A Robotic Fitness Coach for the Elderly

Binnur Görer, Albert Ali Salah, and H. Levent Akın

Department of Computer Engineering, Boğaziçi University,
Istanbul, Turkey
{binnur.gorer,salah,akin}@boun.edu.tr

Abstract. The ultimate goal of ambient assisted living is to help elderly people live a healthy life in the convenience of their homes by making more intelligent technology bring them a set of required assistive tools. In this paper we describe a robotic fitness coach that learns a set of physical exercises from a professional trainer, and assists elderly subjects in performing these gestures. The gestures were selected from an actual training programme at an elderly care home. When demonstrating gestures, the robot performs the learned gestures to the best of its abilities, and while monitoring the elderly subject with an RGB-D camera, provides verbal guidance to complement the visual display, correcting gestures on the fly. We provide a detailed description of the training programme, the gesture acquisition, replication and evaluation algorithms, our solution to the robot stability problem, and a set of preliminary user tests to validate our approach.

1 Introduction

Ambient assisted living is a concept that summarizes the effort to create intelligent technologies to help elderly people live their lives without constant supervision from costly health personnel, as well as to improve their quality of life by offering solutions to typical problems related with age and its physical and social implications [1]. The primary goal in this enterprise is a preventive approach of healthcare for elderly, sometimes summarized by the concept of 'successful aging', where the subject retains and sustains its physical and mental well-being. Both physical and mental health require regular activity (possibly in form of regular exercises) for this purpose.

Performing regular physical exercise has well-known benefits for the elderly [2]. Through improvements in blood pressure regime, it helps reducing heart-related problems, most importantly helping the prevention of coronary heart diseases. As such, it makes sense to consider approaches to promote physical activities for the elderly. While there are findings that hospital-based rehabilitation is more effective than unsupervised home-based exercises [3], the introduction of smart technologies to supervise the latter may help in bridging the gap.

This paper proposes an approach to create a robotic fitness coach, and primarily concerns itself with the physical, rather than the mental fitness of the subject. Here, an early disclaimer is in order. A human fitness coach performs a series

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of complex tasks including assessing a subject's physical condition, creating a fitness program for the subject by taking into account a number of observed and known physical constraints, monitoring and adapting the program according to the progress and engagement of the subject (or the lack thereof), and performs all these while bearing responsibility for the health condition of the subject. We do not use the term 'coach' to incorporate all these functions, as many of which are beyond the abilities of current robotic and expert systems. The system we propose has the much more modest goal of assisting a real fitness coach in letting an elderly subject perform a given set of physical exercises.

The adaptation of the exercise program to the subjects individual needs requires expert knowledge. Once a set of individualized exercises are developed, the subject needs to perform these regularly over long periods. It is at this point where a robotic companion would play an important role, by monitoring the subject and its performance, as well as by motivating the subject through an engaging and fun interface. Subsequently, we propose two different modes of operation. In our application scenario, the robot learns the set of exercises from the physician or the fitness coach by observation and imitation. When in operation, the robot performs the exercises to the best of its abilities, and supervises the performance of the subject. Every once in a while, the fitness coach assesses and revises the exercise program. It is not practical to let a computer scientist encode new exercises into the coaching robot each time, so the robot should learn exercises automatically from the fitness coach. This part stands for the practical significance of our work. We facilitate the imitation system for gesture realization on real robot and investigate the applicability of this system for a robotic fitness coach by evaluating the user responses.

The first challenge in the proposed method is to analyse the coach's gestures automatically to form a good representation of the performed gesture. This is accomplished by the recently popularized RGB-D camera approaches to track the body of the coach. The second challenge is due to the fact that the robot possesses a different physical embodiment than the fitness coach (or the subject, for that matter) and hence is an imperfect intermediary interface. We discuss how the mapping of human gestures to the robot can be accomplished. The performance criteria for the robot's gesture are the stability and smoothness of the actual move, as well as the perceptual validity of the appearance of the robot.

The second operation mode of our application consists of exhibition of the learned gestures by the robot and providing vocal explanations about the performed motion. The challenge is to synchronise vocal explanation with the shown gesture so that both auditory and visual perception of the subject are kept active. The robot also gives vocal feedback on the success of the imitated gesture to correct it, if necessary.

