DEVELOPING A FITNESS COACH ROBOT FOR ELDERLY PEOPLE IN ASSISTED LIVING ENVIRONMENTS

by

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ABSTRACT

DEVELOPING A FITNESS COACH ROBOT FOR ELDERLY PEOPLE IN ASSISTED LIVING ENVIRONMENTS

Ambient assisted living is a concept that summarizes the effort to create intelligent technologies to help elderly people to live without constant supervision by 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. The primary goal in this endeavor is to develop a preventive approach of health care for elderly, sometimes summarized by the concept of ‘successful aging’, where the subject retains and sustains his physical and mental well-being. Both physical and mental health require regular activity (possibly in the form of regular exercises) for this purpose. In this study, we aim to develop a fitness coach robot which can help elderly people in their daily physical activities. The overall scenario includes two different parts. First, a human supervisor performs fitness motions and the robot will learn them by analyzing the behavior of the demonstrator. In the second part 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. The gestures were selected from an actual training programme at an elderly care home in order to create a real world scenario. A humanoid robot, Nao, is used for this study and a 3D depth sensor, Microsoft Kinect sensor is utilized to analyze human gestures.

ÖZET

ÇEVRE DESTEKLİ YAŞAMA ORTAMLARINDAKİ YAŞLI KİŞİLER İÇİN EGZERSİZ EĞİTMENİ ROBOTU GELİŞTİRİLMESİ

Çevre destekli yaşam, yaşlı kişilerin sürekli bir sağlık personeli gözetimi altında olmaksızın, akıllı teknolojiler yardımı ile yaşlılığın getirdiği fiziksel ve sosyal etkilerin yarattığı problemlere çözüm sunmak ve kişilerin yaşam kalitelerini artırmak için oluşturulmuş bir kavramdır. 'Sağlıklı yaşlanma' olarak da özetlenebilen bu konsept çerçevesinde öncelikli amaç, yaşlı kişilerin sağlık hizmetleri için koruyucu bir yaklaşım izleyerek kişinin fiziksel ve zihinsel sağlığını devam ettirebilmesidir. Fiziksel ve zihinsel sağlığın korunması düzenli egzersiz hareketlerinin yapılmasıyla mümkündür. Bu çalışmada, bahsedilen teknolojinin bir parçası olarak, yaşlı kişilere günlük egzersiz hareketlerinde yardımcı olabilecek bir egzersiz eğitmeni robotu geliştirilmesi amaçlanmıştır. İnsan ve robot arasındaki etkileşim senaryosu temel olarak iki farklı kısımdan oluşmaktadır. İlk kısımda, robot bir dizi egzersiz hareketleri sergileyen egzersiz eğitmeninin hareketlerini analiz ederek bu hareketleri nasıl yapması gerektiğini öğrenecektir. İkinci kısımda ise, robot eğitmenden öğrendiği bu hareketleri yaşlı kişinin karşısında yaparak ona gösterecek ve ondan kendisini tekrar etmesini isteyecektir. Kişinin hareketleri doğru yapıp yapmaması üzerine geri bildirimlerde bulunarak istenilen performansın elde edilebilmesi için yaşlı kişiye yardımcı olacaktır. Robotun yapması planlanan egzersiz hareketleri gerçek dünya ile benzerlik taşıması açısından bir huzur evinde gerçekleştirilen toplu egzersiz seansları sırasında sergilenen hareketlerden seçilmiştir. Çalışmamızda Aldebaran şirketi tarafından üretilen insansı robot Nao ve insan hareketlerini analiz edebilmek için Microsoft Kinect algılayıcısı kullanılmıştır.

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b_t	Filter trend output at time t
d	A demonstration
d_t	Modeled dynamic configuration of the robot at time t
D	A set of demonstrations
g	Gravitational acceleration
i	A link
I_x	x component of inertia moment
I_y	y component of inertia moment
j	A joint
j_1	Shoulder pitch joint angle
j_2	Shoulder roll joint angle
j_3	Elbow roll joint angle
j_4	Elbow yaw joint angle
J	A set of joints
J_1	A position of joint in 3D coordinate system
J_2	A position of joint in 3D coordinate system
k_t	Robot kinematic configuration at time t
L_1	Upper arm length
L_2	Lower arm length
m_i	Mass of link
m_t	Human kinematic posture at time t
M	Mapping from a set of states to another
$P(A_r)$	Convex hull of robot's feet support
s_t	Full state of the robot at time t
S	A set of states which are not fully observable
S_t	Filter output at time t
T	Transition function
V_1	A vector in 3D coordinate system

V_2	A vector in 3D coordinate system
x_{ZMP}	x coordinate position of ZMP
XY	XY plane
XZ	XZ plane
y_t	Filter input at time t
y_{ZMP}	y coordinate position of ZMP
YZ	YZ plane
Z	A set of states where the learner has access to observe

α	A damping factor
γ	A damping factor
θ	An angle
θ_{ix}	Angular velocity around x axes
θ_{iy}	Angular velocity around y axes
π	A policy
$\sigma(A_r)$	Center of mass of the robot
ϕ_x	Angle of joint x

LIST OF ACRONYMS/ABBREVIATIONS

2D	Two Dimensional
3D	Three Dimensional
API	Application Programming Interface
ARMA	Auto Regressive Moving Average
COM	Center of Mass
DBN	Dynamic Bayesian Network
DOF	Degree of Freedom
ECA	Embodied Conversational Agent
GEQ	Game Experience Questionnaire
HMM	Hidden Markov Model
HRI	Human Robot Interaction
IK	Inverse Kinematics
IMU	Inertial Measurement Unit
GMM	Gaussian Mixture Model
GMR	Gaussian Mixture Regression
kNN	k Nearest Neighbor
LfD	Learning From Demonstration
MoCap	Motion Capture
NN	Neural Network
PCA	Principal Component Analysis
RGB	Red Green Blue
RGB-D	Red Green Blue - Depth
ROS	Robot Operating System
SAR	Socially Assistive Robot
SGPLVM	Scaled Gaussian Process Latent Variable Model
SOGP	Sparse On-line Gaussian Processes
ZMP	Zero Moment Point

1. INTRODUCTION

Recent developments in robotics has brought robots into prominence for human service in indoor environments. Composition of a multitude of key technologies allows developing robots which can be used to perform a variety of tasks such as cooking, shopping and guidance. As the capabilities of service robots increase, the idea of a robot assistant for humans in their living environments gained importance and started to play a role in real life scenarios. The main aim of service robots is to assist people by facilitating daily tasks, such as serving a soda to the user from the refrigerator.

The world population is rapidly aging. According to a report of the World Health Organization, the proportion of the world's population over 60 years will double from about 11% to 22% between 2000 and 2050 [1]. The statics shows the same trend also in Turkey. The proportion of elderly population in the total population is expected to increase to 20.8% in 2050 [2]. This increase in the number of elderly all over the world motivates the service robot research towards the application of assisting elderly in their daily tasks.

Ambient assisted living is a concept that uses technological solutions as a way of supporting elderly care, and controlling expanding health costs [3]. As people get older, most of them need support as a consequence of decrease in their mental and physical capabilities. Ambient intelligence refers to intelligent environments, which can help the elderly to handle the problems caused by the impacts of aging. The primary goal is to sustain the mental and physical health of the elderly while providing comfort to her in her own home.

Performing regular physical exercise has well-known benefits for the elderly [4]. Through improvements in blood pressure regime, it helps reducing heart-related problems, most importantly helping the prevention of coronary heart diseases. The improvement of the lipid profile also helps prevention of type 2 diabetes [5]. Other benefits of regular exercise include osteoarthritis, osteoporosis, neurocognitive function improvements, decreased mortality and age-related morbidity [4]. 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 [6], the introduction of smart technologies to supervise the latter may help in bridging the gap.

This study proposes an approach to create a robotic fitness coach, and primarily concerns itself with the physical, rather than the mental fitness of the subject. A typical human fitness coach performs a series of complex tasks including the assessment of the 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 them are beyond the abilities of current robotic and expert systems. The system we propose has the much more modest goal of only demonstrating a set of predesigned physical exercises to an elderly subject, and giving constructive feedback on the performance.

The adaptation of the exercise program to the subjects' individual needs however 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 in an automated manner from the fitness coach.

The first challenge for the proposed method in this study is analyzing the coach's gestures autonomously to form a good representation of the performed gesture. This is accomplished by using the recently popularized RGB-D camera approaches to track the body of the coach. The second challenge is that the robot possesses a different physical embodiment than a human fitness coach (or the subject, for that matter) and hence it is an imperfect intermediary interface. We design and implement a method for mapping human gestures to the robot. The performance criteria for the learned gestures of the robot's are the stability and smoothness of the actual move, as well as the perceptual validity of the gestures of the robot. This validity is determined by the correct transfer of the intended gesture.

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 here is to synchronize 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, whenever necessary.

The system was evaluated through the experimental user studies which were carried out with a group of young subjects from our department, a set of the residents of Etiler nursing home and a small set of middle aged people who are unfamiliar with the concept of exercising. The results show that the visual and vocal explanation performance of the system are good enough to allow the subjects perceive the exercise motions and replicate with the robot. On the other hand, the subjects stated that the system suffers from the lack of social aspects which are necessary to motivate them for exercising with a robot.

The organization of the rest of the thesis is as follows. In Chapter 2 we give brief information about whole body human motion imitation on bipedal robots, imitation methodology, human-robot interaction and the currently developed robotic exercise coach systems and their advantages and shortcomings. In Chapter 3, an overview of the system is presented. Our proposed system is detailed in Chapter 4. We provide initial results obtained with a working prototype, and report a set of preliminary user studies in Chapter 5, and conclude the thesis with a discussion of the challenges and future directions envisaged for this work in Chapter 6.

2. BACKGROUND

2.1. Systems for Capturing Human Motion

Human motion capture is the process of recording human movements. It is used in a variety of industrial and research areas such as film making, computer animation, medical applications, and robotics. In recent years, these systems have been utilized heavily in robotics with the idea of robot learning from human demonstrations. Remote controlling of robots, and teaching robots some simple tasks such as getting a spoon from table and bringing it to its mouth are some of the applications [7]. Depending on the system used in motion capturing, 2D or 3D position information of human joints can be recorded.

MoCap systems used in human motion imitation in robotics can be reviewed under two main categories: optical and non-optical systems.

2.1.1. Optical Motion Capture Systems

Optical systems use data captured from image sensors. Traditionally, data captured from sensors is used to construct the 3D position of a subject using one or more cameras calibrated to get overlapped projections. Data acquisition can be done using markers located on the subject as shown in Figure 2.1 or in a markerless way by using advanced computer vision algorithms to process the whole image captured by cameras in order to extract information about movements of the subject as shown in Figure 2.2 [8]. Although, marker based approach requires the subject to wear special costumes, it increases the accuracy in position information of human body parts.

Do *et al.* [10] use both markerless and marker based optical motion capture systems to imitate human upper body motion using the humanoid robot ARMAR-IIIb. Commercially available Vicon system [11] is used as the marker system. The markers are located on the predefined body parts desired to be tracked. The system uses artificial reflective markers and infrared cameras. Each camera emits a light signal, which is reflected by the markers. The

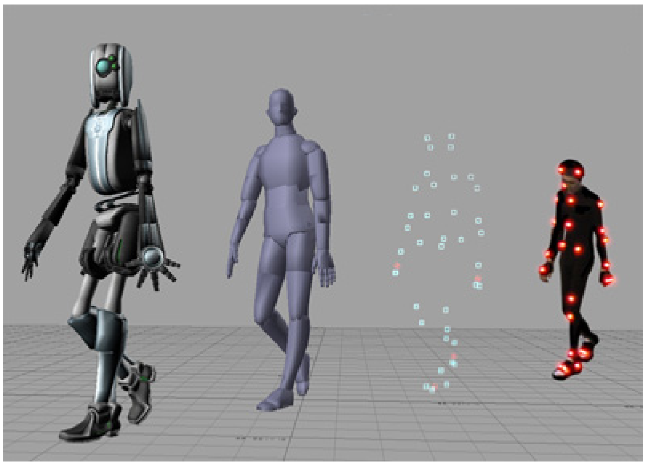


Figure 2.1. Markers are located on the desired body parts of the subject. Captured motions are then simulated on a 3D human body model, from [9].

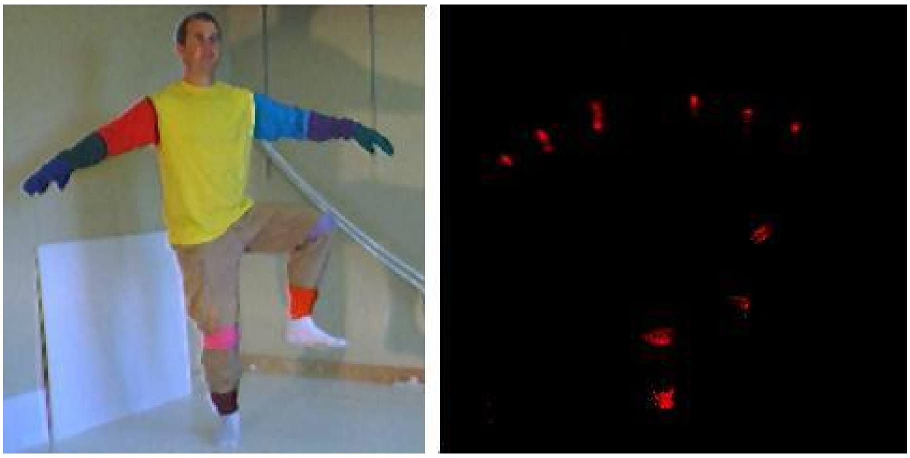


Figure 2.2. The probability map for the 2D locations of each joint for the video frame shown on the left, from [8].

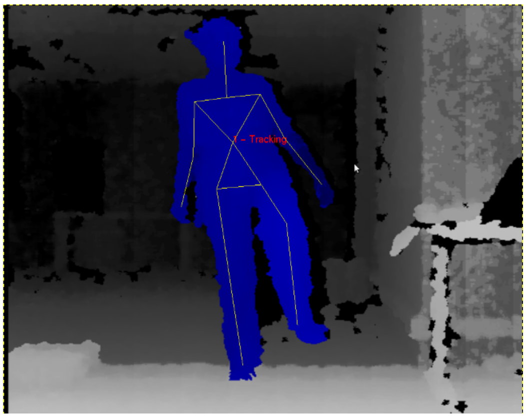


Figure 2.3. Depth image and fitted skeleton using the OpenNI software.

2D position information can be gathered from each camera and the information from all of the cameras is used to extract 3D position data of human body parts with markers. They use built-in stereo cameras of the robot and apply a color segmentation algorithm for the image processing part and a particle filter algorithm with 3D kinematic model of human body for movement tracking. Their markerless system can do an on-line tracking of the upper body movements of the subject with a frame rate of 15 Hz. on a powerful computing hardware. On the other hand, Do *et al.* depict that, besides time consuming preparation and calibration setup of Vicon system, it provides more accurate human motion capture with high capture rates. Grimes *et al.* present a study on dynamic imitation of a humanoid robot using marker optical system [12]. Cole *et al.* extend Grimes *et al.*'s study and do pose estimation using monocular video [8]. They factor in additional sensory noise to make the system more robust to a larger degree of noise and uncertainty.

On the other hand, with the emergence of low cost RGB-D cameras, markerless optical systems lost their significance in human motion capturing. Kinect sensor [13], which was released first in 2010, provides an RGB camera, a depth sensor and a multi-array microphone as a hardware platform. The point cloud returned by the depth sensor can be processed to detect humans in the scene and a software is used to fit a skeleton on the detected human depth map. Afterwards, the joint positions are revealed using the skeleton depth information. A depth image and fitted skeleton using open source natural interaction library OpenNI is depicted in Figure 2.3.

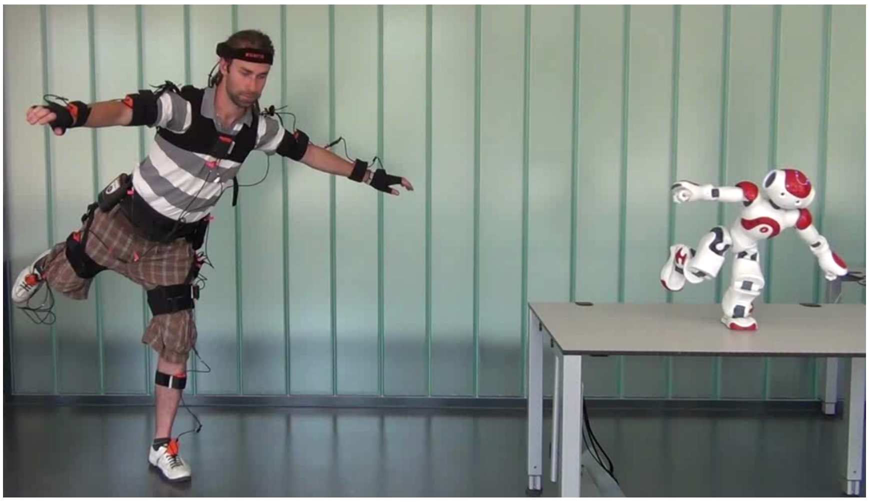


Figure 2.4. Koenemann *et al.* use inertial MoCap system to imitate gestures on the *Nao* robot, from [14].

2.1.2. Non-optical Motion Capture Systems

Non-optical motion capture systems can be grouped into three classes which are inertial systems, exo-skeleton systems and magnetic systems. Inertial systems use inertial sensors (mostly gyroscopes to measure rotation rate in the joints) to record movements. Exoskeleton systems require the subject to wear a skeletal like structure and as they move, the relative movement changes in this structure are recorded. Magnetic systems calculate position and orientation by the relative magnetic flux of three coils attached to each of the joints. These systems have higher costs relative to the optical MoCap systems, however they are much more accurate.

