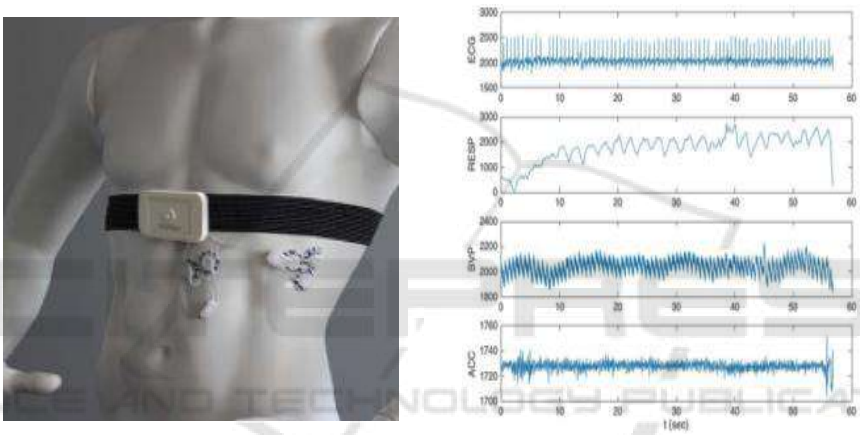
Fig. 1. Organization of the contributions of the different project work packages in the research component of the AHA: Augmented Human Assistance project.

5 Results

The principal achievements of the AHA project will be presented in the following five sections: (1) Human State Awareness; (2) Augmented Reality Training; (3) Virtual Coach; (4) Robotic Assistance Platform; (5) End user evaluation.

Human State Awareness

Physiological Sensing. The sensing system also includes a physiological platform, BiosignalspluxTM available commercially. This system, as shown in Figure 2 (a), is a wearable and wireless signal recorder that acquires several body signals. The radio transmission is performed via Bluetooth to a computer or mobile using the Opensignals open-source software. This software is versatile and scalable software for biosignals visualization and analysis.



a) b)

Fig. 2. (a) BiosignalspluxTM. (b) Signals acquired by the Biosignalsplux during an exercise. ECG =Electrocardiogram, RESP = Respiratory rate, BVP = Blood Volume Pressure; ACC = Accelerogram.

The signals depicted in Figure 2 (b) were acquired during an exercise trial and they consist in four biosignals used in the context of AHA project: electrocardiogram (ECG), which measures the different stages of the heart beat; respiration (RESP), measurement of the periodic changes of the thorax movement while breathing; blood volume pressure (BVP), an optical sensor that acquires the changes in volume of the capillaries, transducing the blood pulse; accelerometer (ACC) in three axis, recording the variation of movements of the person in the different directions. Biosignalsplux has been used successfully in several research and clinical applications (Barandas et al., 2015; Rebelo et al., 2013).

Apart from these biosignals, bibliography has validated the grip strength as a measurement of physical condition. This indicator may be used as a predictor for disability and is considered to be useful for screening middle-aged and older adults (Bohannon, 2008). Therefore, in the context of this project and to assess physiological measurements that could estimate the physical condition and evolution of the elderly user, a new portable device was developed that measures the force applied by the grip. Since the device is to be grasped, other three opportunistic signals can be extracted from the hand without the use of gel electrodes. The extracted biosignals are not only BVP and ACC, but also the electrodermal activity (EDA), which measures the changes in skin conductivity controlled by the sympathetic nervous system. This gadget is ergonomic and communicates wirelessly with Biosignalsplux, allowing for direct connection to Opensignals for data visualization and analysis.

Signal analysis follows the acquisition, and relies on the morphological representation of the signal. Since the realization of the physical exercises require movement, the signals may present noise and artifacts. The need to find clean areas for signal processing resulted in two algorithms, one that identifies the noisy areas (Rodrigues et al., 2017) and other that learns the signal morphology and replicates it for heavily corrupted data (Belo et al., 2017).