This paper is structured as follows. In Section 2, we describe some related work in this area. Our proposed system is detailed in Section 3. Section 4 provides a list of most common exercises performed in training sessions for elderly. We provide initial results we have obtained with a working prototype, and report a set of preliminary user studies in Section 5, and conclude the paper with a discussion of the challenges and future directions envisaged for this work in Section 6.

2 Related Work

A social assistive robot (SAR) is a socially interactive robot whose primary goal is assistance [4]. Our approach is positioned in the related literature primarily as a SAR with non-contact assistance. There are a number of existing SAR systems [5], Marcel Heerink gives a detailed overview of these in [6]. Most of these systems focus on monitoring the elderly [7], or in helping them in their daily tasks. There are relatively few systems that target physical exercise applications. Rehabilitation robots that are created for physical training usually do not have a person-like embodiment [8], and lack the social aspect completely, which is found to be useful in elderly care scenarios [9].

Most existing systems for home based elderly physical training do not involve robots at all. An example is Respondesign's MayaFit Virtual Fitness Trainer, which uses Kinect-based motion analysis and a screen-based interface to guide subjects through physical exercises [10]. This system requires the precise specification of each gesture, and does not involve automatic imitation based learning. In [11] a web system is proposed for facilitating repetitive movement training. The subject is tracked with two cameras attached to a home PC.

Obviously, an embodied conversational agent (ECA) or a similar 3D avatar displayed on a screen would provide a much more realistic visualization of the target exercise. In [12] such a system was proposed. However, lacking physical and tangible embodiment, such a system may be at a certain disadvantage in terms of engaging the subject, when compared to a social robot. Indeed Fasola and Mataric have contrasted the user responses to physical robot and virtual robot in an exercising scenario, and found that the subjects rated the robot to be more engaging, enjoyable, and a better exercise partner [13]. In [14], the authors show that the mimicking tendency of the subjects are higher for real robot than virtual robot in a scenario of physiotherapy where the robot is utilized as an assistant to the physiotherapist.

In [15], a robotic exercise coach is proposed for chair aerobics, and the authors evaluate the motivational aspects of this scenario extensively. For instance, the robot always provides positive feedback on successfully completed exercises, and never gives negative feedback, because sustaining motivation over longer periods is one of the keys to building a successful system. One of the motivational factors the authors have used is providing numeric feedback on the task success, which 'gamifies' the experience, and makes it more engaging through the feeling of challenge.

In [16], a humanoid RoboPhilo robot is used in a physical exercise scenario that is similar to the one we propose. This robot has 20 degrees of freedom (DOF) that enable the turning movements of the head, waist, and thighs and joint movements of the limbs. In the proposed scenario, computer vision techniques are used to detect the face and hand positions, from which two gestures are detected: head turn, and hand raise, respectively. The robot gives vocal feedback when the gesture it performs is successfully imitated by the elderly. However, the feedbacks do not include any corrective information for the gestures which can not be imitated correctly by the elderly and they are provided for only two types of gestures.

For analysis of the gestures performed by the elderly, visual assessment is preferred to wearable sensors for ease of use. In [17], the robot compares the user's current arm angles to the pre-specified goal arm angles to determine whether an exercise is performed correctly, or not. A standard RGB camera is used for gesture analysis, and the visual analysis is performed against a uniform background which is not preferable for a daily use system such as robotic fitness coach. In this approach, there are no gesture-specific weights assigned to different joints, whereas in most physical exercises, the value and range of some angles are much more important than others.

Other approaches to exercising the elderly involve for instance the design of interactive games. Playful interaction for serious games is a recent area that is receiving more attention. Representative examples for physical exercise scenarios are given in [18] and [19]. A taxonomy of games for rehabilitation is given in [20].

3 Methodology

We use a robot, a Kinect, and a robotic simulator in the proposed scenario. The system works in two modes. In the first mode, the human coach 'teaches' the robot the desired exercise, and records the accompanying verbal description. In the second mode, the robot demonstrates the exercise to a subject, monitors and provides feedback on the performed gesture.