Inertial systems are the frequently used ones in motion imitation studies. Koenemann *et al.* use Xsens MVN motion capture system consisting of inertial sensors attached to the body to imitate the gestures on humanoid robot Nao [14]. Their system is shown in Figure 2.4. Miller and colleagues use accelerometer, magnetometer, and gyroscope readings provided by an IMU sensor to estimate the orientation of a rigid body [15]. They use this information for teleoperation of NASA Robonaut.

2.2. Learning and Recognizing Human Motions for Robotic Systems

Human motion analysis is a research area which has a wide range of applications. We can group the studies under three main classes as surveillance, analysis and control [16]. Surveillance applications are developed for tracking and automatically observing humans in a variety of environments such as airports, subways, and homes. Depending on the aim of the study, the methods followed to analyze human motions can change. For example, in the airport surveillance case, the aim can be locating a person by tracking the walking pattern of him on a recorded video. On the other hand, more detailed motion analysis should be applied in an ambient assisted living case where we want to recognize the motions performed by the elderly such as walking, lying, exercising, etc. to allow the ambient intelligence system to respond accordingly. Analysis applications such as performance evaluation of an athlete or gait analysis of a patient in a rehabilitation center requires more domain specific approach. Control applications where the estimated motion parameters are used to control some intelligent devices are the ones which have been most popular among others recently. Interactive games, virtual reality applications and remote device control systems are in this group. This application group also covers the human controlled robotic systems such as telerobotics, task-oriented human-robot collaboration etc.. In telerobotics, the user can control the robot by sending motion commands via a wireless connector. However, this do not always require a joystick to give direction and speed to the motors of the robot. The user can control the robot remotely using his own body actions such as raising his left arm to make the robot raise his left arm with efficient human motion detection and recognition algorithms. One of the most popular methods applied in robot learning using human demonstration is named as “learning from demonstration method” or simply “imitation learning” in the literature.

2.2.1. Learning from Demonstration Method

The problem of learning the mapping between the real world states and the robot system generates motivation for many research studies in robotics. Manual programming of robots for a particular task such as gathering and conveying a box requires many redundant efforts. Since, any small change in the definition of the task such as a change in the size of the object which robot interacts, or any shift in the position of the object and/or the obstacles on the path of the robot to reach the goal requires to start afresh. *Learning from demonstration (LfD)* method has brought a new ground on programming robots in this context. The theory behind this methodology is to learn a policy to map state-action pairs between the real world and the robot from examples or demonstrations performed by a human teacher. In this method, the complexity of the search space for learning reduces dramatically. Good examples performed by the human demonstrator can be used as a starting point in the search space to reach a possible solution or bad examples can be eliminated from the search space to reach an acceptable solution. As expected, the former is a better way in terms of complexity issues.

There are various studies which apply LfD method to teach a task to the robot. A human demonstrator can move the limbs of the robot to achieve a specific task such as grabbing trash from a table top and putting it into a dust box. Kinesthetic sensors located on the joints of the robot are generally used to measure the speed, the translation and the rotation that arises in the joint. The trajectory followed to achieve the task should be learned by the robot to be able to regenerate the demonstration. However, the initial and final positions in this trajectory can be different for different experimental settings (i.e. if the position of trash and dust box are changed for the scenario depicted above). Hence, multiple demonstrations for the same task with different settings are necessary to make the robot learn how to achieve conveying some objects from the table top to the dust box. Multiple examples are also required to handle non precise behaviors of the human demonstrator and sensor noises. Hence, it appears necessary to develop a method that would consolidate all demonstrated movements.

LfD can be considered as a subset of *Supervised Learning*. Teacher demonstrations are used as the training dataset. We address the formal construction of the LfD problem from the study of Argall *et al.* [17].

Definition 2.1. *The* LfD method *is a 7-tuple* (S, A, T, Z, M, π) *where:*

- S *is a set of states which are not fully observable.*
- A *is the set of actions.*

- *T is the state transition function which determines the probabilities of the possible next states given the current state S and the current action a.* $T(s'|s,a) : S \times A \times S \rightarrow [0,1]$
- *Z is a set of states where the learner has access to observe through mapping $M : S \rightarrow Z$.*
- *π is a policy which selects actions based on observations of the world state.* $\pi : Z \rightarrow A$

A demonstration $d \in D$ is a pair of observations and actions: $d = (z_j, a_j), z_j \in Z, a_j \in A$. The training dataset can be built by the demonstration or the imitation approach. For the demonstration approach, the trials are performed on the actual robot learner. Hence, there is no need for embodiment mapping between the robot and the teacher. In the imitation approach, the training dataset is constructed by collecting data from the sensors located on the teacher or the external observation of human demonstrator using a vision system.

Policy learning calculates a function which approximates the state to action mapping, $f() : Z \rightarrow A$ [17]. The general approaches for this mapping can be grouped as classification and regression methods. Classification methods produce discrete outputs which are action classes for robot state inputs. Gaussian Mixture Models (GMM), Hidden Markov Models (HMM), k-Nearest Neighbor (kNN) classifiers are some of the techniques used in learning from demonstration problems. Lockerd *et al.* uses Bayesian likelihood method to select appropriate actions for button pressing task [18]. Pook *et al.* maps states to motion primitives at first, then uses kNN to classify primitive membership [19]. The classified motion primitives are recognized in the whole demonstration using HMM and combined accordingly to regenerate the egg flipping task using a robotic hand and arm.

Regression approaches map demonstration states to continuous action spaces [17]. Various regression methodologies have been used for LfD problems. Neural networks (NN) are used to drive a van autonomously on a variety of roads [20] while Sparse On-line Gaussian Processes (SOGP) teaches an AIBO robot to perform basic soccer skills [21]. Furthermore, trajectory learning problems are widely solved by using Gaussian Mixture Regression (GMR) models which are also applicable to the imitation of human movements scenarios. Since, it is a significant approach to the first part of our project, we describe it in a more

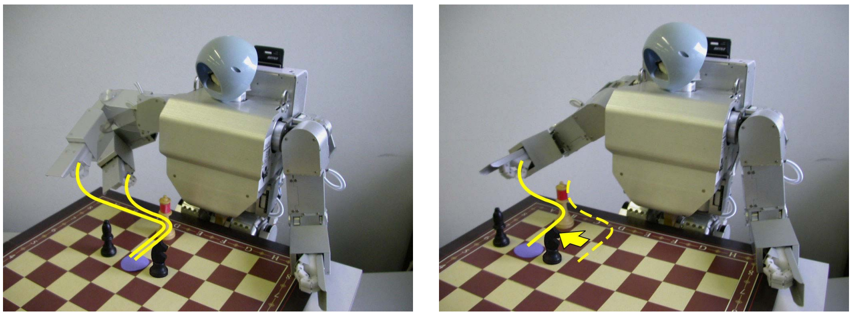


Figure 2.5. Experimental setup for chess piece manipulation task, from [22].

detailed manners giving some application results from the literature.

Calinon *et al.* applies GMM and GMR to reproduce joint trajectories to solve constrained manipulation tasks [22]. First, they project joint angles and hand path motions collected from a human teacher into a latent space using GMM spreading across spatial dimensions of the motion. In the second step of probabilistic encoding, HMM is utilized to extract spatio-temporal variations. Finally, GMR is used to learn those latent space parameters and generalize the trajectories considering the constraints in the task space.

In Figure 2.5, the experimental setup environment used in [22] for the task of moving a chess piece to a position on the chess board is shown. Two demonstrations of the task performed on the robot by moving its arm and hand. Then, a different setup with a change in the position of chess pieces are used to test the learned model. The robot successfully moves the chess piece by selecting a controller that fulfills the task constraint determined after demonstration phase.

The four joint angle trajectories of the robot arm are collected through five demonstrations. A number of gaussians is then fitted on the trajectories. The gaussians which have too small variances means that the task is constrained during the time interval the gaussians span. When considering the scenario, the path to bring the hand of the robot to the chess piece can vary a lot depending on the initial position. On the other hand, after grasping the piece, the trajectory should be followed in order to put the piece to the desired position requires a nearly same joint angles in all of the demonstrations.

For our scenario, the task constraints can be thought as joint angles which should be performed in order to do an exercise motion activating the necessary bones and muscles successfully. However, the demonstrations should be performed by an expert physical fitness coach who is eligible to comment on the non constrained and constrained parts of a motion. Such an approach also encodes the domain knowledge of the expert to give efficient feedback to the subject.

2.3. Real Time Human Motion Imitation

Humans discover and learn new skills through imitating each other and sharing a joint attention. This biologically viable learning method inspires researchers to make the intelligent agents acquiring new qualities by imitating more competent other intelligent beings or humans. This approach seems to provide an easy and efficient way to develop robots which can imitate our actions without additional programming. Especially, for motion tasks which require complex kinematic and dynamic calculations, imitation learning methodology brings an efficient solution with some challenges related to the difference in physical capabilities of a robot and a human.

The word "imitate" may not simply imply replicating the movements of the model but rather is an attempt to achieve the task in the model by developing a novel action which has the highest similarity with the one in observed model [23]. Although most of the currently available imitation systems are developed using *off-line learning* where a model is learned from collected demonstrations before the action is reproduced using that model, real time imitation methodologies play a significant role in terms of immediate feedback possibility of demonstrator to the action of the robot. The demonstrator can enhance the imitation accuracy of the robot by observing it and giving feedback on the performance or changing his own demonstration manner of the desired task to make the robot imitate himself in an easier way. Hence, real time imitation allows the robot and the human to control each other in a closed loop.

As depicted above, imitation may not be a mere replication of human movements spread along time. The robot may need to understand the intention of the demonstrator behind the action he performs. This arises fundamental questions for research for imitation learning. Breazeal *et al.* presents these questions as follows in [23]:

- *How does the robot know when to imitate?* The robot should understand the intention of the instructor to perform the observed action and has to consider when to imitate in order to maximize its own benefit. However, this requires the robot to have deep cognition and planning skills.
- *How does the robot know what to imitate?* As humans, we have complex motion, cognition and social abilities and are competent enough to manage and control all of them simultaneously. Furthermore, we do not behave in a completely task oriented manner and can perform inconsequential actions which do not have any value for achieving the target task. For example, an instructor may wipe his brow while trying to open a glass jar [23]. The robot should focus on the vital actions to imitate the target task correctly (hand motions of the instructor for this case) and should ignore redundant behaviors (wiping brow) in order to determine what to imitate in a demonstration correctly.
- *How does the robot map observed actions into behavioral responses?* Since, the robot and the human have different physical embodiment capabilities, direct mapping of human joint angles to robot generally does not produce feasible solutions for the imitation problem. The robot should realize the motion performed by the demonstrator and the limits of its motor capabilities, then should try to find a suitable mapping to its own motor coordinates by considering his physical constraints. This is also known as *correspondence problem* in the literature. The details are given in Section 2.3.1.
- *How does the robot evaluate its actions, correct errors, and recognize when it has achieved its goal?* This question should be answered depending on the goals and the intentions of the task. If the task is to open a glass jar, then opening and putting the lid of the jar to the table is the expected outcome of the task. However, as in our case (imitating exercise motion shown by demonstrator), the accuracy in mimicking the whole trajectory done by the human demonstrator can be the decisive criteria on how well the robot achieve the task.

Next, we give some details of the methodologies used in human motion imitation on humanoid robot systems. Some of the studies only cover upper body imitation, while the others propose solutions for the whole body imitations considering the stability problem. Hence, we choose to present them under two different topics focusing on the challenges each has.

2.3.1. Correspondence Problem

The correspondence problem can be considered as the inability to apply direct matching between the body parts of two different agents. To be able to imitate an agent, the imitator should have more or the same competent physical skills with the demonstrator or should develop an action control realizing its own capabilities. Furthermore, the agents may not necessarily have the same embodiment properties even for the ones that belong to the same species. Hence, the correspondence problem is a fundamental challenge to be handled in the imitation scenarios.

Alissandrakis *et al.* propose the ALICE (Action Learning via Imitation Corresponding Embodiments) framework which creates a *correspondence library* to relate the actions of the imitator to the actions of the imitator agent depending on its embodiment and affordances [24]. Their key point is to compose a correspondence library which stores actions that can be applied as a responce to the perceptions of the imitator. When a new action is observed to imitate, the agent first queries the library and does a metric evaluation in order to measure its effectiveness. If the existing actions are not satisfiable, then a new action is generated and added to the library. Hence, their solution constructs an incrementally growing library to solve correspondence problem.

2.3.2. Upper Body Motion Imitation

Bandera *et al.* use a look-up table approach to imitate human upper body motions using humanoid robot HOAP-I with 20 degrees of freedom, including 4 on each arm [25]. When a new observation arrives, the similarity confidence level of it with the ones in the memory is considered. If the robot has already imitated the behavior previously, the corresponding action is fetched from the memorized behaviors. Otherwise, it performs an active imitation

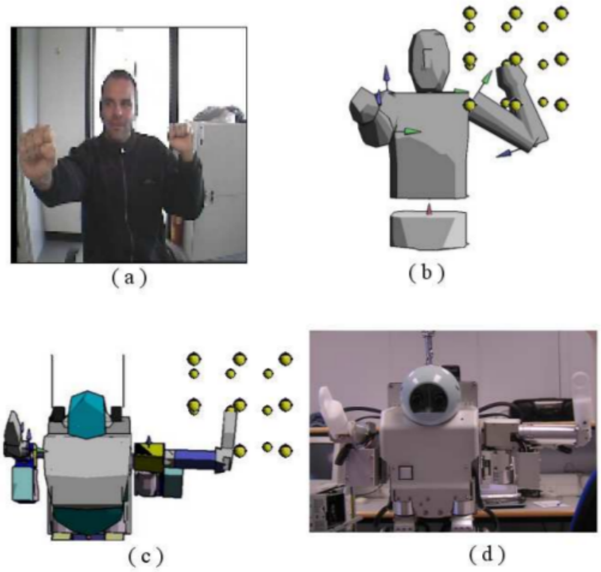


Figure 2.6. Overview of the grid based solution to correspondence problem in visuo-motor mapping, from [25] : a) demonstrator; b) human model with the grid (only sub-region related to the gesture is shown); c) humanoid model; d) humanoid imitator

by visuo-motor mapping. A grid-based approach is adopted to solve the correspondence problem in visuo-motor mapping. They only use positions of the hands of the demonstrator to imitate arm gestures, not necessarily respect to follow arm joint angles of imitator. In grid based approach, the grid provides a quantization of the demonstrator range of motion and its cells can be related to the imitator grid. The dimensionality differences of the limbs of demonstrator and imitator is solved by re-scaling. This approach learns a function which determines the imitator cell associated to a demonstrator cell. Their approach is shown in Figure 2.6.

In [26], Matsui *et al.* map human upper body motions to the android called *Repliee Q2*. They use 3D marker based motion capture system to measure the positions of limbs of the human and the humanoid. Since *Repliee Q2* is modeled after a Japanese women, it has the appearance of a human. However, their kinematically different design prevents one-to-one correspondence. Their aim is to control the android to get same postures with the human using position information of limbs, since the dimensions of body parts of android are almost the same with the ones of human. Joint angle extraction is not an appropriate solution because of the kinematic differences.

Figure 2.7. *Repliee Q2* imitates upper body postures of performer. The number represents the steps, from [26].

Matsui *et al.* adopt a three layer neural network to construct a mapping from the human's marker positions to the joint angles of android. This feedforward neural network takes the error calculated by a feedback controller as the difference of marker positions of human and android to integrate system noise into the learned model. The initial weights of the network is obtained from another neural network encoding the mapping between the joint position to joint angle of android which is previously trained by 50000 samples collected by moving the android randomly. The experimental results are shown in Figure 2.7.

2.3.3. Whole Body Motion Imitation

2.3.3.1. Stability Problem. Whole body motion imitation puts another burden namely the *stability problem* on the imitation task. Stability refers to satisfying balanced postures of the robot with prevention of falls. Bipedal robots are inherently unstable systems. Several control algorithms are applied to support balanced motions on those systems to achieve locomotion and motion tasks successfully as presented in Section 2.3.3.2. Stability can be divided into the static and dynamic stability based on the stability criteria:

(i) *Static Stability:* In case of static stability, the robot is stable without any need of motion at every moment of time. Robots with three or more legs are statically stable so that their center of mass is completely within the *support polygon*. Support polygon refers to the convex hull which is defined by the ground contact points.

(ii) *Dynamic Stability:* A dynamic stable robot is stable while moving. Dynamic stability can allow for greater speeds but require harder control since there are many dynamic kinematic parameters that should be considered in real life problems.

Most of the bipedal robotic systems are not dynamically stable. There is no general algorithm to solve the problem of dynamic stability for bipedal robots; often used approaches are based on the *zero moment point (ZMP)*. The ZMP is the point where the robot has to base on to keep its balance. When the robot should move forward it has first to compute the ZMP and after that it has to step the appropriate leg exactly to the computed position. The ZMP is often described in robotics as the point on the ground where all momentums are equal to zero [27]. The ZMP can be calculated using equation 2.1 and 2.2 where $(x_{ZMP}, y_{ZMP}, 0)$ are the ZMP coordinates in the Cartesian coordinate system. (x_i, y_i, z_i) is the mass centre of the link i, m_i is the mass of the link i, and g is the gravitational acceleration [28]. I_x and I_y are the inertia moment components, θ_{ix} and θ_{iy} are the angular velocity around the axes x and y.

$$x_{ZMP} = \frac{\sum_i m_i(z+g)x_i - \sum_i m_i x z_i - \sum_i I_{iy}\Theta_{iy}}{\sum_i m_i(z+g)} \tag{2.1}$$

$$y_{ZMP} = \frac{\sum_i m_i(z+g)y_i - \sum_i m_i y z_i - \sum_i I_{ix}\Theta_{ix}}{\sum_i m_i(z+g)} \tag{2.2}$$

2.3.3.2. Literature Survey. Dariush *et al.* solves whole body control of humanoid robot ASIMO by formulating the human to humanoid mapping as a task space control problem [29]. The retargetting algorithm produces joint space trajectories commanded to the robot. The objective is to track desired task descriptors extracted from performance of human demonstrator by satisfying the constraints such as joint angle limitations, collision avoidance and balance. The balance problem is solved by shifting the torso in x and y directions while controlling the ZMP.