Computer-based System for Assisting and Automating Functional Fitness Assessment. The assessment of functional fitness components in older adults is important to identify functional mobility disabilities and then targeted individualized exercise program. This assessment is typically done through validated battery tests such as the Senior Fitness Test (SFT; Rikli & Jones, 2013). The SFT is designed to be easy to administer while not requiring extensive time, equipment or space. It is a valuable instrument for professional in evaluating and identifying risk factors, planning and assessing training programs, educating and setting goals. For the AHA human state awareness module we developed a computer-based system for assisting and automating SFT administration and scoring in the elderly population (Gonçalves et al., 2015). We considered the following domains and subtests of the SFT:

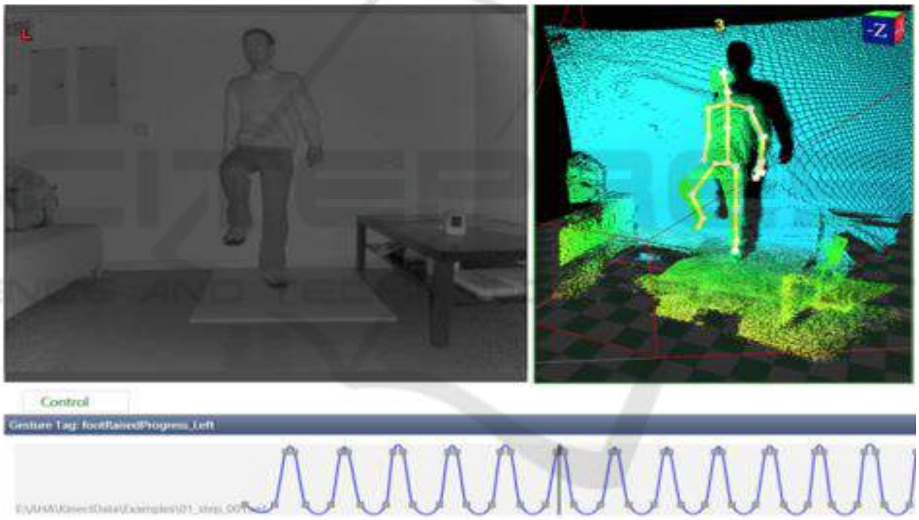
– *Lower Body Strength:* measured through the 30-second Chair-stand Test that consists on counting the number of times a participant can fully stand and sit from a chair, with the arms crossed, during a 30 seconds interval.

– *Aerobic Endurance:* assessed with the 2-minute Step Test. The test consists on having the participant step in place for 2 minutes, raising the knees up to a height marker placed halfway between the knee level and hip level. The number of times each knee reaches the target height is the score of the test.

– *Agility* and *Dynamic Balance:* measured with the 8-foot Up-and-go Test. In this test, starting from a seated position, the user stands on a "go" signal, walks 2.4 m, turns around, walks back to the chair and sits. The participant practices once and then perform two trials. The score is the fastest time of the two trials.

Our system automates scoring of these tests through the use of a Kinect V2 RGB-D sensor for body tracking and gesture detectors for the evaluation of movement execution. Marker-less infrared systems present the lowest cost option for body tracking. These devices estimate human body poses by analyzing the 3D depth information from a scene while requiring minimal setup and no markers. They have been widely used in research, for example, for designing full-body interactions in exergaming for older-adults (Gerling et al., 2012); for motion tracking in gait evaluation (Gabel et al., 2012; Stone & Skubic 2011; Chaaraouiet al., 2015); as a guidance, correction and scoring prototype for shoulder abduction exercises (Gama et al., 2012); for gesture detection associated with muscle and joint pain, common in older-adults (Saha et al., 2013); or as a tool to assist in the medical diagnosis and monitoring of Parkinson's disease through movement analysis (Spasojević et al., 2015).