3.1 Gesture Learning from a Human Demonstrator

In our system, the human demonstrator is expected to perform the gesture in front of the robot, while marking the gesture boundaries via simple vocal commands such as "start" and "end". The robot is then expected to imitate the motion sequence performed between this interval, and store it for further reference. The visual input (i.e. the exercise performed by the human coach) is acquired with a Kinect camera, and the skeleton is extracted with the OpenNI software. The obtained joint angles are transformed to a set of corresponding Nao joint angles. The exercise is then assessed for the physical limits of Nao; if it involves stretching of limbs, or rotation of joints not available to the robot, the vocal assistance module is assumed to complement the system. At this moment, this is simply a recording (and replication) of the coach's vocal instruction (e.g. "...and stretch both arms"). Then the exercise plan is passed to the Webots simulation software, which assesses the stability of the gesture. If this check is not passed, joint angle positions are optimized to obey stability conditions in a way to produce minimal deviation from the desired appearance. Then the exercise is stored in a database

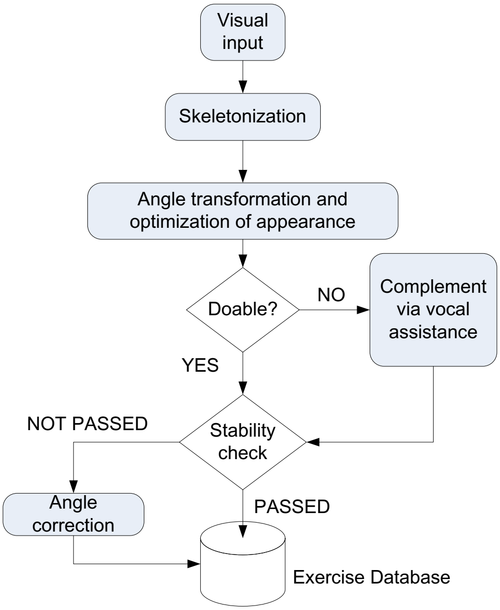

Fig. 1. Flowchart of the proposed system for gesture learning from a human demonstrator

for further reference. A flowchart is given in Figure 1 to summarize the proposed system.

Gesture Imitation. In order to map human gestures to the robot, the first challenge to be handled is to specify the embodiment differences between human and robot. Due to the anatomic differences, the robot is not able to imitate every motion of the human successfully. The Nao robot has a much smaller number of degrees of freedom than the human and the limits of each joint differs from the corresponding ones in humans. Hence, a robust mapping system is needed to allow the Nao to be able to imitate as many different motions as possible. We represent the gestures in terms of a 3D skeleton of joints and their connections.

We use two main criteria to determine the success of the gesture generated by the robot through the mapping system: the stability of the robot, and the similarity between the robot's motion and the human's motion, respectively. We use a simple approach for the similarity, and take the sum of absolute values of joint angle differences in the human and the robot. As mentioned earlier, a better approach would be to consult the physician about the relevance of each gesture component, for each gesture. That would, however, require explicit supervision. Another possibility is to let the fitness coach demonstrate each gesture multiple times, and discount joints that show high variance in their angle values. This in turn would require that the fitness coach is aware of this procedure, and exhibit such variance consciously.

The stability of the robot is a very important restrictive factor in exhibiting whole body motions. Especially raising a leg usually requires that the arms help in stabilizing the robot, lest it should fall. On the other hand, upper body motion imitation can be performed much more easily. Hence, the overall system should be evaluated separately for upper body motion and whole body motion imitation.

Upper Body Motion Imitation. The Nao robot has four degrees of freedom in its arm, which are shoulder pitch, shoulder yaw, elbow yaw, and elbow roll joints, respectively[1]. Humans also have the same number of DOF in their arms, but there are three of them in the shoulders and only one DOF is used for the elbow [21]. Hence, direct mapping from human arm joint angles to the Nao angles will not produce correct motions. To handle the difference in embodiments, a combination of inverse and forward kinematics is used.