A team from Robocup Standard Platform Soccer League, *rUNSWift*, applies multi-goal reinforcement learning to dynamically stabilize the Nao robot by using lateral movements. They state that, the system allows self-stabilization of the robot through challenging tasks such as standing on either foot, standing upright and switching between these behaviors.

In [14], Nao humanoid robot is used to perform complex whole body imitation task. Koenemann *et al.* uses highly accurate Xsens MVN motion capture system to extract positions of the limbs of the performer. They consult to inverse kinematic solutions to handle mapping from human to the robot. To be able to perform dynamically balanced real time imitation, the system actively balances the center of mass over the support polygon of the robot's feet. They first find valid feet positions of the robot in the target task space so that the feet can be planar and the center of gravity falls into the support polygon. Then, leg joint angles are calculated via inverse kinematics.

A recent study which uses a Kinect sensor as the motion capture modality refers to direct angle transformation of corresponding joints between the human and the robot [30]. Extracted joint angles using the Kinect sensor are preprocessed to obey joint limits. To obtain a more exact motion trajectory with the performer, an offset to handle the distance bias between motors of robot is added to each of the joint angles. Nguyen *et al.* also integrate ZMP and center of mass (COM) balance controllers into the system to be able to imitate lower body motions successfully. Successful reproduction of the performed motions by their approach can be seen in Figure 2.8.

Seekircher *et al.* also use the Kinect sensor with the Nao humanoid robot for whole body imitation scenario [31]. The parameters of the model used for angle transfer from the human to the robot are optimized using three different algorithms which are CMA-ES, xNES and PSO. All of the algorithms perform well in learning models which can reproduce stabilized motions.

Dance motions are taught the *HRP-IS* humanoid robot by imitation using camera based MoCap system [32]. They extract *primitive motions* from the performer's continuous and complex dance movements. Then, these primitive motions are realized on the robot by considering the limits of the joint angles and balance problem. They keep the robot's feet fixed

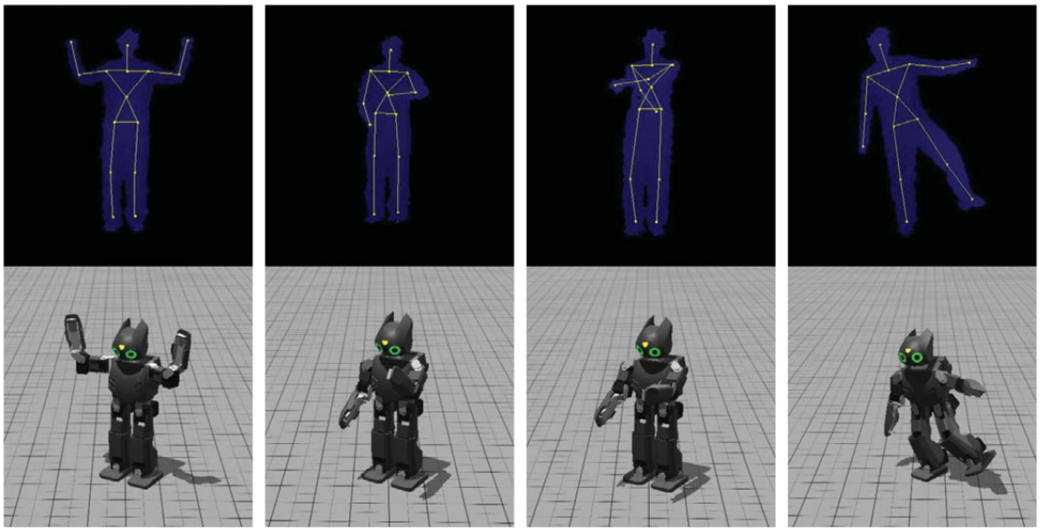


Figure 2.8. Virtual *Darwin-OP* humanoid imitates the full body motions of demonstrator, from [30].

while dancing but the balance problem still exists for fast movements of torso such as swinging arms. ZMP is controlled to be kept within the support area during motion imitation.

Nakaoka *et al.* also use imitation learning to perform whole body dance motions on the *HPR-2* humanoid robot [33]. Upper body motion and lower body motions are processed separately, then the generated motions are combined to reproduce the original dance motion. Upper body motions captured by marker based MoCap system are directly processed by the upper body processor which calculates the corresponding joint angles in the robot by performing inverse kinematic calculations. For lower body motions, primitive segments are detected by analyzing the velocity of a body part related to a target primitive. The predefined task primitives are *squat, roll, pitch, yaw* for waist, and *right step and left step* for foot (see Figure 2.9). The system expects the lower body motions of the dancing performer as a combination of those task primitives. Each primitive has its own parameters such as the destination angle for the primitives *roll, pitch, yaw* and waist height distance between the initial state and the medium state for the primitive *squat*. The position of the waist and feet are set to realize the detected primitive with its parameters. Then, joint angles of the legs are calculated by inverse kinematics (IK). The task processor also refines the primitive parameters if they do not satisfy physical constraints of the robot. The calculated whole body joint angles are processed by the yaw compensation module before sending

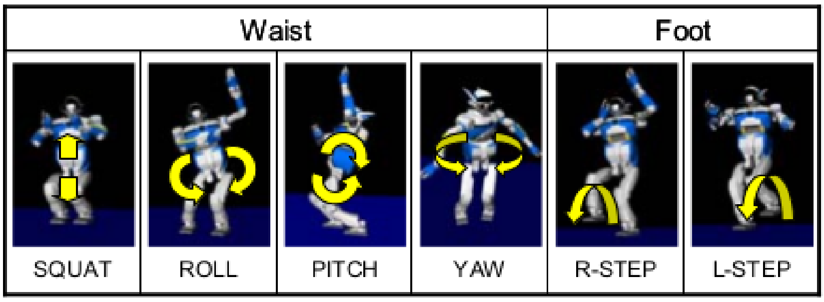


Figure 2.9. Task primitives, from [33].

Figure 2.10. Imitation performance of the *HPR-2* robot, from [33].

to the ZMP compensation filter. The yaw compensation module prevents slipping of the supporting sole when the robot stands on one foot. It adjusts the waist yaw joint according to the yaw moment. Finally, whole joint angles are sent to the ZMP compensation filter with the desired ZMP to balance the robot. Upper body is shifted if necessary to keep ZMP in support polygon. Experimental results are shown in Figure 2.10.

Chalodhorn *et al.* use a nonlinear autoregressive network to learn a model which takes the joint angles projected into low dimensional space and gyroscope signals which are used to determine the balance state of the robot [34]. According to the predicted sensor value by the model, a point which corresponds to the current action of the performer is selected in the search space of low dimensional latent space in order to optimize balance. This point is then converted into high dimensional joint angles by inverse mapping.

Grimes *et al.* adopt a probabilistic approach using dynamic Bayesian networks (DBN) to learn the mapping function [12]. Bayesian networks provide a theoretical framework for combining prior kinematic information (from observing a human demonstrator) with prior dynamic information (based on previous experience) to model and subsequently infer motions which, with high probability, will be dynamically stable. DBN is used to infer imitative motions. It depicts a set of variables with arrows representing conditional dependencies between variables. Variables which are observed are shaded blue. Latent action variables are modeled as generating both the human kinematic postures m_t and the robot kinematic configuration k_t. The modeled dynamic configuration of the robot d_t, augments the kinematic information to form the full state of the robot s_t. All conditional dependencies are shown between the first and second time slices. Subsequent time slices are shown with the arrows based on the state variable s_t, revealing the simple first order Markovian structure of the DBN.

Nonlinear time scaling of the joint trajectories refers to the acceleration or deceleration of the motion in order to satisfy the necessary ZMP trajectory for dynamically balanced motions [35]. However, this approach may require the joint angle trajectories to be accelerated to catch up the performer's motion and be in synchronization. Joint angle trajectory optimization is formulated as to minimize the difference between imitated and performed motion while satisfying constraints related to balancing and the physical properties of robot.

Shon *et al.* advocate that, at its core, imitation learning reduces to a regression problem. They apply Gaussian process regression method to map human joints to the ones of the robot [36]. The model learns a two way transformation; first from the human joint space to the latent space and from that latent space to the robot joint space. The model is trained with joint angle pairs of robot's and human's. They also state that, the usage of several low dimensional latent spaces (5 separate 2-D latent spaces dividing the skeleton as *left leg, right leg, left arm, right arm,* and *torso*) is advantageous compared to using a single, high dimensional latent space (a single 10-D space). In other words, several regression models yield better results than using a single, more complex regression model. The experimental results for walking imitation case are shown in Figure 2.11.

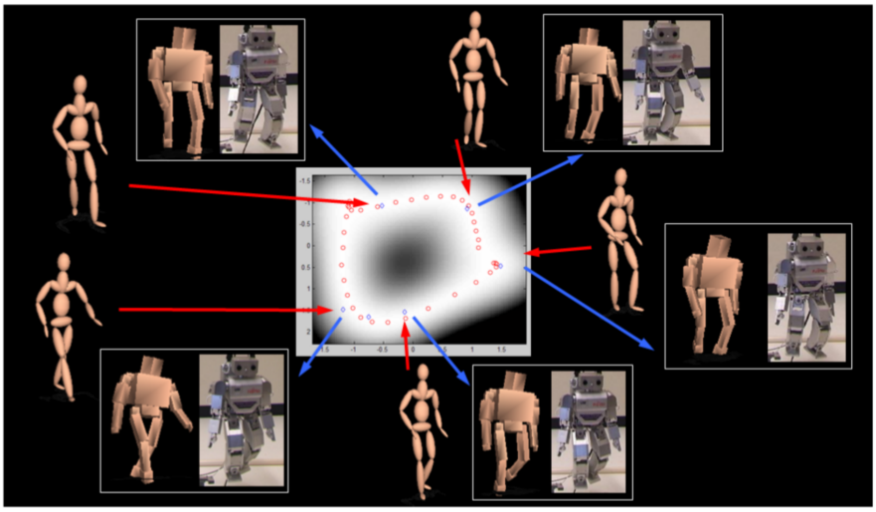


Figure 2.11. The *HOAP-2* humanoid robot imitates gait. The red arrows show mapping from human joint space to 2-D latent space while blue arrows show mapping from selected testing points (shown in blue in latent space) to robot joint angle space, from [36].

2.4. Human Robot Interaction

Social intelligence refers to the ability of living beings to negotiate social relationships with each other and with their environments. The richness of this capability shows the human beings' difference from other living beings. As humans, we desire to communicate with our environments by sharing emotions with using social signals such as speaking, laughing and crying. In return, we anticipate others as socially interactive agents.

The idea of social intelligence for robots has a recent history [37]. Integrating social abilities to a robot stems from two fields. First, biologically inspired robotics proposes to develop robots by mimicking the nature. This idea implies the concept of possibility of interaction between a robot and its environment. Secondly, the robots which are planned to be used in indoor environments with humans have to respect the human's way of living and behave accordingly. This requires providing a healthy communication between a robot and a human. At that point, social capabilities of a robot plays great role to be acceptable by ourselves and integrated into our environments naturally.

In this case, researchers in the human-robot interaction (HRI) field put an open to debate question. “What social skills does a robot needs to satisfy the social needs of the human he interacts and which measures can be used to determine the quality of the interaction?” These questions should be answered and evaluated in terms of the requirements and properties of the application area where the robot is used and the characteristics of the society whom the robot interacts. On the other hand, the diversity in the human-robot applications prevents researchers to define common metrics to measure the performance of human-robot interaction. Steinfeld *et al.* say that, metrics can be classified to facilitate comparison of research results [38]. They analyze HRI in terms of three aspects: performances of the robot, human and the system. They determine some fundamental tasks frequently utilized in robotics applications as navigation, perception, management, manipulation and social, and describe metrics specific to each task. In our scenario, social interaction plays a significant role. Hence, we describe some metrics specific to the task “social”.

According to T. Fong *et al.*, there is a distinct difference in biologically inspired designed robots and functionally designed robots [39]. In the latter, the purpose is to develop a robot which seems to be socially intelligent for certain cases when interacting with human, even if the internal design does not adopt the aim to have social intelligence like humans. Therapy robots and health care robots are generally classified into this group. Steinfeld *et al.* list the social metrics given below, although this division for intelligent robots affects the critic of *social effectiveness* [38].

- *Interaction characteristics:* The robot can have its own interaction style. The conversation can be shaped by analyzing the context of the interaction or the social signals of the humans. This metric is highly important for biologically inspired social agents. Hence it is not considered for robotic fitness coach.
- *Persuasiveness:* The robot can change attitudes or feelings of the human as in autism therapy.
- *Trust:* Trust is an important metric to measure the relaxation of the human when interacting with robot. Since, it affects other emotions such as engagement and being persuadable. Unexpected behaviors of the robot can cause anxiety in humans.
- *Engagement:* Engagement is “the process by which two (or more) participants es-

Figure 2.12. The *Paro* robot is used to establish social interaction with elderly people, from [41].

tablish, maintain and end their perceived connection during interactions they jointly undertake." [40]. The effect of various engagement methods such as dialogue and emotional transfer through gestures can be measured to decide on the engagement power of the robot.

- *Compliance:* The physical and social properties of robot affect the cooperation a human provides to a robot in scenarios where the human and the robot take action together. This metric is critical for health care to evaluate the performance of the system.

2.4.1. Influences of Human Robot Interaction on Elderly

As people get older, over time physical and mental disabilities emerge. This requires a supervision of elderly in order to retain his life. On the other hand, a continuous care of an elderly puts major workload and stress on the supervisor. At that point, the idea of a robotic assistant to reduce the necessary effort or complete replacement of the supervisor with a robot stresses the importance of study of robot-elderly people interaction.

Wada *et al.* present their user study with the robot *Paro* (see Figure 2.12) in a nursing home over five months [41]. They allow elderly people to play with *Paro* two days a week. The subjects are questioned to choose their mood level using the face scale [42] shown in Figure 2.13 before and after the interaction sessions. They evaluate the effect of the interaction of the robot on the moods of elderly people. Results show that there is a significant increase in the happiness level of elderly people after interacting with *Paro*.

J. Pineau *et al.* develop a cognitive agent, *NurseBot*, for nurses and elderly people in

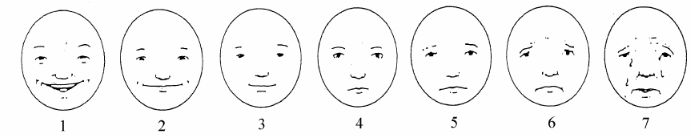


Figure 2.13. Face scale to evaluate person's moods, from [42].

assisted living facilities [43]. The robot autonomously provides reminders and guidance to the elderly. It uses speech and visual inputs as well as user preferences to decide on the action plan and behave accordingly. Another important feature of this robot is being adaptable to the properties of subjects. Its planning mechanism takes into account the physical and psychological aspects of the subject. The robot interacts with the elderly via a speech unit and touch sensitive graphical display unit. The user study performed with *NurseBot* shows the success of the usage of the robot assistance in elderly care by handling the differences in individuals' behaviors thanks to its user adaptable planning mechanism. On the other hand, they do not perform a study to grade the interaction performance of *NurseBot*.

2.4.2. Aspects of Human Robot Interaction in Exercise Coach Robot Case

In [44], Fasola *et al.* present a comprehensive study on design methodologies and their effects on the user's psychology for the case of robotic fitness coach system. They perform a user study with 33 subjects which is a high number to be able to evaluate the findings statistically reached at the end of the experiments.

The design principles considered in the study [44] are as follows:

(i) *Motivating :* Performing exercise motions correctly and regularly is a challenging task for an elderly. Hence, the motivating aspects of HRI play significant role for increasing the overall effectiveness of the system. Fasola *et al.* employ a feedback mechanism based on scoring the success of the subject in performing the motion shown by the robot. This approach gamifies the exercise interventions and motivates the subject to do better to reach higher scores.

(ii) *Fluid and Highly Interactive :*Flow stands for the turn taking principle in social interactions to allow the dialogue to be continued without interruptions. For the robotic fitness coach system, the robot perceives and recognizes the gestures of the user and provides active feedbacks for correction or motivation. Then, the user adjusts his own gesture according to the feedback received from the robot. This allows the flow of the interaction between robot and the subject.

(iii) *Personable :* The robot should interact with the user using the individual information about it to establish close and personal relationship. This personal relationship is important for the robotic exercise coach case to achieve success since this system is based on one-on-one interaction between the subject and the robot. The subject anticipates personal interest from the interaction with robot. Bickmore *et al.* say that, referring to the user by her name increases intrinsic motivation [45]. Moreover, Fasola *et al.* propose to develop a 'personal' fitness coach robot which remembers the past performances of the user in exercise interventions and provides feedback to the user's individual performance level by evaluating the overall performances up to now.