The system was developed and trained with optimal data collected in laboratory conditions [as shown in Figure 3 (a)], its performance was evaluated in a real environment with 22 elderly end-users and compared to traditional SFT administered by an expert, seen in Figure 3. Results show a high accuracy of our system in identifying movement patterns (>95%) and consistency with the traditional fitness assessment method scores, further details about the performance and results can be found in the authors' original publication (Gonçalves et al., 2015). In the Figure 3 b) it is possible to see a depth and skeleton view of the Kinect V2 during an 8-ft Up-and-Go. The results suggest that the technology is a viable option to support health and fitness professionals in the assessment of physical function in the older population and could be deployed for at home use in the context of fitness programs with the potential to be used autonomously by non-experts.



a) b)

Fig. 3. Laboratory collected data being used to train a step detector for the 2-minute Step Test.

Augmented Reality Training

Exergames. Research has shown effectiveness and benefits of active-play with Exergames, which are videogames that use body movement as input control and promote some form of exertion while playing, having impact in both physical and cognitive functions (Molina, et al., 2014). A set of 4 Exergames was brainstormed, designed and developed along various stages using human-centered techniques which involved the end-users and health professionals (Gonçalves et al., 2017; Muñoz et al., 2018). The duration of the process was 19 weeks divided in four main stages: conceptualization, initial development, rapid contextual design and iteration, and polishing. ACSM' recommendations were followed in the different fitness domains by means of offering training personalization with fine game parametrization. Exercises incorporated in the Exergames were developed by sport science professionals, which targeted dimensions such as: motor ability (balance, agility and flexibility), aerobic endurance and muscular strength (lower and upper limbs, and trunk).

Considering that the target population would feel more identified and engaged with the Exergame experiences, the set of Exergames was inspired on a virtual tour in Portugal. Traditional experiences were incorporated in the scenarios, such as miming the smash of grapes for wine production, transporting the wine barrels along the river, experiencing a toboggan ride in Madeira island, and playing piano on a fado house (Figure 4).

The developed games went through a process of multiple iterations involving the target population, as well sports and health professionals and scientists, game designers and developers, till being ready for a controlled longitudinal study aiming to assess their effectiveness among the senior population. The whole design process is described in (Muñoz et al., 2018).

Fig. 4. Screenshots of the 4 developed Exergames (Gonçalves et al., 2017).

Integrative System for Exergames. Due to the highly configurable nature of Exergames, managing and preparing training sessions can be difficult and time consuming when faced with complex and a large amount of parameter choices. An integrative system that can aggregate independent Exergames, such as the ones previously presented, was also ideated and designed using human-centred techniques, involving the main prospective end-users of the configurable User Interface (UI), namely health and sports professionals (Paulino et al., 2018). This integrative system will allow configuring and managing the different Exergames through a common UI. Data derived from physical and cognitive assessments from users will serve as input to provide decision support on the creation of training/rehabilitation plans adapted for each end-user profile. Data from the training sessions will be hosted both locally and in a cloud database enabling easy access and meaningful visualization of the historical progress of end-users (*Figure 5*).

The initial steps carried out to design the integrative system were divided in 3 major stages: requirements engineering, software design, and human-computer interaction. Techniques such as semi-structured interviews, card sorting, and paper prototyping were used to involve the main interactors of the envisioned system in the design process allowing to design with the consideration of their preferences and needs. Future work will involve a usability study after the basic UI implementation.

Fig. 5. Integrative system's overview.

PEPE (The Portable Exergame Platform for Elderly). In this section, we describe the design and test of PEPE - The Portable Exergame Platform for Elderly. This is a hardware and software system that incorporates the data acquisition, augmented reality serious games (floor projections) in a wheeled base and foldable mechanical structure. This platform does not contain the autonomous robotics components that, due to cost, is inaccessible to many institutions. Instead, the platform can be manually moved by the professionals in the institutions and serve users either in public or private rooms.

Our design approach was based on user-centered design (Abras et al., 2004), according to the following three stages.

– On the first stage, we defined the main requirements: software and hardware specifications to execute the Exergames and the easy operation and deployment within a typical elderly care institution.