We use an additional external RGB-D camera (i.e. Kinect) mounted on Nao's platform in this study. The positions of joints for the human skeleton are provided by the OpenNI software[2]. When the bones are treated as vectors whose initial and terminal points are defined by the two joint positions J_1, J_2 respectively, the angles between the bones and the XY, YZ and XZ planes give the angle ϕ of the joint J_1:

$$\begin{array}{l} \phi = \arccos(|V|/|Proj(V_x)|) \\ x \in \{XY, YZ, XZ\}, V = \overrightarrow{J_1 J_2} \end{array} \tag{1}$$

The angle between the upper and the lower arm is found using the following formula:

$$\theta = \frac{V1 * V2}{|V1|.|V2|} \tag{2}$$

where $*$ stands for scalar product of vectors, and $V1$ and $V2$ represent upper arm and lower arm, respectively. The same formula can be used for the angle between upper and lower legs.

These joint angles are first pre-processed to obey the limit angles of robot joint intervals. Afterwards, a Kalman filter, given in Eq. 3, is applied to eliminate the sudden changes in skeleton joint positions due to camera noise:

$$\begin{array}{l} p = p + q; \\ k = p/(p + r); \\ x = x + k * (m - x); \\ p = (1 - k) * p \end{array} \tag{3}$$

where p is estimation error covariance, q is process noise covariance, r is measurement noise covariance, k is the Kalman gain, x is the proposed value and m is the observed joint angle value.

For the upper body imitation case, the pre-processed shoulder pitch, shoulder roll and elbow roll angles from the human are directly usable in the robotic joints. For the elbow yaw joint, we need to approximate Nao's motion. In order to

[1] The more advanced versions of Nao also have a wrist joint, not used in this study.

[2] http://www.openni.org

achieve this, the position of the human hand is calculated by forward kinematics, using the first three determined joint angles. Denavit-Hartenberg notation is adopted for kinematic calculations. Table 1 shows the parameters for the right arm of Nao robot, where j_1, j_2, j_3 and j_4 stands for shoulder pitch joint, shoulder roll joint, elbow roll and elbow yaw joints, respectively. L_1 denotes the upper arm length, and L_2 denotes the lower arm length. In order to find the interpolated position of the hand of the robot using the shoulder pitch, shoulder roll and elbow roll joints, the transformation matrix is calculated using the Denavit-Hertenberg kinematic parameters of Nao [22].

Table 1. The Denavit-Hartenberg parameters for the right arm of Aldebaran Nao Humanoid Robot

i	α_i	a_i	Θ_i	d_i
1	$-\pi/2$	0	j_1	0
2	$\pi/2$	0	$\pi/2+j_2$	0
3	$\pi/2$	0	$\pi+j_3$	L_1
4	$\pi/2$	0	$\pi/2+j_4$	0
5	$-\pi/2$	L_2	0	0

The result is where the hand would be, if the shoulder yaw joint was in a neutral position. This position is measured in the 3D space relative to the shoulder. The spatial difference between this interpolated position and the real position of the hand needs to be compensated by the elbow yaw joint in the robot. Hence, the next step is to apply inverse kinematics to find the most suitable angle for the elbow yaw joint. Intuitively, the proposed approach tries to exchange the role of the shoulder yaw joint in the human with the elbow yaw joint in the Nao robot.

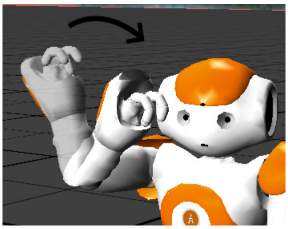

Fig. 2. The spatial difference between interpolated position and real position of the hand is compensated by the elbow yaw joint

Whole Body Imitation. There are few approaches where the gesture of the demonstrating human is transferred to a humanoid robot. Koenemann and Bennewitz implement a scenario where human gestures are transferred to a Nao robot, using an Xsens MVN motion capture system with inertial sensors attached to the body of the demonstrator [23]. Inverse kinematics is used to correct the transferred sensor positions for stability. They do not use this system in a particular application scenario.