(iv) *Intelligent :* Users of an autonomous system want to trust on the working principle of the system so that the system is intelligent enough to perceive its environments correctly and respond in a logical way accordingly. This should be a key component in an assistance robot system to be able to establish a close relationship with the user since the robot is responsible to help and care the user. The user should feel in a way that the robot is intelligent enough to not do anything wrong which can harm the user and should believe that the system is competent to provide functionalities expected from such a system.

The following should be considered to satisfy trust condition in robotic fitness coach system according to Fasola *et al.* [44]:

- Evaluation of the user performance should be accurate. The robot should not provide redundant feedbacks when the user performs the gesture sufficiently. Likewise, deficiency in performed motions should be detected and the user should be warned to correct herself in order to make her believe that the robot tracks her continuously.
- Feedback phrases should be varied to prevent repetitions. Repetitions tend to cause negative effects on user motivation [46]. For example, the robot can select randomly from a positive feedback list consists of phrases like "excellent", "so

good", "nice job" to not be repetitive.

(v) *Task-driven :* Although the design criteria presented above plays a significant role for developing an effective system, the main goal of the system should not be forgotten. The task aimed is to help elderly people to retain their well being by exercising with the help of proposed system. Hence, the main objective is to provide consistency in interaction towards accomplishing the health care task [44]. Otherwise, the perception of the robot by the user may change into entertainment rather than caring.

Fasola *et al.* perform 20 minute long exercise sessions for four times during two weeks. They apply questionnaires to evaluate the interaction and the robot's effect on the users at the end of first and fourth exercise sessions. They request the users to give scores on some pre-defined adjectives that describe the questioned component of the system on a 10 point scale. Their measures are classified under three topics which are the evaluation of the interaction, the evaluation of the robot and user performance measure. The evaluation of interaction consists of *enjoyableness of the interaction* and *value or usefulness of the interaction*. For the evaluation of the robot, they measure *companionship of the robot*, *helpfulness of the robot*, *intelligence of the robot*, *social attraction towards robot*, *social presence of the robot* and *the robot as an exercise partner*. Besides, questionnaires applied to the users, they use user performances during exercise interventions as an evaluation metric. The adjectives and measures to describe the questioned components used in study by Fasola *et al.* are listed in Table 2.1.

They relate each of the measurement to the design principles described above to evaluate the overall system effectiveness. The experiments are held in two groups of people. The first group of subjects interacts with a virtual robot and the second one is exercised with the real robot. The subjects favor the real robot to the virtual robot for all of the design criteria discussed. This finding from Fasola et al. contrasts with the results from Heerink *et al.* [47] who also study the effect of the embodiment differences on interaction with elderly people. Fasola *et al.* explain the reason behind this variation as the number of times the experiments done before collecting the results of questionnaires. They say, the initial results collected after the first exercise session show more or less same values for the subject groups with virtual

Table 2.1. Questionnaire details taken from the study of Fasola *et al.* [44].

Evaluation of Interaction		
Measured Component	*Adjectives Used in Questionnaire*	*Scaling*
Enjoyableness	enjoyable, interesting, fun, satisfying, entertaining, boring, exciting	1-10
Usefulness	useful, beneficial, valuable, helpful	1-10
Evaluation of Robot		
Measured Component	*Adjectives and Questions Used in Questionnaire*	*Scaling*
Companionship	bad/good, not loving/loving, not friendly/friendly, not cuddly/cuddly, cold/warm, unpleasant/pleasant, cruel/kind, bitter/sweat, distant/close	1-10
Helpfulness	useful, beneficial, valuable, helpful	1-10
Intelligence	competent, clever, intelligent, smart	1-10
Social Attraction	I think, the robot could be a friend of mine, I think, I could spend a good time with the robot, I could establish a personal relationship, I would like to spent more time with the robot	1-7
Social Presence	unsociable/sociable, impersonal/personal, machine-like/life-like, insensitive/sensitive While you were interacting with the robot, how much did you feel as if it was a social being? While you were interacting with the robot, how much did you feel as if it was communicating with you?	1-10
As an Exercise Partner	How much did you enjoy exercising with the robot? How likely would you be to recommend the robot as an exercise partner to your friends? How much would you like to exercise with the robot in the future? How much have you been motivated to exercise while interacting with the robot?	1-10
User Performance Measures		
Game Type	*Measures*	
Exercise Game	average time to gesture completion number of seconds per exercise completed number of failed exercises number of movement prompts feedback percentage	

and real robot. However, the answers of questions returned from this two groups changed significantly through the end of fourth exercise intervention. The results of user performance measures which are *completion time of gestures* and *feedback percentage* also support the proposal of Fasola *et al.* [44].

2.5. Currently Developed Rehabilitation and Fitness Coach Systems

A social assistive robot (SAR) is a socially interactive robot whose primary goal is assistance [48]. Our approach is positioned in the related literature primarily as a SAR with non-contact assistance. There are a number of existing SAR systems [49], Heerink gives a detailed overview of these in [50]. Most of these systems focus on monitoring the elderly [43], 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 [51], and lack the social aspect completely, which is found to be useful in elderly care scenarios [41]. On the other hand, we briefly present those systems as they have some common properties with the exercise coach systems such as performing motions and evaluating the performance of the subject. We will investigate the currently developed fitness coach systems basically by considering the following:

- Are exercise motions learned from a human demonstrator or predefined static motions used?
- If there is an embodied agent, is he able to perform leg motions or only arm motions?
- Is the agent capable of giving feedback to the subject to enhance the performance of the elderly?

2.5.1. Virtual Rehabilitation and Fitness Coach Systems

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 [52]. This system requires the precise specification of each gesture, and does not involve automatic imitation based learning. However, the system provides verbal feedback and allows the subject to see his own gestures in a small frame on the screen. This frame also shows the important key positions of the currently performed gesture by the animated instructor which should be repeated by the subject to perform the motion correctly. In [53] a web system is proposed for facilitating repetitive movement training for stroke rehabilitation. The subject is tracked with two cameras attached to a home PC.

Some systems use a robot just for mobility, and use screens for interaction. In [54], the authors use a tablet PC interface mounted on a Pioneer robot to implement an exercise coach system. The exercises are displayed on the tablet screen, and the subject is queried from time to time via short questionnaires to adapt the system automatically. In [55], a table-top robot was proposed as a daily weight-loss advisor, which also used a touch screen interface. It also gives feedback to the user by comparing the goal to the activities done by the user. It also try to help the user to reach the goal by suggesting diet programs.

2.5.2. Physically Embodied Robotic Rehabilitation and Fitness Coach Systems

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 [45] 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 relational robots and nonrelational robots, and found that the subjects rated the robot to be more engaging and interesting [56].

Fasola *et al.* propose a robotic exercise coach for chair aerobics which are predefined and coded statically. The authors evaluate the motivational aspects of this scenario extensively [56]. 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. The

Figure 2.14. A wheeled robot *Bandit*, from [56].

system also includes an imitation game which allows the subject to show some gestures to the robot and waits for him to imitate herself. This can be used to teach arm gestures to robot by human demonstrator as in our study. However, the authors do not give any information about it.

For the analysis of the gestures performed by the elderly, visual assessment is preferred to wearable sensors for ease of use. In [57], 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. In this approach, there are no gesture-specific weights assigned to the different joints, whereas in most physical exercises, the value and range of some angles are much more important than others.

Fasola and Mataric use a Bandit robot in [56] that has a humanoid torso with 19 degrees of freedom (DOF) on a mobile base. (6 DOF arms (x2), 1 DOF gripping hands (x2), 2 DOF pan/tilt neck, 1 DOF expressive eyebrows, and a 2 DOF expressive mouth). A standard RGB camera is used for gesture analysis, and the visual analysis is performed against a uniform background (i.e. a black curtain). This puts restrictions on the exercise motions which can be performed. The range of the arm movements is planar and constrained to the sides of the body to maximize the vision system accuracy when tracking the subject. However, the authors note that future versions will incorporate RGB-D solutions to the problem. Their experimental setup is depicted in Figure 2.14.

Matsusaka *et al.* develop the *TAIZO* robot as an exercise assistant to a human demonstrator [58]. In their scenario, human demonstrator leads the exercise program and the robot follows. *TAIZO* can be controlled by both voice commands and key inputs from a keypad. Their research focuses on the demonstrative of these two different modalities. The *TAIZO* robot can perform exercises which requires to use whole body joints by means of its humanoid embodiment. They utilize a motion database which contains preset joint angle values for each exercise motion and a speech database which contains prerecorded voice commands as the explanations of gestures. On the other hand, the system does not adopt ant feedback mechanism.

Recio *et al.* use the *Nao* humanoid robot to research the affect the assistance of robot in geriatric physiotherapy rehabilitation [59]. Nine preselected exercises are programmed statically, and are employed during physiotherapy interventions. The experiments are applied using a real robot and the simulated version of the same robot on a screen. Each exercise is assigned to three different experimental setups which are physiotherapist only, physiotherapist and virtual robot and physiotherapist and the real robot. Recio *et al.* say that, the embodiment and speed of the Nao affect the mimicking capabilities of the subjects of Nao's motions. The subjects respond to the robot and try to synchronize himself with Nao if their speed is similar. Otherwise, this effect is not observed. Moreover, experiments with real Nao show that, the subjects are more careful in mimicking the ones done with the virtual robot. Another important finding of Recio *et al.* is that, the physical inabilities of the robot results in performing the exercise not in a totally correct way. This causes the subject to repeat an incorrect exercise observed from the robot. This problem also applies in our study. We try to bridge the gap induced by the physical constraints of the robot using vocal explanations of gestures.

In [60], the *RoboPhilo* humanoid robot is used in a physical exercise scenario that is similar to the one we propose. This robot has 20 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. On the other hand, using a RGB camera in such an experimental setup requires providing the required illumination conditions in the room and the user should be away from camera in a distance dependent on his height to be able to process whole body image. The robot gives vocal feedback when the gesture it performs is successfully imitated by the elderly.

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 [61] and [62]. A taxonomy of games for rehabilitation is given in [63].

Another study related to the rehabilitation robots is the one performed by Ros *et al.* which is realized with children as a target user group [64]. They develop a system which teaches a dance to hospitalized children according to their capabilities. The methodology adopted in the study regards adapting the dance movements and the robot's interaction based on the physical capabilities and personal traits of the child. They use *Nao* as robot platform and the dance movements are designed using the Choregraphe software. They have a feedback mechanism to guide the child during the dancing interventions. The session is then adapted to make the robot dance along with the child according to the responses of child to these feedbacks. The priliminary results of their user study are promising so that the child tend to engage more with the robot as the robot adapts itself depending on the observations of the child. Hence, their interaction design criteria can also be applied in our robotic fitness coach scenario with elderly people in order to increase the motivating aspect and effectiveness of the system.

3. SYSTEM OVERVIEW

In this chapter, we outline a whole process from imitation of exercise motion on robot which is performed by human demonstrator to exercise interventions of robot with an elderly. The overall system is overviewed in two different parts in Section 3.1 and 3.2.

3.1. Imitation of Exercise Motions Performed by Human Demonstrator by Robot

In this part of the project, the robot learns exercise motions from human demonstrator by imitating him in real time. Exercise motions are acquired as 3D skeleton data extracted from depth images of the human performer. For the exercise motion imitation case, contrary to other many imitation studies, mimicking body movements considering the positions of limbs in 3D space is not a correct approach. Since, the physical properties of the human and the robot differ considerably, the necessary joint angles to move the joints into the same position in 3D space relative to the torso changes also for the human and the robot. However, the value of angle performed in a joint affects the magnitude of contraction in the muscles bonded to the bones articulated in that joint. To be able to perform an exercise motion in a 'healthy way', the joint angle value and the duration of the joint in that angle value are vital criteria. Hence, our imitation is based on joint angle values extracted from the skeleton data.

Since direct transformation of captured motion data is not applicable due to dynamic and kinematic constraints, the data must be converted to realize on the robot. This process mainly consists of generating motion data for the robot. Because of the stability problem for the motions including leg movements, this process adopts different approaches for arm motions and whole body motions. Arm movements require solving the correspondence problem only, while whole body motions also require to take the balance constraint into the consideration. Whole body motion generation uses the recognition of support foot additionally. To sum up, motion generation uses both the captured skeleton data and the result of analysis of support foot for leg movements. Through the conversion process, the speed and smoothness of motion can be edited by adjusting capturing frequency.

We adopt real time imitation to allow the performer observe the imitated motion on the robot, and adjust his own demonstrations if the imitated motion is not satisfactory. For example, due to the angle interval of elbow roll joint of the *Nao*, it can not perform gesture, *putting hands on head*, like we humans can do. Hence, the performer is expected to recognize this inability and try to achieve such a gesture considering its physical constraints (such as raising shoulder more instead of bending elbow roll too much).

We use the *Nao* robot platform which has also virtual physical model on some simulation environments such as Choregraphe and Webots. The validity of the generated motion data is first tested on Webots simulation environment which has whole real world physics which allows to test balance states and falling conditions and, then performed on real robot. The overall system for this part of the project is depicted in Figure 3.1.

In the following sections, the details of each process are presented.

3.1.1. Capturing Human Motion

Although the *Nao* robot used in the project has two RGB cameras with 960p resolution output at 30 fps frequency, we utilize the Kinect sensor as the motion capture system. In Figure 3.2, a human demonstrator in front of Kinect is shown. There are two underlying reasons behind this choice among various MoCap system described in Section 2.1 :

(i) Since, we are interested in extracting joint angles in 3D space, depth information in addition to RGB image is necessary. Multiview camera systems can be used to get depth information by locating the RGB cameras accordingly in order to have intersected view angle. However, it is a challenging setup and replacement is not easy. In our scenario, the elderly does not always have to perform exercise interventions in the same place of home and the system should have a straightforward utilization for every day use (or three days in a week). Hence, mobility and plug and play properties of the setup play a vital role. We also do not consider marker based MoCap systems for the same reason. They have inappropriate designs and calibration difficulties even if their high accurate outcomes bring advantage over optical MoCap systems.

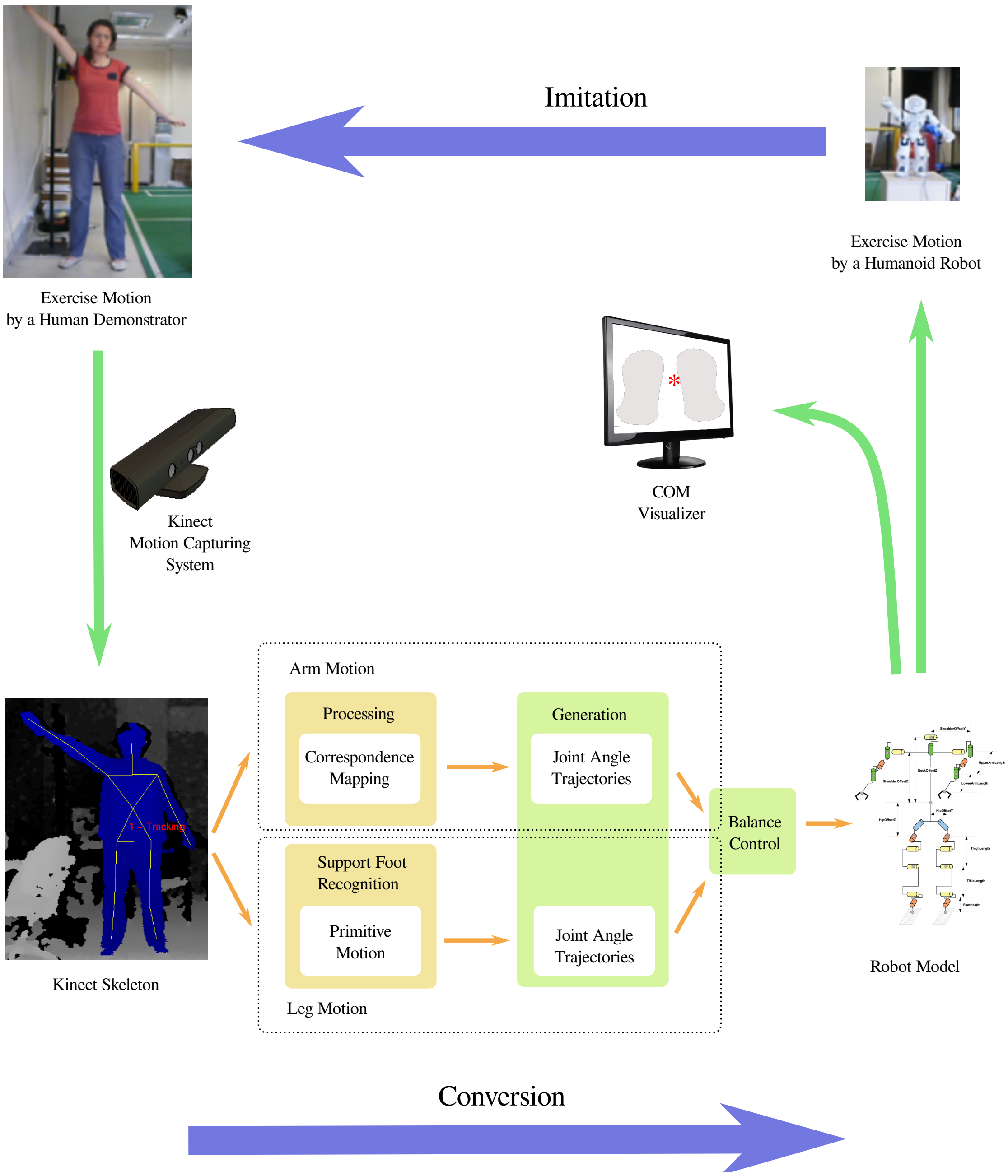


Figure 3.1. The overview of imitation system.