– In the second stage, we visited the institutions with an early prototype. This prototype was used to do thematic analysis (Braun & Clarke, 2006), using quantitative and qualitative data extracted through questionnaires and semi-structured interviews regarding functional aspects, possible usability, appearance, and physiological measurement requirements. The intention of this process was to involve the people for whom we are developing in an iterative process (Baek et al., 2008). To collect a large heterogeneous users sample, our study included an array of multidisciplinary professionals (p=6) and people from the geriatric segment (u=24) across three different institutions. Regarding the appearance of PEPE, there was no consensus among the interviewee's sample. We proposed several concepts using bidimensional sketches and tridimensional modeling [Figure 6, (a); (b) and (c)] to explore different alternatives.

– On the third stage, we repeated the second phase focusing on the alternative concepts that we did for the cover and interfaces, based on the previous results coming from the thematic analysis. We used PEPE as a way to study its purpose as a motivational and physical exercise elicitation device and also as a validation platform to test some components that can be implemented later on the robot Vizzy.

a) b) c)

Fig. 6. Appearance of PEPE: bidimensional sketches and tridimensional modeling

Following the results of our studies, we have to converged to the design of PEPE shown in (Figure 7). The core aspects leading to the final design were related to the mandatory empathic aesthetics of the platform, simultaneous usability for the seniors and healthcare professionals and, the adaptation/customization of the Exergames to the multiple constraints that seniors might have that increase success rates (Harriette, 2013). The platform allows Exergames to be played not only by healthy people but also by people with some physical and/or cognitive impairment. We also can extend the number of people that interact with the platform, since PEPE is capable of going near people who can't move.

Fig. 7. PEPE Platform.

PEPE was also seen as a dynamizing tool that can optimize the traditional process inside institutions, being helpful to Physiotherapists, Psychologists, and Occupational Therapists during their performances. Our findings show that users can be proactive in engaging in physical exercise with PEPE thus serving the purpose of sedentary preventions and rehabilitation while being also entertaining. Further information regarding the results of this section can be found in the author's original publication (Simao & Bernardino, 2017).

Virtual Coach

A Virtual Coach is an attentive personalized system that monitors the context of a user to provide a feedback or assistance. It leverages machine learning with sensor data to understand user contexts (e.g. locations, physical activities, emotions, and social). For instance, a Virtual Coach can monitor repetitive rehabilitation exercises and assess patient's exercises performance and provide corrective feedback. This feedback can ensure the correct execution of rehabilitation exercises and motivate patient's engagement. In addition, therapists can judge the quality of in-home rehabilitation with quantitative performance data. We first describe our methods to develop a Virtual Coach for stroke rehabilitation exercises and then demonstrate its capabilities.

Methodology. A Virtual Coach system assists a patient to engage correctly in rehabilitation exercises with minimal supervision of a therapist. To mimic a therapist's vision-based assessment of rehabilitation exercises, the Virtual Coach utilizes a Kinect sensor to track kinematic positions of a patient and employs machine-learning algorithms to provide assessment and guidance

Given an exercise trial, the system assesses a performance score along with corrective feedback on joint positions. The performance score will be stored to record a patient's progress. The assessment module quantifies the quality of an exercise and collects performance data. First, we analyzed the existing manual clinical stroke assessment tools (i.e. Fugl Meyer Assessment and Wolf Motor Function Tests) and in discussions with therapists developed three performance metrics of stroke rehabilitation: *'Precision', 'Smoothness', and 'Compensation'*. The *'Precision'* metric represents how accurately an exercise is performed. The *'Smoothness'* metric indicates the level of trembling. The *'Compensation'* metric checks whether a patient involves any compensatory movements (e.g. leaning torso forward).

The Virtual Coach system extracts normalized kinematic features and applies Deep-Reinforcement Learning to identify important features. The system then trains binary (correct, incorrect) classifiers to classify the correctness of an exercise movement in terms of the three performance metrics. Utilizing these classifiers, the system can quantify the probability of being a correct movement yielding a performance score.