In our system, the gesture is performed by a human demonstrator in front of the RGB-D camera and the joint angles, being derived by the external computer in real-time, are sent to the robot. Let A_h denote the joint angle vector for the human demonstrator. This vector will be mapped to a joint angle vector A_r for the robot. Two problems that we need to solve are the limited joint angle ranges of the robots (similarity) and the balance problems that arise during the performance of the gesture. For the latter, not only the center of mass of the robot needs to be maintained within the convex hull of the feet of the robot, but the time needed to interpolate between different gestures should also be taken into account: fast gesture changes can cause the robot to fall down, whereas the same gesture, performed slowly, may not. However, our application scenario of displaying gestures to the elderly permits the robot to move slower than the originally demonstrated gesture. Subsequently, we ignore speed-related instability here. Figure 3 shows examples from stable and unstable exercises.

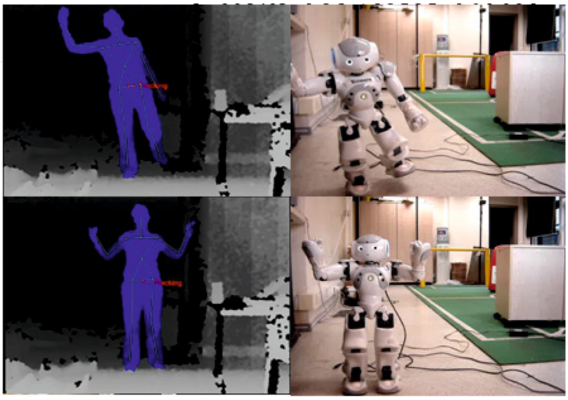

Fig. 3. Demonstration and imitation of two different exercises. The upper exercise is unstable, and if performed rapidly, can cause the Nao to fall, whereas the lower exercise is stable.

The whole body imitation problem is considered as a linear optimization problem in our proposed approach. There are two main requirements to be satisfied for a robot coach imitating a human, which are self-balance and maximum similarity with the human demonstrator, respectively. Our system tries to find joint configurations for the robot which have minimum difference from the ones collected from human and also satisfy balance constraints. Hence, the objective function we use is the minimization of the sum of the absolute differences between joint angles of the robot and the human demonstrator, subject to the stability constraint function that ensures that the ground projection of the center of mass of the robot lies within the support polygon of the robot. Moreover, ankle pitch angle of the foot in contact with the ground should be equal to zero minus of the sum of the related knee pitch angle and hip pitch angle, in order to satisfy the parallelism of the foot to the ground:

$$\begin{aligned} \min |A_h - A_r| \; s.t. & \\ & \sigma(A_r) & \in P(A_r), \\ & \phi_{anklePitch} & = \text{-}\phi_{kneePitch}\text{-}\phi_{hipPitch}, \\ & A_r^j & \in [A_{min}^j \dots A_{max}^j], \quad \forall j = 1 \dots J, \end{aligned} \tag{4}$$

where $\sigma(A_r)$ denotes the center of mass of the robot, and $P(A_r)$ is the convex hull of its feet support, both as functions of the joint angle vector A_r. The individual joints $j = 1 \dots J$ each should be within their respective minimum (A_{min}^j) and maximum (A_{max}^j) limits, at all times. To solve the optimization problem, we make use of COBYLA algorithm [24] from the NLOpt library [25].

3.2 Interaction with the Subject

In the second mode of the system, the robot performs the learned gestures to the subject and asks the subject to imitate them. While showing the motion, a verbal explanation of the gesture is also provided to the subject by the robot to make the perception of the gesture easier and to compensate for the differences between the physical embodiment of the robot and the human.

The robot monitors the subject during the exhibition of the motion and gives vocal feedback on the success of the imitation of gesture. The aim is to force the subject to repeat the performed gesture successfully and motivate the subject to continue with the exercise program. One challenge is to adjust the timing and the amount of verbal feedback in the exercise sequence.

In our approach, the feedback is given to the subject when the robot completes to demonstrate the gesture, and stays in the final posture of the gesture. The robot determines when the imitation of the gesture by the subject is terminated by analysing the stability of the subject, as indicated by the variances of all the joint angles over a sliding window of five seconds. However, the subject may not be able to perform the gesture simultaneously with the robot, or the performance speed may be different. The dynamic time warping algorithm is used to normalize gestures in time by stretching the shorter sequence. The feedback message is verbally given, but it is not pre-recorded. It is composed on the fly, by analysis of the imitated gesture. The joints that have high variance (called "gesture characterizing joint") are compared to the original stored gesture template, as performed by the coach. The feedback then consists of simple sentences such as "please raise your right arm up slightly" or "please spread the arms to both sides as much as you can", depending on the difference from the template. Each message consists of an action verb (e.g. "raise", "lower", "spread"), the target limb (e.g. "right arm", "both arms") and a modifier indicating the amount of correction (e.g. "slightly", "as much as you can"). Finally, the feedback text is converted to an audio file using a text to speech module, and played on the robot.