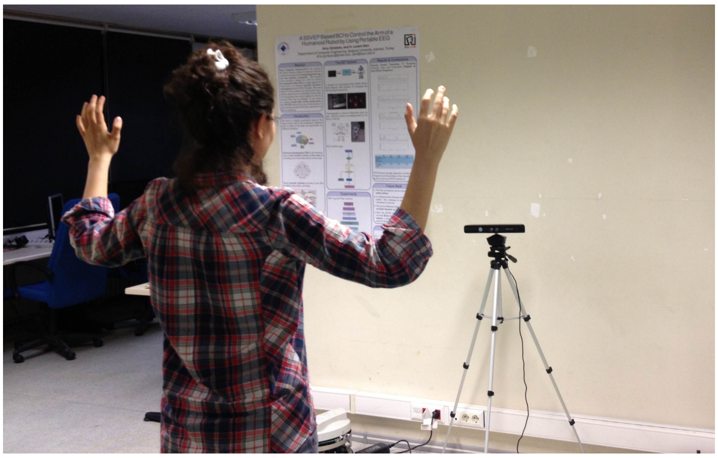


Figure 3.2. The Kinect sensor as motion capture system.

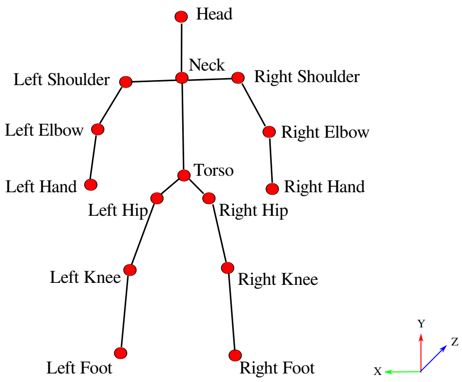


Figure 3.3. Joints provided by skeleton fitted on human depth image using OpenNI framework.

(ii) RGB-D cameras are novel sensing systems that capture RGB images along per-pixel depth information [65]. Research problems such as processing of this depth information to construct the models of objects in the view of the camera or enhancing performance of mapping algorithms stand in another side and are not our primary concern in this project. Hence, we utilize the OpenNI framework for processing of depth images which is used for the development of 3D sensing middleware applications by many developers [66]. It provides skeleton information with 3D positions of each 15 joints as shown in Figure 3.3. The skeleton is fitted to the human model extracted from the background environment in depth image.

3.1.2. Conversion of Motion Data

Direct transformation of joint angles of human to robot is not possible due to differences in the physical properties of the human and the robot. Hence, a correspondence process before realizing motions on the real robot is inevitable. Arm joint angle conversion is handled by a correspondence mapping module by matching 3+1 DOF system of the arm of the human (3 DOF in shoulder and 1 DOF in elbow) to 2+2 DOF system of robot arm (2 DOF in shoulder and 2 DOF in elbow). Furthermore, joint angle limits are scaled considering the maximum rotation degree of robot joints.

Realization of leg motions on the robot requires a more complex conversion approach. Some exercise motions are performed on only one foot such as stretching the left leg to the left. Direct transformation from the human to the robot causes the robot to fall in those states where the support foot changes. Hence, our system recognizes the change in the support foot mode of the robot (standing on both feet, standing on only left foot and standing on only right foot) and a selected statically balanced motion primitive considering the previous support foot state of the robot and current support foot state is integrated into the imitated motion. In other cases, the static balance condition, where the projection of COM should be within the support polygon, is regarded. If the joint angle configuration gathered from the human demonstrator disturbs static balance, then the robot does not move into that configuration and stays still. We adopt such an approach since the adjustment of joint angles to keep in balance the robot may damage the characteristic of the exercise motion. Instead, the human performer should try to perform the motion in a slightly different way keeping the robot in balance by looking up the COM visualizer provided by our system. Of course, the human demonstrated should be aware of constraints of the exercise motion and sacrificeable joints in terms of angle value. The demonstration scenario has a closed loop as shown in Figure 3.4.

3.2. Performance of Exercise Motions by Robot in an Exercise Intervention with Elderly

This part of the project covers the exercise interventions performed by elderly person. The flow is shown in Figure 3.5. The robot demonstrates previously learned exercise motions

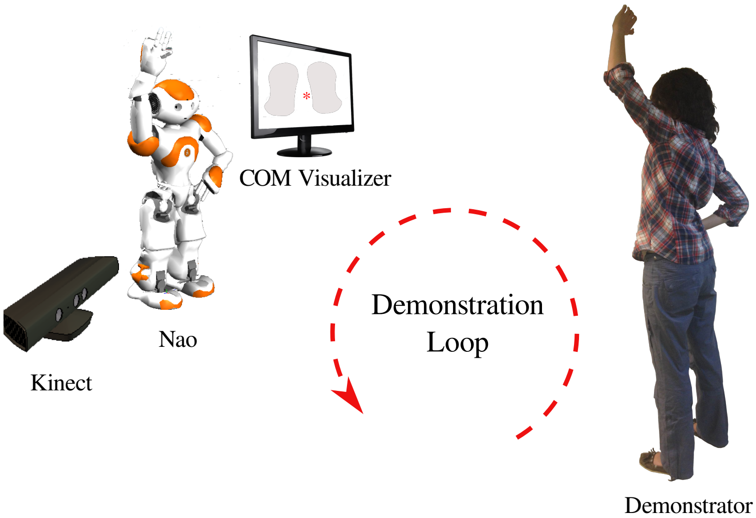


Figure 3.4. The overview of exercise motion imitation by the *Nao* robot observing human demonstrator.

in front of the elderly and expects the elderly to imitate himself. During this process, skeleton of the elderly is tracked. The joint angles performed by the elderly is matched with the ones recorded from the human demonstrator in the first part of the project and vocal feedback is given on the performance of the elderly in repeating the exercise motion successfully. If the robot believes that the performed motion is successful, he switches to the next exercise. Otherwise, he requests the elderly to repeat in order to correct his way of doing the motion. The overall system is depicted in Figure 3.6.

3.2.1. Performing Exercise Motions on Robot

Previously learned exercise motions are stored in a database in the form of joint angle sequences. These joint configurations are transformed considering robot constraints and guaranteed to keep the robot in balance as stated in Section 3.1. Hence, no processing is done while performing exercise motions on the robot in this part, joint angles are just sent to the robot.

We present the motion to the elderly in two different modalities. Vocal explanations are used besides visual performance to make the perception of the motions by the elderly easier. Furthermore, as we stated in Section 3.1.2, the exercise motions which damage the

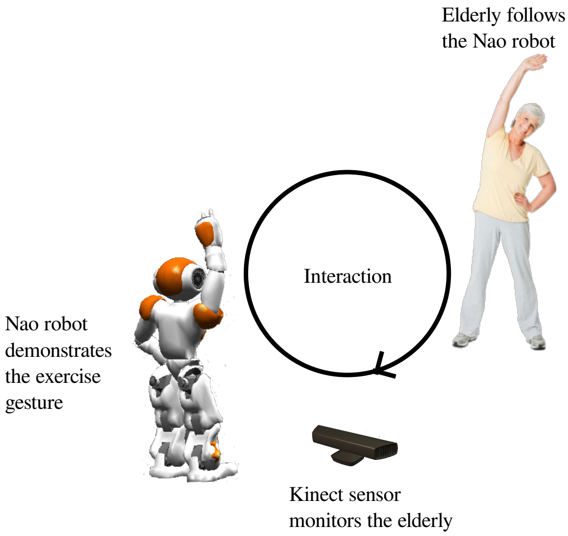


Figure 3.5. The overview of exercise session performed with elderly and the *Nao* robot in the role of exercise coach.

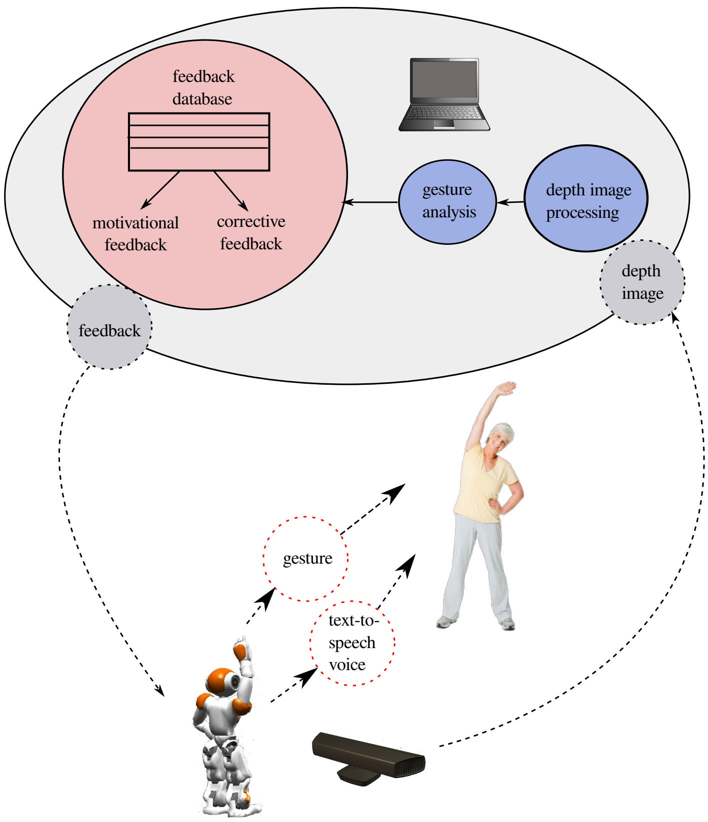


Figure 3.6. The overall system developed for exercising scenario.

balance of the motion are performed up to the point which satisfies the balance condition. However, for representing motions, our reference point is the joint angles showed by human demonstrator. For those motions where the robot is capable to imitate up to some extent, vocal explanations are necessary to make the elderly perform the exercise correctly as the human demonstrator does. For example, the robot may say: “Now, we are stretching our left leg to the left” and after stretching his leg, he can support his demonstration by saying “Please stretch your leg some more as I am not able to do it”.

3.2.2. Tracking Exercising Elderly

The robot starts to track the elderly in the interval of his own demonstration of a motion. However, the elderly may not synchronize herself with the robot sometimes and complete the motion a bit later. To handle such situations, the robot waits for the elderly to stay still upon his own demonstration to evaluate her performance. The system allows delays lower than 5 seconds and the robot switches to the next motion if the user do not complete the current motion. Otherwise, the exercise session will be open to possible perturbations which elderly may cause.

Performance evaluation of the elderly for a exercise motion is done by checking the similarity in the joint angle values of the final posture of that exercise motion. Although an exercise motion is formed from a combination of a set of joint angle trajectories, not joint angle values of a specific frame, a sliding window approach to discover similarities in time intervals is avoided in order to not to bother and confuse the elderly with extensive sound stimuli. The original joint angles recorded from human demonstrator during motion learning process are used to test the correctness of the motion performed by the elderly since robot’s joint angles may differ slightly during conversion process as mentioned in Section 3.1.2.

The performance should be evaluated considering the characteristics of the exercise motion. For example, if the elderly bends his knee slightly during the repetition of motion *stretching arm to the both side*, the robot should not give feedback on incorrect behaviors which may arise in the leg part of the body. This puts force on whole body control during all exercise session which is an undesirable situation. Hence, our system extracts the characteristic of a performed motion by checking variance of joint angles values over time. Then, the system checks the similarity only in those joint angles between original and repeated motion by elderly. Some primitive feedback sentences such as “Please, raise you arm up a bit more” are hard coded into the system and consulted if the detected joint has a varied angle with a considerable difference. Feedback database can grow by adding new dynamically constructed sentences depending on the situation faced with the performance of the elderly.

If the elderly does not correct himself upon a given feedback within a certain duration, the robot gives another one and waits again. He switches to the next motion after the second feedback without considering whether the motion is completed successfully or not. The elderly may not be able to perform that motion either because high pressure may annoy her and cause to lose her whim or due to her physical inabilities.

Besides corrective feedbacks, the robot may give some motivating feedbacks. These sentences such as “Very good” or “You are getting better” are stored in the speech database and used upon successful performances from time to time by selecting randomly from the database.

3.3. Platform of Humanoid Robot

In this study, we use the commercially available robot *Nao* as a humanoid platform which is developed by Aldebaran Robotics. We have “H25”, version 4 *Nao* robot which has 57 cm height and 31 cm width as shown in Figure 3.7. It has a total of 25 DOF which are distributed as 6x2 DOF in arms, 5x2 DOF in legs, 1 DOF in torso and 2 DOF in head. 21 of them, excluding wrist and hand joints in arms, are utilized in this project. Detailed kinematic model of *Nao* is shown in Figure 3.8 which is borrowed from the study of Gouaillier *et al.* analyzing the design of the *Nao* humanoid robot [67].

The *Nao* robot has a Linux based real-time operating system. In order to manage the hardware, a system, called NaoQi, is implemented by Aldebaran Robotics. This system lets us receive sensor values and send commands to the hardware. NaoQi contains different modules for special purposes. For example ALMotion module is used for the motor control,

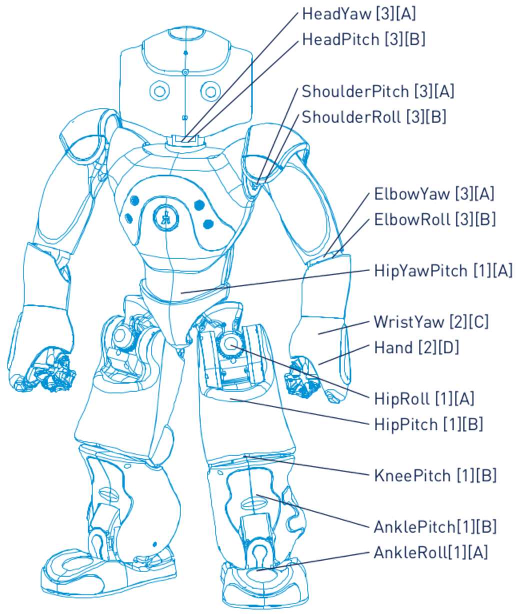


Figure 3.7. The joints of the *Nao* “H25” V4 robot, from [68].

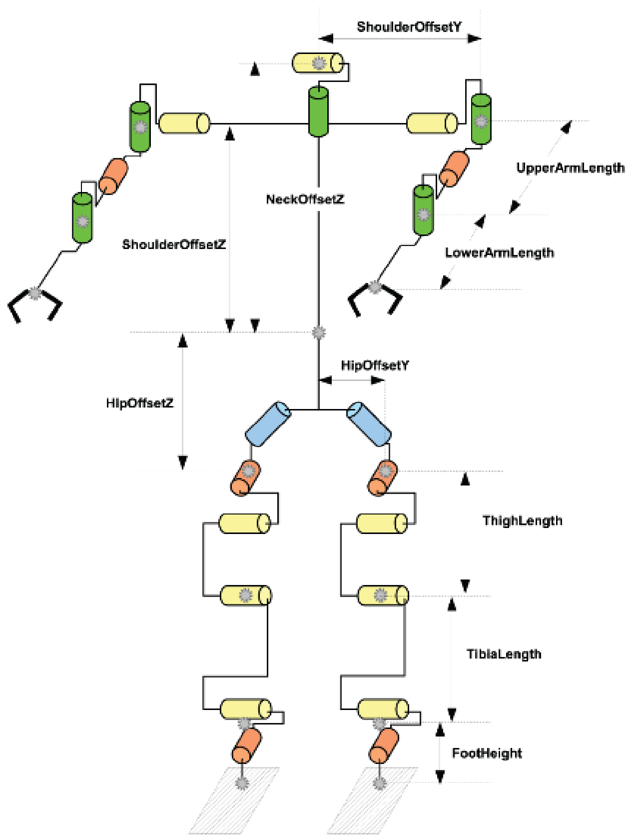


Figure 3.8. The detailed kinematics of the *Nao* robot, from [67].

ALMemory is used for the communication between modules. In the NaoQi infrastructure, it is also possible to implement module.

4. METHODOLOGY

We use a *Nao* humanoid robot, a Kinect sensor, and robotic simulators Webots and Choregraphe 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. ROS (Robot Operating System) [69] is used to provide messaging system between modules shown in Figure 4.1 and Figure 4.2.

4.1. 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 coaches 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 for further reference. A flowchart is given in Figure 4.3 to summarize the proposed system.

4.1.1. 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,

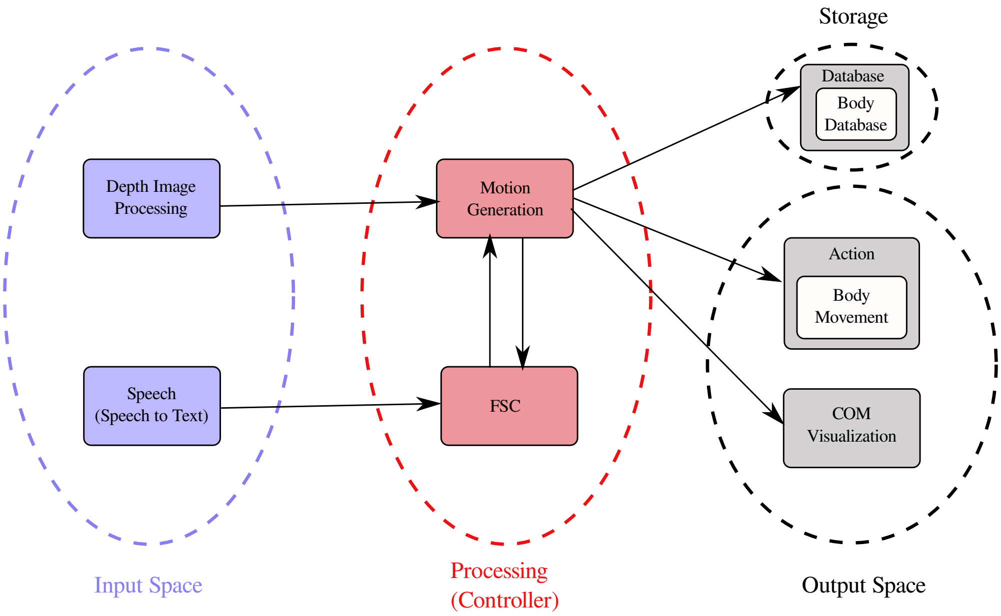


Figure 4.1. The system architecture which shows the modules and their communication for the first part of the scenario.