The guidance module learns sequential joint positions of an exercise and generates corrective high-level instructions (e.g. move your elbow upward) upon detecting an incorrect movement. The system utilizes grid-representation to describe an exercise as sequential pairs of grid-based current and next joint locations. It then trains a model of sequential joint movements to instruct a patient how to correctly place joint positions.

Experiments and Results. To validate the feasibility of a Virtual Coach system, we utilize three upper-limb stroke rehabilitation exercises: Exercise 1 (E1) – *'Bring a cup to the mouth'*, Exercise 2 (E2) – *'Switch a light on'*, and Exercise 3 (E3) – *'Move forward a cane'*. These exercises are selected due to their correspondence with major motion patterns: elbow flexion for E1, shoulder flexion for E2, and elbow extension for E3.

For the data collection, we recruited 15 post-stroke survivors with different level of functional abilities and 11 healthy subjects. A post-stroke survivor performed 10 repetitions of each exercise on both affected and unaffected sides. A healthy subject performed 15 repetitions of each exercise using their dominant side. In total, each upper limb exercise contains 465 trials: 315 trials of correct movements and 150 trials of affected movements. A therapist observed recorded videos of exercise trials and evaluated a score of the three performance metrics on 4-point ordinal scale (0-3).

For classification models, we used Decision Tree (DT) and Hidden Markov Model (HMM) as shown in Table 1. After comparing classification accuracy, we selected DTs for the *'Precision'* and *'Compensation'* metrics and HMMs for the *'Smoothness'* metric. Our assessment module achieves 83.65 – 93.46% agreement with therapist's observation scores for an individual performance metric over the three exercises. The assessment module has an average 78.45% agreement and 0.8223 Pearson's Correlation Coefficient ($p < 0.001$) for all three metrics.

Table 1. Classification Accuracy of Three Performance Metrics with DTs and HMMs.

Metrics	Algorithm	Exercise 1	Exercise 2	Exercise 3
Precision	DT	94.12 ± 1.84 %	98.57 ± 0.50 %	92.26 ± 2.02 %
	HMM	81.90 ± 2.97 %	90.50 ± 2.24 %	72.46 ± 3.41 %
Smoothness	DT	56.85 ± 3.84 %	65.67 ± 3.63 %	63.68 ± 3.71 %
	HMM	82.55 ± 2.90 %	82.09 ± 2.92 %	82.16 ± 2.94 %
Compensation	DT	98.47 ± 0.94 %	97.41 ± 1.19 %	93.55 ± 1.87 %
	HMM	78.62 ± 2.8 %	80.99 ± 3.00 %	76.34 ± 3.22 %

Conclusion and Discussion. Given a set of rehabilitation exercises prescribed by a therapist, a Virtual Coach can use machine learning techniques to evaluate the quality of a movement and generate performance and corrective feedback advice. Our experiments demonstrate the feasibility to learn therapist's assessment and automatically quantify the performance of rehabilitation exercises. Thus, a Virtual Coach has potential to enhance patient's independent engagement in rehabilitation exercises after hospital discharge. From a therapist's perspective, this technology can support remote monitoring of patient's progress. For integration with other work packages in the AHA project, we developed communication channels with a mobile robotic platform and Augmented Reality (AR) training module. The Virtual Coach can support patients or elderly persons from providing simple reminders to guidance throughout an exercise. Leveraging the user state analysis from the Monitoring Module (WP1) and automated assessment, the Virtual Coach can recommend performing more personalized serious games. The current implementation primarily focuses on guidance during an exercise. In the future, it would be interesting to explore the application of a Virtual Coach on more diverse and complex tasks than repetitive exercises.