4 Taxonomy of Physical Exercises

Exercise motions are generally categorized into four classes, which are stretching and relaxation exercises, strength exercises, balance exercises and endurance exercises, respectively. The nursing home that helps us to observe the exercise session hosts seniors whose ages are generally above 75. These exercise sessions are held out three times a week and the same seniors participate in the sessions regularly. Hence, the exercises listed in Table 2 and Table 3 stand for the general and common exercises performed in a real senior fitness scenario. At this point, balance and endurance exercises will not be included for robotic coaching due to the risk of falling, and heart problems, respectively.

With the proposed pipeline of observation, skeletonization and angle matching, the Nao humanoid robot is able to perform six out of 16 stretching motions completely, and three motions partially. Stretching exercises help warming the muscles, protect against injury and allow a maximum range of motion for joints. Hence, these exercises require a muscle system to be exploited properly while being performed within certain minimum or maximum limit angles of joints. Human joints have a greater degree of freedom compared to Nao's joints, and some exercises fall beyond the robots capabilities.

Purely gesture based imitation success in strength exercises is higher. The Nao is able to perform five motions properly and eight motions partially, while four exercises are beyond its physical limits. The main problem in strength exercises is the constraints in the joint angle intervals. Figure 4 shows some exercises, fully learned and imitated by the Nao.

Fig. 4. Demonstration and subsequent imitation of several fitness exercises

The motions that the Nao is not able to perform are displayed with additional vocal assistance. Understanding motion characteristics such that stretching or strengthening may be a difficult task even for the humans; we observed some

Table 2. Analysis of Stretching and Relaxation Exercises Considering Nao Humanoid Robot

Stretching and Relaxation Exercises	**Stance**	**Description**	**Robot Joints**	**Doability**	**Problems**
1.Side lumbar stretching	Standing	One hand is on the lumbar, stretch the body using lumber to the side of that hand	Upper body joints + hip roll	Yes	
2.Lumbar spine relaxation	Standing	Arms are relaxed and swing around body, turn upper body around itself	Shoulder roll + hip pitchyaw	Yes	
3.Whole body stretching 1	Standing	One foot is on front a bit, bend over that foot and stand again by raising and stretching arms		No	Balance problem
4.Upper arm stretching	Standing	Reach the arms at back	Upper body joints	Yes	
5.Circular hip exercise	Standing	Hands on hips, one foot is moved to front, side and back to draw a half circle	Hip pitch and roll	Yes	
6.Upper body stretching	Sitting	Link the hands by raising arms horizontally, stretch upper body back and forth	Shoulder roll + hip pitch	Partially	Nao can not link his hands on front due to embodiment constraint in shoulder roll joints
7.Shoulder rolls	Sitting	Sit up, move shoulders up and down while breathing carefully		No	Nao does not have movable joints
8.Chest stretching 1	Sitting	Link the hands at back, stretch chest area		No	Shoulder joint angles' interval does not allow
9.Neck stretching	Sitting	Move the head back and forth, to the right and left	Head pitch and yaw joints	Yes	
10. Neck side stretching	Sitting	Gently tilt the head to the left and right in turn		No	No head roll joints available in Nao
11. Hand stretching	Sitting	Open and close the hand, spreading the fingers apart		No	Nao does not have motors for hands
12. Chest stretching 2	Sitting	Raise arms and place hands behind your head and stretch	Upper body joints	Partially	Linking okay, but no stretching, no movable shoulder joints
13. Standing quadriceps stretching	Standing	Bend your right knee, grasp your right ankle, gently pull up toward your bottom, repeat for left ankle	Whole body joints	Partially	Nao should tilt sidewards in order to balance itself.
14. Whole body stretching 2	Sitting	Extend one leg horizontally, stretch the upper body over this leg without bending knee		Partially	Nao's body length ratios are different from humans.
15. Back reach	Sitting	Exhale and gently move arms backward. Pause, then return to the start position	Shoulder roll+pitch	Yes	
16. Upper hind leg and back stretch	Sitting	pull the knee to the head level by lowering back		No	Upper body and upper leg lengths are not convenient, hip pitch joint interval is not large enough.