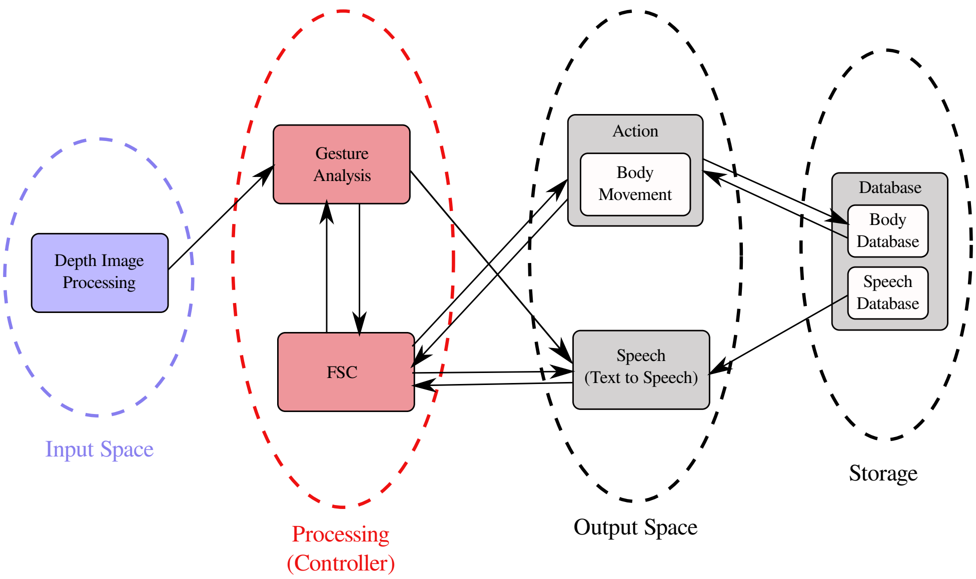


Figure 4.2. The system architecture which shows the modules and their communication for the second part of the scenario.

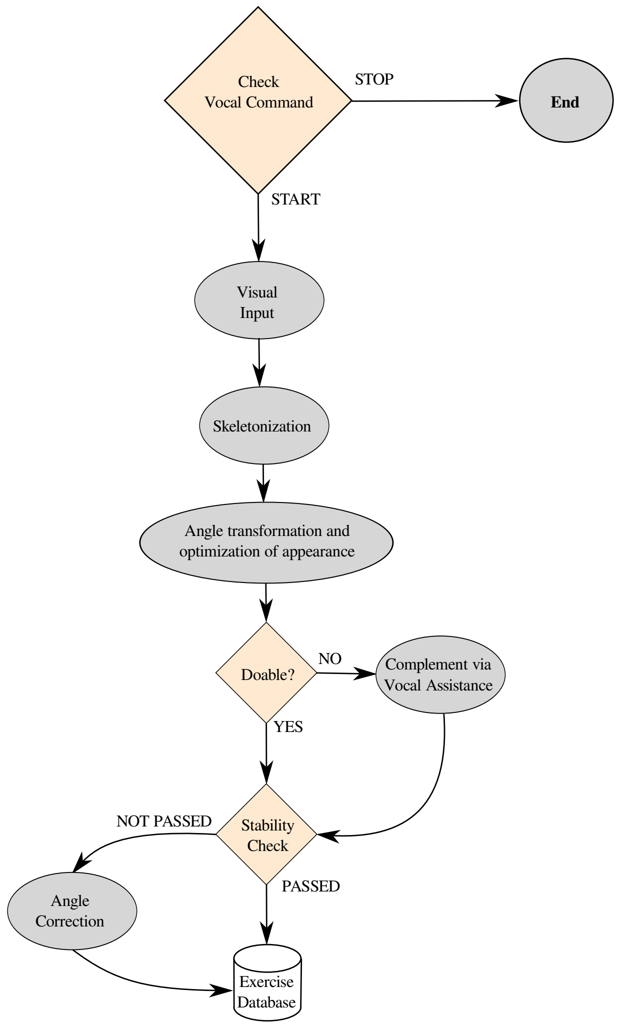


Figure 4.3. The flowchart of the proposed system for gesture learning from a human demonstrator.

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 the 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. However, if the original motion does not include any arm gestures, additional movements added for stabilization spoils the characteristics of the exercise. Furthermore, most of the leg exercise motions for seniors are performed in a sitting position.

At the beginning of the project, we attended exercise sessions three times held in the nursing home which we test our system. We observe and record the motions and then analyze each of them. In the literature, the exercise motions are classified as stretching and strengthening exercises. We follow this taxonomy and extract text description of each movement with the joints used to perform the motion. Afterwards, we try to realize them on the *Nao* robot using the producing company's simulation software "Choregraphe" which allows to set joints manually by using a simple user interface. Though Choregraphe does not have an implied physics engine in it which is necessary to sense the balance condition and fallings for whole body motions, we use the Webots simulator. We can control both of the simulators by the same NaoQi instances. Ultimately, we can observe the simulated motions on *Nao* in real world scene of the Webots simulator using easy to interface of Choregraphe as seen in Figure 4.4.

Our experimental analysis shows that, the *Nao* robot has difficulty or inability to do most of leg motions. On the other hand, it is capable of performing arm motions easily relative to the leg motions. The taxonomy of gestures with text descriptions and doability analysis with encountered problems with *Nao* are shown in Tables 5.1 and 5.2. Gesture imitation gets more challenging directly proportional to the physical qualifications of the robot. The upper body motion imitation can be performed much more easily compared to the lower body motions. Hence, the overall system should be evaluated separately for upper body motion and whole body motion imitation.

4.1.1.1. Imitation of Upper Body Motions. The *Nao* robot has four degrees of freedom in its arm, which are shoulder pitch, shoulder yaw, elbow yaw, and elbow roll joints, respectively. 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 [70]. Hence, direct mapping from human arm joint angles to the *Nao* joints will not produce the 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 Kinect driver [66]. 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 θ of the joint J_1:

$$\begin{gathered}\theta = \arccos(|V|/|Proj(V_x)|) \\ x \in \{XY, YZ, XZ\}, V = \overrightarrow{J_1 J_2}\end{gathered} \tag{4.1}$$

The figures in Figure 4.5 shows the coordinate axes of Kinect sensor and representation of left upper arm of demonstrator in this system. The joint angles are calculated by projecting

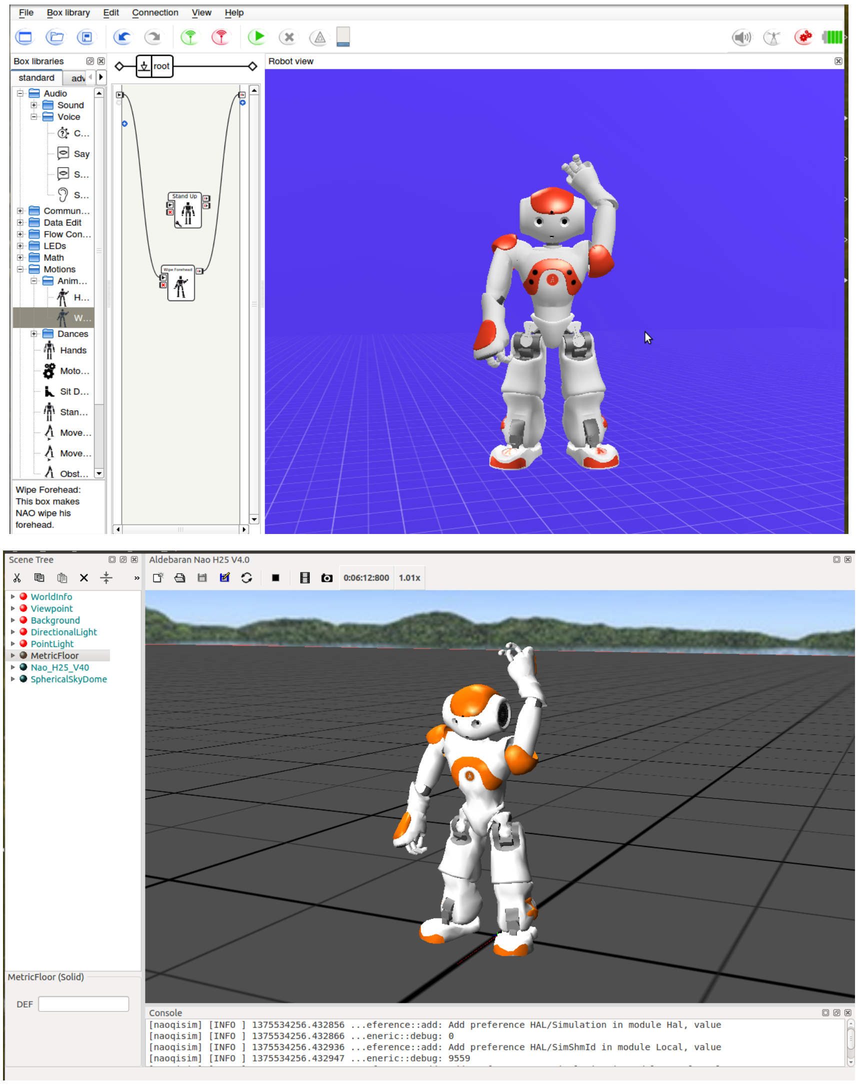


Figure 4.4. Simulator environments: Choregraphe (above) and Webots (below) which can be controlled by the same NaoQi instances. The same motion performed in both simulators is shown.

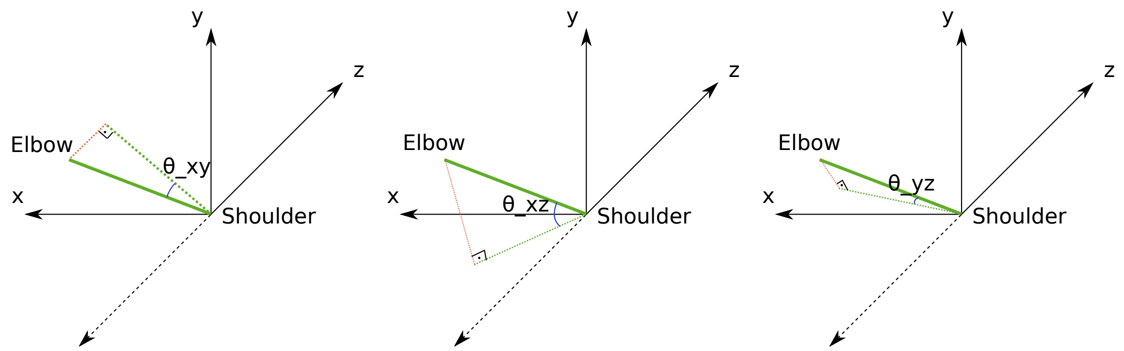


Figure 4.5. The left upper arm of human demonstrator is represented as a vector in 3D coordinate axes of the Kinect sensor. This vector is projected on XY (upper left), XZ (upper right) and YZ (bottom) planes and θ angles between these three planes are calculated as in Equation 4.1.

the vector (shown in green) onto each of three planes which are XY, XZ and XY.

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

$$\phi = \frac{V_1 * V_2}{\|V_1\| \times \|V_2\|} \tag{4.2}$$

where $*$ stands for scalar product of vectors, and V_1 and V_2 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 preprocessed to obey the limit angles of robot joint intervals given in Table A.1. Afterwards, filtering is applied to eliminate the sudden changes in skeleton joints positions due to camera noise. In real time applications, the smoothing with less latency becomes important. However, there is a trade off in the smoothing performance of a filter with latency. For skeleton data filtering, ARMA (Auto Regressive Moving Average) filters are generally used. They are a class of linear filters which gives a weighted average of current and N previous inputs and M previous filter outputs as represented in Equation 4.3.

$$\hat{X_n} = \sum_{i=0}^{N} a_i X_{n-i} + \sum_{i=1}^{M} b_i \hat{X}_{n-i} \tag{4.3}$$

where the first term is named as moving average and second term is named as auto-regressive which helps to track the trend of the filter.

"Double exponential smoothing" filter which is a variant of exponential smoothing filter and a subclass of ARMA filters, given in Equation 4.4, is used to eliminate the sudden changes in skeleton joint positions due to camera noise:

$$\begin{aligned} S_t &= \alpha y_t + (1-\alpha)(S_{t-1} + b_{t-1}); \\ b_t &= \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1} \end{aligned} \tag{4.4}$$

The filter output S_t is a weighted sum of filter input at time t, y_t, and summation of filter output and filter trend output b_{t-1} calculated one step before. α is the dampening factor and takes value in the interval of [0-1]. The larger the α, the filtered output changes fast with the current input value which results in less smoothing with less latency. Otherwise, it follows the trend of the filter which means that older inputs have larger weights in calculating the current filtered value. This trend factor stores the difference between two last filter outputs and is updated with another dampening factor γ at each step. Note that, the filter trend helps to respond to sudden changes in the input sequence more quickly but this can result in overshoots. In Figure 4.6, the output of filter with different α and γ parameters are shown on the skeleton data captured from a human demonstrator who moves her arms up and down too fast. With the increased $gamma$ parameter, the filtered skeleton responds changes in original data immediately as shown in Figure 4.6c and inversely, small value of γ parameter causes high latency in smoothed data in Figure 4.6a.

For the upper body imitation case, the preprocessed 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 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 4.1 shows the parameters for the right arm of the *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

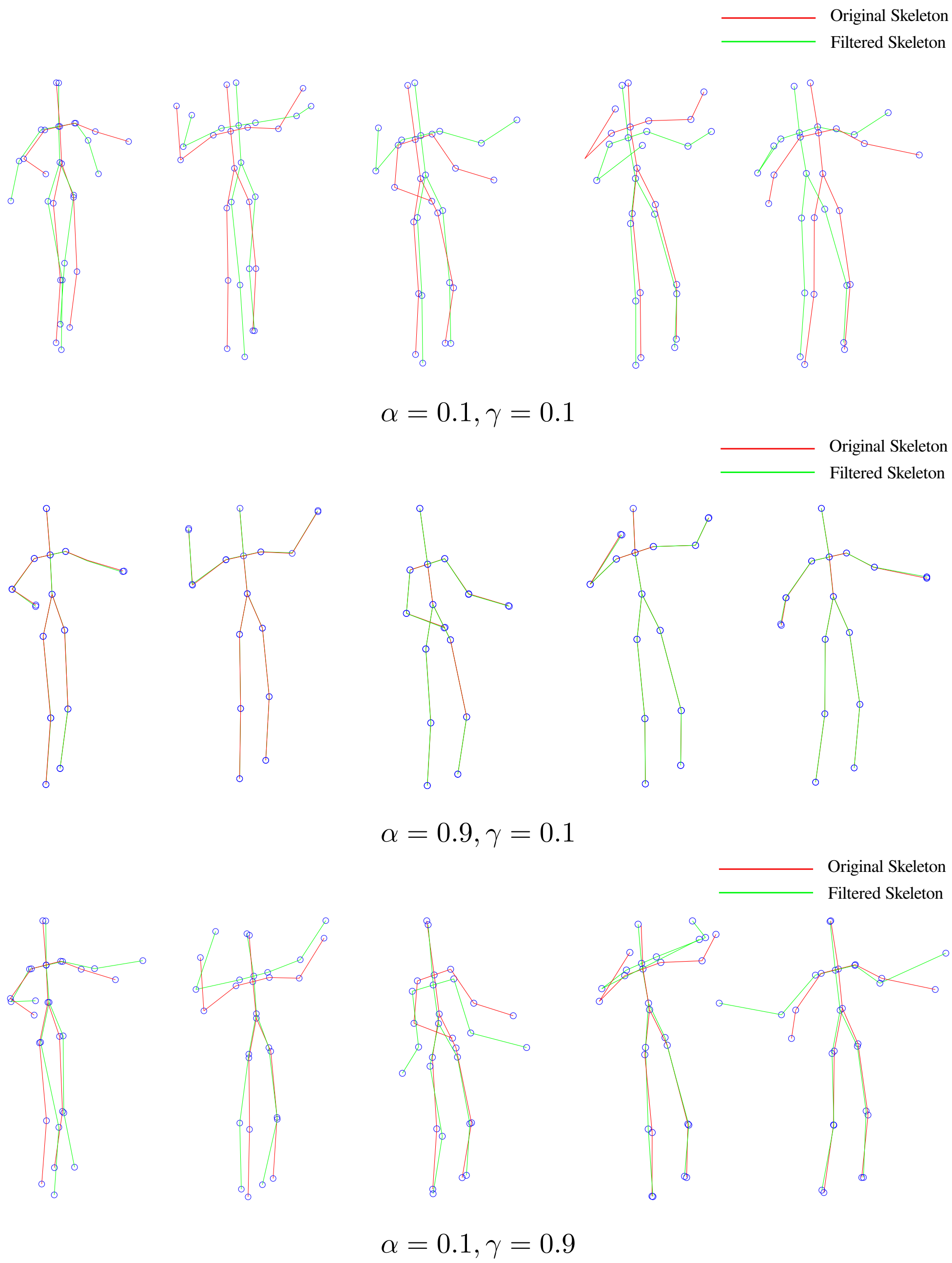


Figure 4.6. The original joint positions and smoothed joint positions after applying double exponential smoothing with different parameters.