Robotic Assistance Platform

On this project, we use the Vizzy robot (Moreno et al., 2016) as a Socially Assistive Robot (SAR) that plays a coaching role during physical exercise and also serves as an assistant for professionals. For a robot coach to be successful, the interaction must be pleasant, and people should perceive it as competent and trustworthy. To evaluate Vizzy's fitness for this role, study current limitations, and experience unforeseen interactions, we deployed it in three elderly care centers in Portugal (LATI - Liga dos Amigos da Terceira Idade, Centro Social Comunitário da Nossa Sra. dos Milagres, and Residência Sénior de Belverde). The robot coached a total of 36 seniors (aged between 65 and 94 years old, μ = 80.83, $\boldsymbol{\sigma}^2$=5.84), inviting, engaging, instructing, and providing motivational feedback while they played the ExerPong exergame. Since dialogue and head gestures are not yet fully automated, we controlled the robot via a Wizard-of-Oz interface. Next, we will describe (i) Vizzy and the technological implementations for the experiment, (ii) the user study, (iii) results and lessons learned.

Technical Details. Vizzy is a general purpose SAR platform with an anthropomorphic upper torso, and biologically inspired head and eye movements (Roncone et al., 2016). Its two arms allow it to perform non-verbal communicative gestures familiar to humans (although still not used in this study). Vizzy uses a mobile Segway platform to navigate autonomously in known areas. Its front and rear lasers allow it to avoid obstacles along its way while localizing itself on a known map. Vizzy has two RGB cameras on its eyes and an RGB-D sensor on its torso that can be used to detect people, objects and obstacles not captured by lasers. The robot can also emit sounds and synthesize speech.

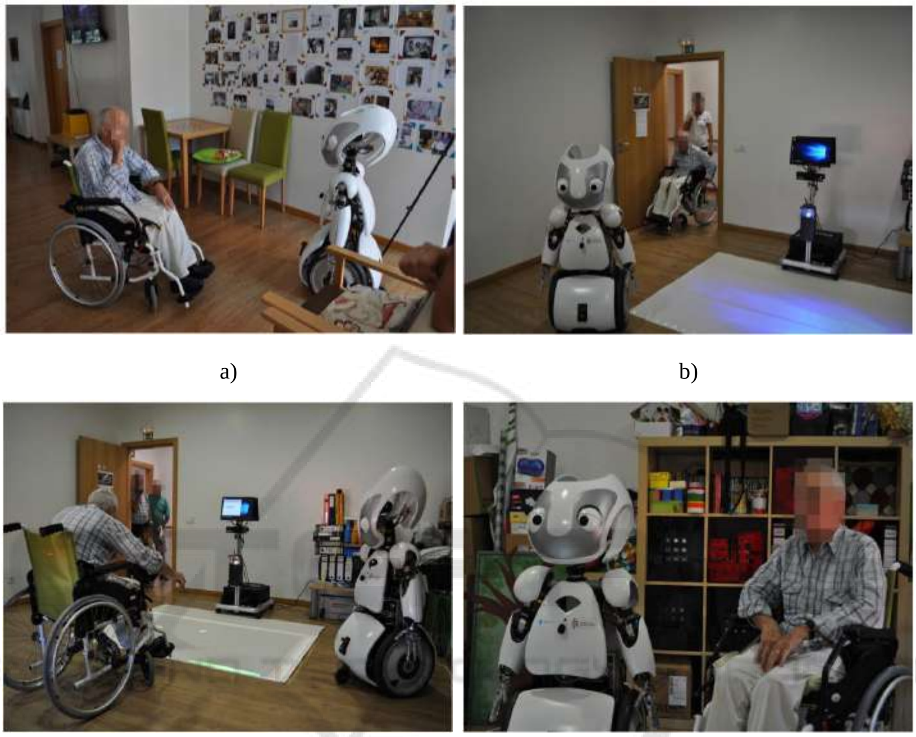
Given the unpredictability of the experimental setup, WoZ interfaces needed to be fast, robust and easy to use. For this purpose, we used two interfaces (Figure 8): a custom-made dialog control interface that can be easily accessed using any web supporting device (but optimally used on a tablet) and a motor control interface using Rviz with custom plugins. To control the robot's gaze and movements we developed two plugins for Rviz: ClickableGazeDisplay and WASDTeleop. The ClickableGazeDisplay lets the "wizard" select the gaze point by clicking on the camera image. The WASDTeleop allows the direct control of wheel velocities using the W, A, S, and D keyboard keys. These plugins' code is open source can be easily modified for other robots, as needed.

a) b)

Fig. 8. Wizard of Oz interfaces.