Table 3. Analysis of Strength Exercises Considering Nao Humanoid Robot

Strength Exercises	Stance	Description	Robot Joints	Doability	Problems
1.Knee extensions	Sitting	Make the legs horizontal to the floor by moving lower leg up and down from the knee	Knee pitch	Yes	
2.Back strength	Sitting	Upper arm is horizontal to the floor, lower arm makes 90 degrees with upper arm, link the arms at front then open towards to the back and close again		Partially	Nao can not link its hands in front because of shoulder roll joint constraints, but can bend the lower arm a bit to perform the motion
3.Shoulder circles	Sitting	Circle shoulders forward and backward		No	Nao does not have movable joints
4.Upper leg strength 1	Sitting	Raise both of the feet up slightly	Knee pitch	Yes	
5.Arm raising and side lumber strength	Sitting	Hold a ribbon, bend over hip to the floor, raise the upper body and arms to the cross side	Hip roll + upper body joints	Partially	Common hip pitch yaw joint does not allow to perform the motion as in human. However, hip roll joint is used to do a similar motion.
6. Upper inner leg strength	Sitting	Raise both feet up, open and close them in a lateral way	Hip pitch+hip roll+knee pitch	Yes	
7. Upper leg strength 2	Sitting	Pull the knee to the head level rapidly and extend leg without bending afterwards		No	Upper body and upper leg lengths are not convenient, hip pitch joint interval is not large enough
8. Ankle exercises	Sitting	Move ankle up and down	Ankle pitch	Yes	
9. Shoulder strength and abdominal region exercise	Sitting	Make the arms cross over each other on the knee (upper body tilted forward), stretch strongly to the back by raising arms up		Partially	Shoulder roll interval does not allow crossing the arms over each other
10. Ankle circles	Sitting	Extend knee and move foot in a circle	Knee pitch+ankle roll+ankle pitch	Partially	Nao does not have ankle yaw joints. Ankle pitch and roll joints are used to perform the motion
11. Lower hind leg strength	Standing	Hands on hips, move through heel to toe on one foot while the other is stable for self balance		Partially	Due to balance problem, the motion can not be performed smoothly while going through heel to toe
12. Upper hind leg strength	Standing	Hands on hips, move forward the legs from the hips	whole body joints	Partially	Due to balance problem, Nao tends to tilt sidewards
13. Shoulder and leg exercise	Standing	Bend knees, cross arms, then stand up while raising the arm up to the head level		Partially	Shoulder roll interval does not allow crossing the arms over each other
14. Hip side extension	Standing	Lift your leg to the side as high as comfortable, then return to the stand position again	Hip roll joint	Partially	Due to balance problem, Nao tends to tilt sidewards
15. Calf raises	Standing	Rise up on toes as high as you comfortably can		No	Balance problem
16. Hip extension	Standing	Extend your leg backward, keeping knee straight.	Hip pitch + knee pitch	Yes	
17. Sit to stand	Standing	Lean forward with bending knees and lower yourself towards the chair as if attempting to sit.		No	Balance problem

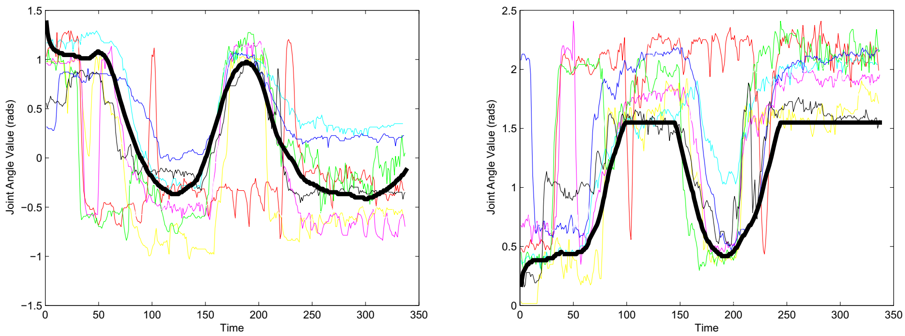

Fig. 5. Left Shoulder Pitch (left) and Right Elbow Roll (right) joint angle trajectories for one gesture. The trajectory of the coach is indicated with a bold line, and the individual subjects are indicated with thin lines. The values are shown without smoothing. In each case, only one subject displays an incorrect gesture.