Table 4.1. The Denavit-Hartenberg parameters for the right arm of the *Nao* robot.

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

of *Nao* [71]. See Section A.2 for details.

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.

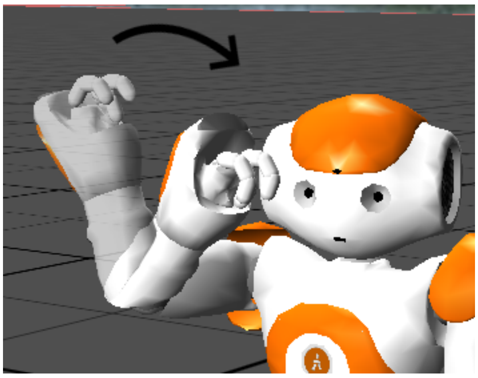


Figure 4.7. The spatial difference between interpolated position and real position of the hand is compensated by the elbow yaw joint.

<ins>4.1.1.2. Imitation of Whole Body Motions.</ins> 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 the *Nao* robot, using an Xsens MVN motion capture system with inertial sensors attached to the body of the demonstrator [14]. Inverse kinematics is used to correct the transferred sensor positions for stability.

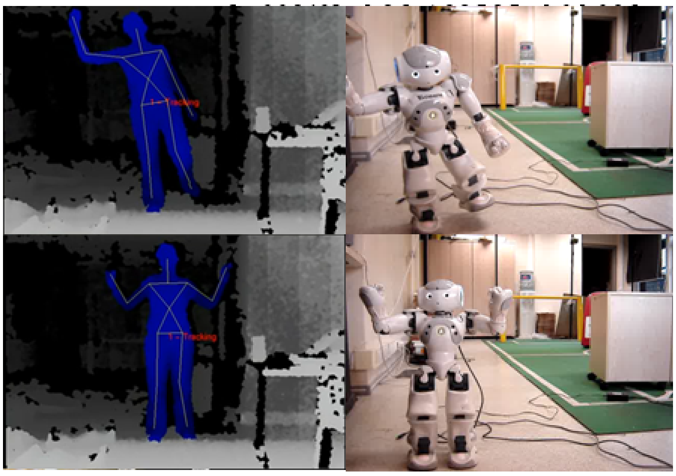


Figure 4.8. The demonstration and imitation of two different exercises. The upper exercise is unstable, and if performed rapidly, can cause the *Nao* robot to fall, whereas the lower exercise is stable.

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, driven 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 is mapped to a joint angle vector A_r for the robot. Two problems 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 and try to keep the robot statically stable. Figure 4.8 shows examples from stable and unstable exercises.

We divided the whole body motions into two parts: motions performed on both feet and motions performed on one foot. Difference in the position value on y axis of right foot and left foot of the demonstrator is used to understand the stance foot. If the status of the stance foot (left foot, right foot, both feet) stays same for more than one second, i.e. for consecutive 15 frames, it is set as the current stance foot status. Otherwise, noise in depth image may be sensed as change in demonstrator status in milliseconds which is not match with our presumption that the demonstrator moves slowly and causes fast movements which are hazardous for balance.

For the former motion types, such as bending knees slightly, stability check is done by controlling whether the center of mass of the robot falls into the support polygon of the robot. If it is so, then the extracted joint angles after preprocessing and filtering are set to the motors of robot. Otherwise, the robot does not continue to imitate the demonstrator because of the stability constraints. We do not adopt any dynamic balance algorithm as stated in Section 2.3.3.2 since it requires to change some angles from the original ones in order to maintain balance. Furthermore, this may cause inappropriate appearance of the demonstrated motion and cause the elderly to exercise the motion improperly. Note that, the ankle pitch joint is left independent from the set angles and adjusted in order to satisfy the parallelism of the foot to the ground. The details of calculation of COM algorithm is given in Figure 4.9. The center of mass is simply calculated by dividing the sum of products of position of limbs with their masses to the total mass. The positions of limbs are found using forward kinematics methods based on DH transformation matrix. $AngleX$ and $AngleY$ sensors of robot are used to get the orientation in left-right and front-back directions respectively. Calculated COM is projected onto the ground to get the real world coordinates.

For the second motion types, we define some primitive actions to avoid complex inverse kinematic solutions. Because of the embodiment differences, the imitation of transition motions between different postures with different support legs (motions done on right foot to double feet or vice versa) is not possible. The robot should determine his own motions to be able to follow the demonstrator and try to perform similar gestures akin to the demonstrator's. Our predefined and statically coded motions are "transition from left foot to double feet", "transition from right foot to double feet", "transition from double feet to left foot" and "transition from double feet to right foot". These motions are more functional and do not have to be same with the human necessarily. If the robot starts to stand on his one foot, then a linear optimization algorithm is consulted to calculate joint angle values of the swinging leg and arm joints. Note that, the angle values of support leg are not changed until a detected shift in support leg.

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:

$$\begin{array}{llll} \min |A_h - A_r| & s.t. & & \\ & \sigma(A_r) & \in & P(A_r), \\ & \phi_{anklePitch} & = & -\phi_{kneePitch} - \phi_{hipPitch}, \\ & A_r^j & \in & [A_{min}^j \dots A_{max}^j], \quad \forall j = 1 \dots J \end{array} \tag{4.5}$$

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 the COBYLA algorithm [72] from the NLOpt library [73].

The pseudocode of our whole body imitation approach is given in Figure 4.11.

4.1.2. Observation of Robot by Demonstrator and a COM Visualizer as Stability Indicator

In our approach, the demonstrator and the robot are in an interaction in terms of observing each other and behaving accordingly. While the robot tries to imitate the demonstrator, the demonstrator also observes the robot and adjusts his own motion in order to be able to

Algorithm $CalculateCOM$

Get $jointAngleList$

for $joint$ in $jointAngleList$ **do**

Compute $jointPosition$ relative to the torso using forward kinematics

$COMPosition \Leftarrow COMPosition + (jointPosition \times jointMass)$

$totalMass \Leftarrow totalMass + jointMass$

end for

$COMPosition \Leftarrow COMPosition \div totalMass$

Project $COMPosition$ onto the ground using $AngleX$ and $AngleY$ sensor values

Figure 4.9. The center of mass calculation by considering the robot body orientation.

Algorithm $PreprocessingStep$

Filter out the 3D coordinate system positions of the skeleton.

Extract $jointAngles$ from the filtered position values.

Adjust the $jointAngles$ in order to be in the interval of rotation limits of the corresponding motor of the robot.

Decide on the $currentStanceFoot$.

Calculate COM.

Figure 4.10. The preprocessing step for whole body motion imitation.

Algorithm $WholeBodyMotionImitationAlgorithm$

Preprocessing step.
if $currentStanceFoot = BothFeet$ **then**
  if $previousStanceFoot = LeftFoot$ **then**
    Perform primitive motion: "transition to standing on both feet from left foot".
    $supportPolygon \Leftarrow$ ground contact area of left foot
  else if $previousStanceFoot = RightFoot$ **then**
    Perform primitive motion: "transition to standing on both feet from right foot".
    $supportPolygon \Leftarrow$ ground contact area of right foot
  else
    if COM is within $supportPolygon$ **then**
      Send $jointAngles$ to the motors of the robot.
    else
      Keep the robot in the previous posture, ignore the movement of the performer.
    end if
  end if
else if $currentStanceFoot = LeftFoot$ **then**
  if $previousStanceFoot = LeftFoot$ **then**
    Keep the position of the support leg (left leg) same.
    Optimize the motion and send optimized $jointAngles$ to the robot.
  else if $previousStanceFoot = BothFeet$ **then**
    Perform primitive motion: "transition to standing on left foot from both feet".
    $supportPolygon \Leftarrow$ ground contact area of both feet
  end if
else if $currentStanceFoot = RightFoot$ **then**
  if $previousStanceFoot = RightFoot$ **then**
    Keep the position of the support leg (right leg) same.
    Optimize the motion and send optimized $jointAngles$ to the robot.
  else if $previousStanceFoot = BothFeet$ **then**
    Perform primitive motion: "transition to standing on right foot from both feet".
    $supportPolygon \Leftarrow$ ground contact area of both feet
  end if
end if

Figure 4.11. The whole body motion imitation algorithm.

Figure 4.12. An example motion that the *Nao* robot can not perform due to its physical constraints.

realize it on the robot. For example, human elbow roll joint has the capability of bending up to 160 degrees approximately. For the motion, *putting hands on head*, humans raise their shoulder up slightly while bending elbow pretty much. On the other hand, *Nao* has an elbow roll joint which has a rotation limit up to 90 degrees. Hence, imitation of human joint angles for this motion can not reproduce the same gesture on *Nao* as shown in Figure 4.12. Instead, our approach proposes to assign the demonstrator the responsibility of observing the robot and comprehend his capabilities and alter his own way of performing the motion.

For whole body motion imitations, the demonstrator should also be aware of the stability state of the robot in order to avoid positions which can cause fall in the robot. We prepare a display which shows the support polygon of robot and COM point. The display is updated at every process cycle of joint angle values. The simulated robot imitating leg motions and the COM visualizer screen are shown in Figure 4.13. The visualizer is updated according to the support foot state of the robot while switching to stand on one foot.

4.1.3. Solution to "When to imitate" Problem

When to imitate problem requires on-line gesture recognition of performed motions to reproduce synchronous gestures with the demonstrator. However, it is another challenging research area and is out of our scope. We handle this problem by referring to the demonstrator's guide. The robot expects *Start* and *Stop* vocal commands from user to decide on imitation time intervals.

Google translate API is utilized for speech recognition. The system takes recording

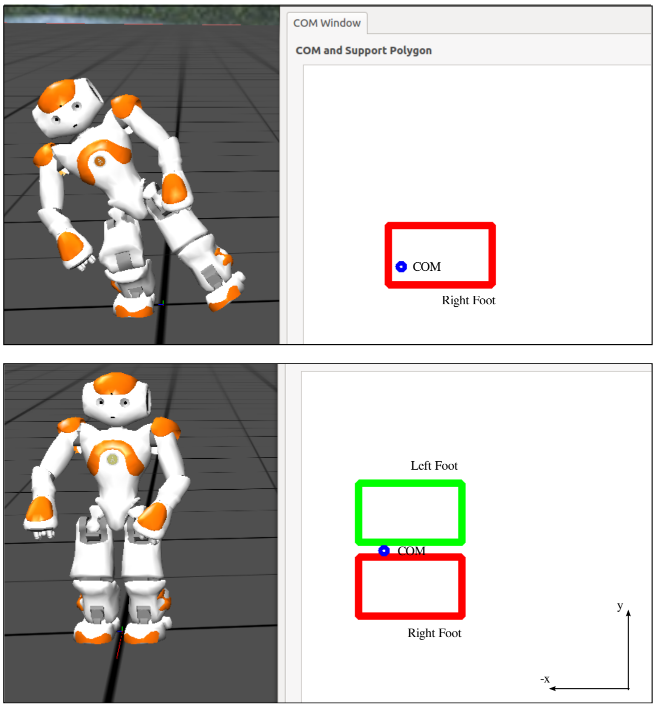


Figure 4.13. The COM visualizer: support polygon switches to right foot from both feet while performing leg motions with stance on one feet. The green and red rectangles stand for left and right foot of the robot respectively. COM point is visualized as a blue point.

for every 3 seconds and sends this recording to Google cloud service. The response returned from the servers are matched with our predefined *Start* and *Stop* keywords. Then, the robot makes a decision about starting or stopping the imitation. Google translate API supports multiple languages including Turkish. This allows human demonstrators who speak only Turkish be able to use the system.

4.2. Interaction with the Elderly and Exercise Session Scenario

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 recorded from human demonstrator 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

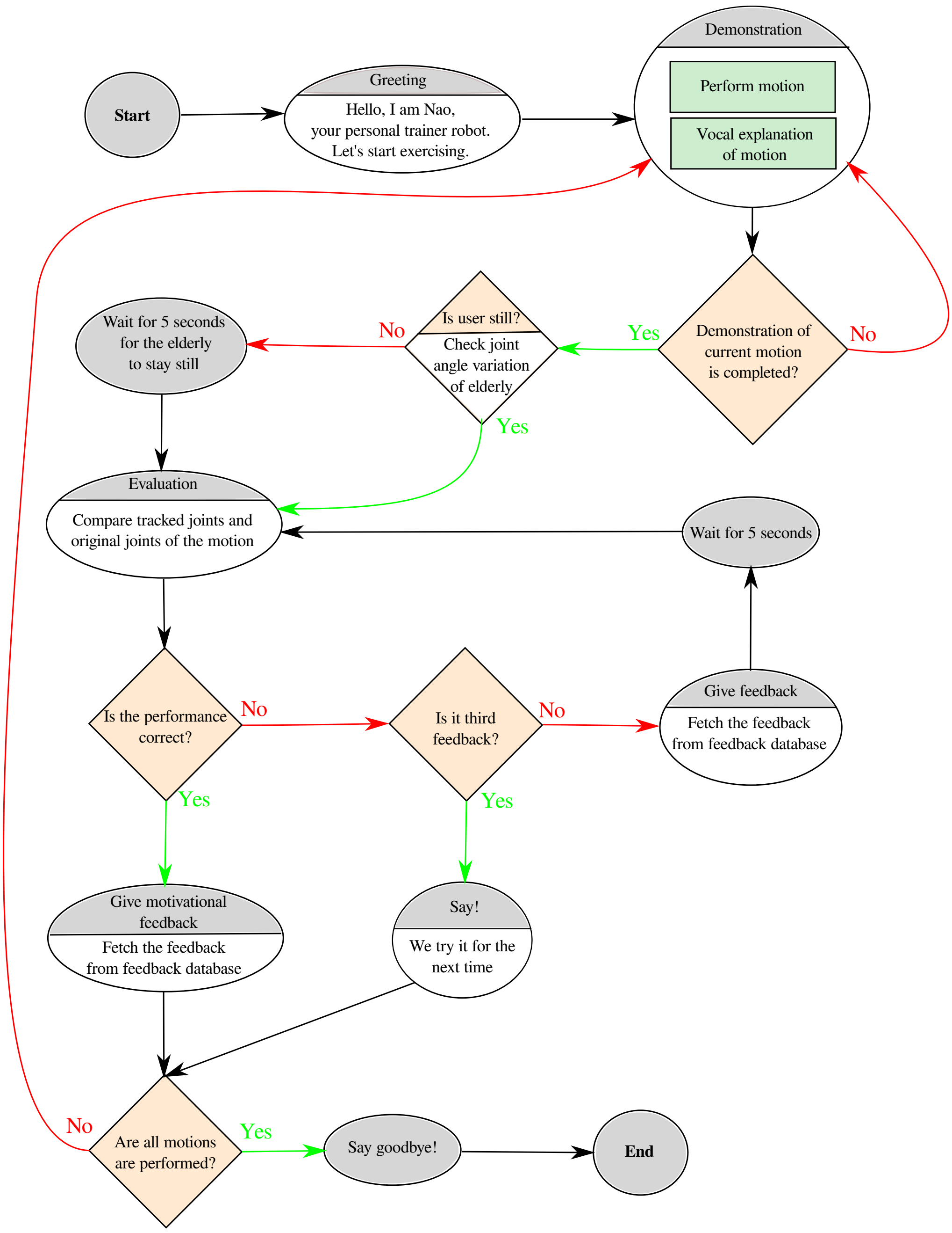


Figure 4.14. The flowchart of the proposed exercise intervention scenario. See text for the details.

subject to continue with the exercise program.

Recorded motions in the motion database are preprocessed before using them in exercise interventions. The joint angle values are not changed, but some analysis are applied for vocal explanation and feedback mechanism.

In exercise sessions, most of the motions are performed by doing the same gesture consecutively like opening and closing arms to sideways for five times. Human exercise coach counts on how many times the gesture repeated while showing the motion. He also counts the repetition time of the the user like “one, two, three” by observing her in order to motivate and insure continuity on the motion.

We also adopt such an approach to support the visual performance of motion with vocal assistance. The cycles in the motion are determined and the corresponding motion frames are marked to give vocal explanations. We apply a simple dimensionality reduction algorithm, namely principal component analysis (PCA), and reduce the data to one dimension from 22 dimensions. Then, the data are smoothed by using the moving average filter with 80 framed-window size (approximately over 5 seconds of motion parts). The smoothed data is normalized between [-1,1] and local maxima detection is utilized to extract the cycles in the motion. In Figure 4.15, the normalized 1-D data and smoothed data with peaks labels are shown. Reduced joint data is informative enough to extract cycles in the performed motion and detect *count feedback* frames.

Another preprocessing applied on the stored joint angles in motion database is to extract the list of joints utilized extensively through the motion in question. Since the given feedback should only consist of a kind of notice about the joints used in exercise, this list is used to avoid redundant feedbacks. The robot should not comment on leg posture of the user if the motion in interest belongs to a class of arm motions. We calculated the variance of each joint angle individually and selected the ones with the variance value larger than 0.01. The threshold is selected empirically. We refer to those joints as *gesture identifier joints* in the rest of the thesis.