Experiment. During the experiment (Figure 9), the robot approached a senior user and invited her/him to play an Exergame. If the person accepted, the robot would guide him/her towards the PEPE platform. Then, the robot introduced the game giving instructions on how to play. During the game, the robot also assists the person with corrective instructions if necessary. A second role of the robot is engaging the person during the game by providing feedback, and by assessing interactively with the person if the game can continue or if it should stop. Afterwards, each participant answered a questionnaire after taking a picture with the robot.

The questionnaire was composed of five-point Likert scale items ("totally disagree" = 1, "totally agree" = 5), adapted from the Godspeed Questionnaire (Bartneck et al., 2009), the ALMERE model (Heerink et al., 2010) and scales proposed by Jian et al., 2000.



a) b)

c) d)

Fig. 9. Experiment steps.

Results and Lessons Learned. Users reported high perceived enjoyment of playing ExerPong with Vizzy (μ = 4.67, $\boldsymbol{\sigma}^2$=0.47), high perceived robot competence (μ = 4.47, $\boldsymbol{\sigma}^2$=0.41) and high perceived trust (μ = 4.36, $\boldsymbol{\sigma}^2$=0.79). On average, people liked the robot (μ = 4.56, $\boldsymbol{\sigma}^2$=0.71) and thought it was cute (μ = 4.36, $\boldsymbol{\sigma}^2$=0.81), but thought it looked artificial (μ = 3.78, $\boldsymbol{\sigma}^2$=1.66) and had a machine-like appearance (μ = 2.39, $\boldsymbol{\sigma}^2$=2.016). They also found the robot's movements elegant (μ = 3.81, $\boldsymbol{\sigma}^2$=0.78). All these items were statistically different than the neutral value when performing a One-Sample T-Test ($p<0.05$ for the human-like - machine-like appearance item, and $p<0.005$ for the remaining items).

Informal observations and interviews also revealed interesting insights that were using for fine-tuning the system and that suggest future improvements. For instance, accurate gaze direction is fundamental for interaction, because otherwise people will be confused, and the robot must use short and assertive utterances during gameplay. More information can be found on the authors' workshop paper (Avelino et al., 2018).

End User Evaluation

Adding Physiological Intelligence to Exergames. By performing a pilot study to investigate the cardiovascular mechanisms that acted during the interaction with a customizable Exergame, we concluded that important heart rate (HR) and heart rate variability (HRV) responses could be modulated by means of adjusting game difficulty parameters (Muñoz et al., 2016). The next step in this research was the idea to create an intelligent adaptation for the Exerpong based on cardiovascular measurements in real time by means of combining two approaches: i) a construct from the physiological computing field called the biocybernetic loop (Pope et al., 2014) and ii) the well-established aerobic training method based on targeted HR levels (Heyward & Gibson, 2014).

Target HR: by following the ACSM guidelines for older adults (Jones et al., 2005), aerobic exercises should be controlled in regards of the intensities levels guaranteeing that older users can maximize the benefits of stressing the heart without over exercising it. This zone of healthy exercise intensity can be defined by means of HR measurements that uses a percentage of the HR reserve (HRR) – which is the difference between maximum HR (HR_{max}) and HR during resting (HR_{rest}) – as expressed in the equation:

$$Target\ HR = [\%\ exercise\ intensity * (HR_{max} - HR_{rest})] + HR_{rest}$$

This target zone is individual for each user and it is recommended older adults to exert under 40 % to 70 % of their target HR (Jones et al., 2005).