elderly having difficulty in properly interpreting the instructions of the human coach. In order to correctly explain the action where needed, the Nao should provide qualitative markers, for instance "pull your knee to the head level", instead of saying "rotate the knee joint 10 degrees and set the hip pitch angle to -40 degrees". The definition and proper use of a set of highly explanatory and practical qualitative markers is at the moment left as a future work.

5 Experimental Study and Results

The proposed system was tested with eight people whose ages are between 25 and 35 in a preliminary user study. Ethical committee approval is pending for the study with a large set of elderly people in the nursing home. The exercise session performed by the robot contains five different gestures. Three of them are arm related exercises (arm stretching and relaxation exercises), while the remaining are leg strength exercises.

The subjects received a brief description about the overall scenario before starting the test. During the session, each gesture is explained verbally by the robot in the beginning of the gesture exhibition. The subjects were monitored during the session and skeleton joint angles were recorded to analyse how the subjects were synchronized with the robot and the performance of the subject in imitating the gesture accurately. Figure 5 shows angles for two different tracked joints (for all subjects) during two different gestures. The gold standard is the gesture performed by the coach, which is indicated by a bold line. Except for one subject, all subjects were able to perform these gestures correctly.

We have also assessed the interaction with a post-exercise study. The subjects were requested to fill out a survey to measure the effects of the system after the exercise session. The survey contains questions adapted to our scenario based on the the Game Experience Questionnaire (GEQ) that measures different emotional responses to a game-like experience [26]. We used questions related to positive and negative affect, flow, immersion and challenge. A 5-point Likert scale was used with 1 being the lowest score, and 5 being the highest. Each component is tested with five questions, which results in 25 questions in total, given in a random order to the subject. The results are given in Table 4. The designed system scores high on immersion and positive affect, and on a smaller degree on flow. The flow is affected by the lack of smoothness in the robot's gestures. The scores on challenge and negative affect are small, indicating an easy-to-use system.

Table 4. Results of user evaluation

Component	Mean	Standard Deviation
Positive Affect	3.625	0.7206
Negative Affect	2.2	0.6761
Flow	3.25	1.1301
Immersion	3.675	0.3694
Challenge	2.65	0.7151

6 Conclusions

Most assistive robotics research focuses on helping the elderly to perform daily tasks more easily (like intelligent wheelchairs or easily operated robotic arms), or to monitor the elderly to ensure their safety and well-being. Yet robotic solutions for improving the physical condition of the elderly can be very useful. We describe a method to teach a humanoid robot to perform physical exercises for the purpose of implementing a robotic physical exercise coach. We have observed an actual training program running in an elderly care facility, and provided a taxonomy of exercises. Our initial results reveal that one third of these exercises can be easily performed by the robot, one third can be partially performed, and one third requires some additional tricks to overcome the physical limitations in the robot. We use audio feedback to deal with these cases in particular.

At the moment, we are comparing the success of the robot in providing coaching by letting different groups of subjects observe either a human coach or the robot. The system then converts the performed gestures of the subjects into a skeleton representation, and compares joint angles to the ground truth (i.e. the angle representation of the human coach) to compare the two demonstration methods.

A proper assessment of an elderly assistance scenario requires monitoring of the elderly over long periods of interaction, as well as follow-up assessments, typically spanning one or two years of observations in total to get a thorough understanding of the physical implications [27]. We work with an elderly care facility, where the robotic fitness coach was warmly received by the inhabitants.

Our plans for near future include assessing interaction aspects for perceived usefulness, perceived ease of use, and for variables that relate to social interaction [28].

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