Biocybernetic Loop: this concept relies on the detection of human states based on physiological sensing in order to modify the system behavior in real time. By using novel and minimally intrusive wearable sensors, HR and HRV measurements can be recorded with high levels of accuracy during exercise routines. HR data in real time can be used to modify game parameters in order to keep users exercising at desirable intensities, the targeted HR levels in this case.

To evaluate the effectiveness of a Cardio-Adaptive Exergame based on biocybernetic adaptation that uses the target HR approach, we carried out a within subjects experiment comparing our adaptive training routine against conventional group fitness sessions leader by sports science professionals.

Cardio-adaptive Exerpong Approach

Exergame Design and Setup: a customizable Exergame inspired in the classic 2D pong was created: the Exerpong. Players are challenged to hit a ball using a virtual paddle, which is mapped to the player's waist position via the Kinect V2 sensor (Microsoft, Washington, USA). Exerpong was designed and developed in the game engine Unity3D (Unity Technologies, San Francisco, USA) which conveniently allows a complete game customization and data logging. Exerpong allows a physical training of balance and agility while the physiological adaptation is oriented to maximize aerobic performance. The Exerpong is projected on the floor on a white 2.5 x 3.0 surface (see Figure 10).

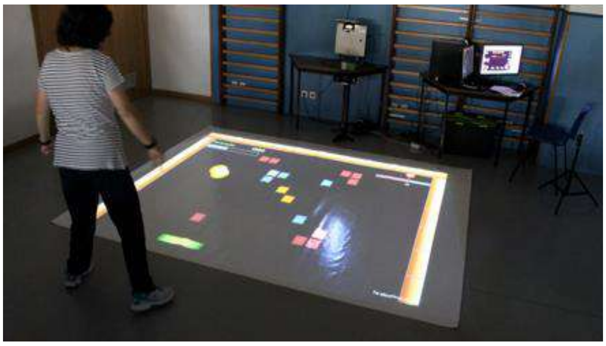


Fig. 10. Image showing the final setup of the Exerpong.

HR Data: to record the cardiovascular responses, we used a Motorola 360 smartwatch which streams computed HR data with a 1 Hz sampling frequency to a custom-made software called the Biocybernetic Loop Engine (Muñoz et al., 2017), which is in charge of creating the physiological adaptation and the communication with the Exerpong.

Adaptation Rules: to help players reach their individual target HR levels while keeping them motivated to exercise, the Cardio-Adaptive Exerpong uses a dual adaptation rule (Sinclair et al., 2009).

Gameplay Adaptation: the paddle size increase once players miss balls and vice versa, the ball velocity automatically decreases if the player misses three consecutive balls.

HR-based Adaptation: the ball velocity increases if the 30 seconds HR average is under the target HR and decreases it otherwise.

Preliminary Results. By analyzing the time fifteen older adults (11 females, ages 66 ± 7 years) spent in their individual targeted zones during 20 minutes of exercise with the Cardio-Adaptive Exerpong, we demonstrated that our biocybernetic system led players to exert around 40% more time in this recommended zone once compared with conventional training. Moreover, we also showed the feasibility of use the HR data from the smartwatch to assess HRV changes during the interaction with the adaptive system (Muñoz et al., 2017).

Finally to extend our approach, we are currently carrying out a 6-weeks study aiming at quantify the long-term effects of training with the Cardio-Adaptive Exerpong in a local senior gymnasium.

6 Conclusions

A new generation of ICT based solutions for promotion of physical exercise in the older population, either for the prevention of inactivity-related diseases or for the rehabilitation of motor deficits are developed with AHA project. This is very important to better understand the end-user challenges when engaging with technological solutions for physical activities, namely, the combination of customized augmented reality games and assistive robot coaching. The three main contribution of AHA project are: (a) a Mobile Augmented Reality Platform that projects Serious Games in the environment for the training of several fitness dimensions in the older persons (balance, mobility, agility, strength, endurance, etc); (b) a set of human-robot interaction modalities to engage and motivate users in the exercises, and (c) a set of automated senior fitness tests to assess the functional fitness levels of the users combined with a web-based platform to create and store the users' profiles.

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