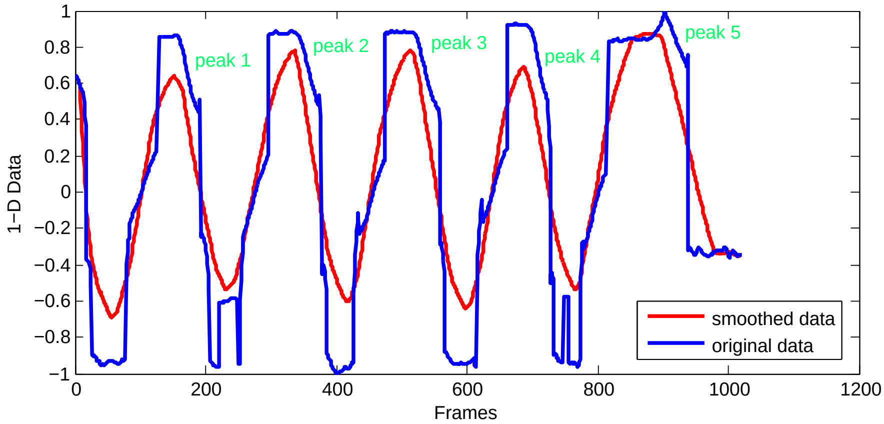


Figure 4.15. 1-D representation of the joint data of the motion opening-closing arms to sideways. The same gesture is performed five times.

One of the challenges encountered in developing the feedback system is to adjust the timing and determine on the number of times verbal feedback should be given 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 analyzing the stability of the subject. If the variance in the gesture identifier joints of the subject skeleton is nearly zero during the last five seconds upon completion of exercise performance of the robot, then the user is accepted as stable and finished imitating the robot. Otherwise, the robot waits for another five seconds to allow the user in order to finish his move. If the user has not been stable yet, then the feedback mechanism is activated without waiting further.

Our system allows to compose the feedback messages on the fly without need of pre-recording. On the other hand, we have some primitive feedback sound files stored in the feedback database which can be used if they have the expected message content. This approach relieves the system from regenerating same messages redundantly. Our aim is to enhance feedback database by adding dynamically composed ones during exercise sessions.

The system decides on when to activate the feedback mechanism by comparing the recorded skeleton data of the subject to the original stored gesture template, as performed by the coach considering the gesture identifier joints. Our similarity metric is simply the difference of those two joint angle sequences. If it is larger than an acceptable value which is determined for each joint angle empirically, then a text message in the form of action verb (e.g. “raise”, “lower”, “spread”) + target limb (e.g. “right arm”, “both arms”) + a modifier indicating the amount of the correction (e.g. “slightly”, “as much as you can”) is added to the current feedback message. 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. Finally, the feedback text is converted to an audio file using a text to speech module, and played on the robot.

There is another important point in the feedback mechanism. The subject may not be able to perform the gesture simultaneously with the robot, or the performance speed may be different. If that is the case, one-to-one matching results in erroneous outcomes. Dynamic time warping algorithm is used to normalize gestures of human demonstrator and subject in time by stretching the shorter sequence. It is a simple sequence matching algorithm which takes two input sequences as input and gives one warped sequence as output. First it constructs a distance grid which includes the difference of each element of the first input vector from each element of the second input vector. Then, the optimal path with minimum differences on this grid is found. Figure 4.16 shows the original left elbow roll joint values gathered from human demonstrator during imitation of the gesture and from the subject during exercise session for opening and closing the arms to sideways. Note that, the subject follows the pattern of the robot but with a joint angle nearly half of the original one. For this case, it means, the subject did not open her arm necessarily up to 90 degrees as robot does.

Besides corrective feedbacks, the robot also gives motivational feedbacks upon successful completion of a gesture by the subject. The motivational feedbacks are prerecorded and stored in feedback database. The system selects randomly among them and say it to the subject to inform her about the success on the performance and strength flow and motivation of the subject to the exercise intervention. Some motivational feedbacks are “You are really good”, “Perfect”, “Congrats!, you successfully completed the motion”. Selection in random order is important in order to not bother the user and keep interest of her on the robot.

Google Translate API is used again in order to convert text messages into sound files. The recorded sound files are then sent to the robot and played. Note that, this module requires

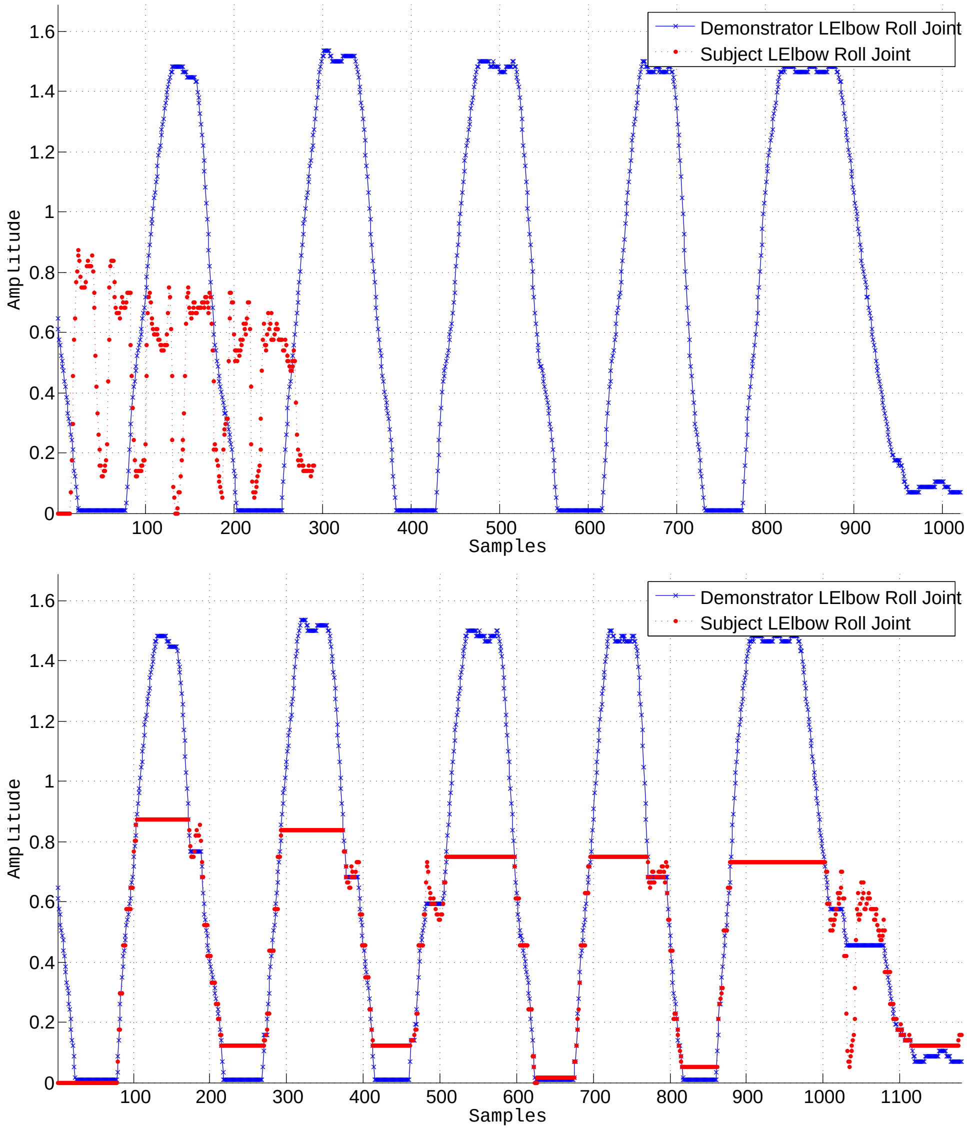


Figure 4.16. The original and tracked angle trajectory for left shoulder roll joins (upper image). Tracked joint trajectory is extended to original one using DTW (bottom image).

the Internet connection.

The flowchart is given in Figure 4.14 to summarize the proposed exercise intervention system.

4.3. Questionnaire Design

We adopt two different questionnaires to be applied after the exercise interventions to measure the demonstration performance of the robot as a robotic fitness coach and its social aspects.

The first 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 [74]. We used questions related to *positive* and *negative affect*, *flow*, *immersion* and *challenge* components. The positive affect questions are included to measure the general impact of the system on the subject. The negative affect questions are asked for crosscheck. An easy to use system is targeted in order to minimize confusion and to concentrate the subject's attention on the exercise intervention. The convenience of the system from this standpoint is tested with the flow component. The immersion component is questioned to test how well the subject is motivated to participate in the exercise intervention. The challenge component is included for a crosscheck of the flow component. It questions how much the subject has difficulty in following the robot and replicating the exercises during the session. A 5-point Likert scale is 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. Occupation, age and gender information is also asked to the subjects for further analysis of the relationship between these properties and the positive affect of the system. The questionnaire is given in Table C.1.

On the other hand, the later evaluations and the feedbacks received from the subjects who filled the survey showed that this survey is not competent enough to measure the effect of the robotic fitness coach system. Hence, we changed our survey design. A second survey is prepared which includes questions to measure the perception of robot, human-robot interaction, and exercise session by the subject. It is prepared considering some design criteria explained in Section 2.4. The components depicted in Table 2.1 in the study of Fasola *et al.* [44] are included in the survey. The interaction is evaluated over enjoyableness and usefulness constituents. The subject is asked to rate the how much the exercise session is enjoyable, interesting, satisfying, boring, exciting for enjoyableness and how much useful, beneficial, valuable for usefulness property. A 10-point Likert scale is used. In order to evaluate the robot, the components of companionship, helpfulness, intelligence, social attraction, social presence are questioned. For the questions related social attraction module, a 7-point Likert scale is used. A 10-point Likert scale is utilized for the questions related to the other components. The opinions of the subjects on the performance of the robot as a fitness coach are also inquired by four questions with a 10-point Likert scale.

We also include a question to learn the background of the subject with robots in the second survey. We think that the familiarity with robotic systems may affect the acceptance of our system. The questions for occupation, age and gender information are again included for the same purpose applied in the first survey. Furthermore, the physical performance of the robot in expressing the exercise motions visually and vocally is asked to rate over a 10-point scale. The performance of feedback mechanism is rated over 3-point scale. The survey is concluded with a drawing of seven faces with each face depicting a slightly different mood state from very happy to very sad, which is from the study of Lorish *et al.* [42]. The subject is asked to select one of the faces which best shows the way he feels after the exercise intervention. We want to analyze the effect of the system on the mood of the subject in the long run. The questionnaire is given in Table C.2.

5. EXPERIMENTS AND RESULTS

In order to the create a real scenario, we first visited the nursing home and attended the exercise sessions three times to observe the gestures performed by the physiotherapist who leads the sessions. We noted the vocal commands provided by the physiotherapist to correct the movements of the attendees, and to ease the control of the session flow, to utilize them in our system. As explained in Section 5.1, we formed a taxonomy of the exercise gestures and analyze their demonstration feasibility considering the physical properties of the *Nao* robot.

After completion of the first prototype of the system, we demonstrated five exercise gestures selected from the ones performed in the nursing home which are *chest stretching*, *upper arm stretching*, *back strength* as upper body motions, and *hip side extension* and *hip extension* gestures as lower body motions (see Tables 5.1 and 5.2). We recorded videos of the demonstration of the gestures by the human performer. Then, these videos were used to teach the gestures to the robot. This demonstration setup however did not adopt a closed loop approach as explained in Section 4.1.2. In other words, the human demonstrator did not adjust her motions by observing the robot in real time. The imitation performance results of the robot for these gestures are given in Section 5.2.

Although our essential aim is to hold an experimental study with a set of elderly people, we first carried out an initial user study with nine young subjects whose ages are between 25 and 35. The details of the experiment is mentioned in Section 5.3.1. The aim of this study is to calibrate the exercise system by receiving feedback on the gesture performance of the robot and to determine on the expectations from such a robotic exercise coach system. The young subjects stated that the leg motions are tiring and difficult after completing the upper body motions in the standing pose.

Based on this feedback, we changed the exercise scenario slightly and used the *side lumber stretching (to both side and three times for one side), upper arm stretching (five times)*, *back strength (five times)*, *knee extensions (both knees and five times for one knee)* and *ankle exercise (both ankles and five times for one ankle)* gestures. The subject was allowed to sit down after the last two motions in this setup so as not to tire the subject too much. These gestures are also selected from the ones depicted in Tables 5.1 and 5.2. While showing the gestures to the robot, the demonstrator observed the robot and changed her way of doing the motion in order to increase the imitation performance of the robot. The results of the upper body motion imitation for the second scenario are given in Section 5.2.

Upon obtaining the ethical committee approval from *İnsan Araştırmaları Etik Kurulu-INAREK* (Human studies ethics board) to hold a study with humans and an approval from *Aile ve Sosyal Politikalar Bakanlığı* (the Ministry of Family and Social Policies) to study in the nursing home, we tested our updated system with six elderly people who reside in the nursing home. The design of the experiment is detailed in Section 5.3.2. The subjects were from the attendees of the exercise sessions carried out in the nursing home. Hence, they were familiar with the exercises performed by the robot.

To determine the effect of previous knowledge on the perception of the gestures performed by the robot, we applied another user study with four subjects who are relatively younger than the nursing home residents as explained in Section 5.3.3. These subjects do not have any exercise routine in contrast with the subjects in the nursing home and they were unfamiliar with the gestures. The second exercise intervention scenario was applied during the second and third user study.

5.1. 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. The exercises listed in Table 5.1 and Table 5.2 stand for the general and common exercises performed in a real senior fitness scenario. At this point, we do not consider balance and endurance exercises for robotic coaching due to the risk of falling, and heart problems, respectively.

Table 5.1. The analysis of stretching and relaxation exercises considering the *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 + hippitchyaw	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. 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	Whole body joints	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	—-

Table 5.1. The analysis of stretching and relaxation exercises considering the *Nao* humanoid robot (cont.).

Stretching and Relaxation Exercises	**Stance**	**Description**	**Robot Joints**	**Doability**	**Problems**
16. Upper hind leg and back stretching	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 5.2. The analysis of strength exercises considering the *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	Upper body joints	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	Upper body joints + hip yawpitch	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	Whole body joints	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

Table 5.2. The analysis of strength exercises considering the *Nao* humanoid robot (cont.).

Strength Exercises	**Stance**	**Description**	**Robot Joints**	**Doability**	**Problems**
13. Shoulder and leg exercise	Standing	Bend knees, cross arms, then stand up while raising the arm up to the head level	Whole body joints	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

Figure 5.1. Demonstration and subsequent imitation of several fitness exercises.

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 four 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 the joints of *Nao*, and some exercises fall beyond the robots capabilities.

Purely gesture based imitation success in strength exercises is higher. The *Nao* robot 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 5.1 shows some exercises, fully learned and imitated by the *Nao* robot.

The motions that the *Nao* robot is not able to perform are demonstrated with additional vocal assistance. Understanding motion characteristics such as stretching or strengthening may be a difficult task even for the humans; we observed some elderly having difficulty in properly interpreting the instructions of the human coach. In order to correctly explain the action where needed, the *Nao* robot 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.

5.2. Evaluation of the Gesture Imitation Performance of the *Nao* robot

As mentioned before, the *Nao* robot can not imitate all of the motions performed by the human demonstrator due to its physical inabilities. Imitation of the arm motions is easier than the leg motions since there is no balancing constraint. We evaluated the imitation performance of the robot by considering a metric which is the absolute difference of the joint angles sent to the robot and the original joint angles of the human demonstrator. The performance is calculated for each joint except the ankle joints and the elbow yaw joints which are left independent to handle the correspondence problem and the balance constraint. The evaluation is performed over the exercise motions adopted in the user studies.

In Table 5.3, the imitation performances of three upper body motions and two leg motions used in the first experimental study are shown. For the upper body motions, the robot is less successful in performing the *chest stretching* motion compared to the *upper arm stretching* and the *back strength* motions based on the value of the differences in arm joints. The differences are approximately the same for the left and right arms since these upper motions are performed using the left and right sides of the body in a symmetrical manner. The performances for the leg motions, namely the *hip side extension* and *hip extension*, are not satisfactory for the swinging leg joints. However, this is expected since the joint angles for the swinging leg of the motions performed on one leg are optimized in order to satisfy the balance constraint.

Table 5.4 shows the imitation difference results for the upper body motions adopted in the second user study. Note that, there are some common gestures which are also used in the first user study with enhanced imitation performances. This difference results from the change in the demonstration style of the human performer. When the performer demonstrates the gestures considering the physical constraints of the robot, the imitation performance also increases.

Table 5.3. The absolute differences between the joint angles of the robot and the human demonstrator per frame for the motions adopted in the user study with the young subjects (the values are in radian).

	Chest stretching 2	**Upper arm stretching**	**Back strength**	**Hip side extension**	**Hip extension**
Left Shoulder Pitch	0.23	0.17	0.17	0.03	0.03
Left Shoulder Roll	0.11	0.22	0.26	0.04	0.03
Left Elbow Roll	0.32	0.06	0.18	0.04	0.04
Right Shoulder Pitch	0.23	0.17	0.20	0.04	0.04
Right Shoulder Roll	0.09	0.20	0.19	0.06	0.04
Right Elbow Roll	0.32	0.04	0.22	0.03	0.05
Left Hip Roll	0.05	0.07	0.13	0.69	0.54
Left Hip Pitch	0.01	0.02	0.14	0.98	0.79
Left Knee Pitch	0.20	0.20	0.34	1.18	1.25
Right Hip Roll	0.01	0.02	0.08	0.10	0.06
Right Hip Pitch	0.02	0.02	0.14	0.06	0.09
Right Knee Pitch	0.20	0.21	0.26	0.20	0.23

Table 5.4. The absolute differences between the joint angles of the robot and the human demonstrator per frame for the motions adopted in the user study with the elderly subjects (the values are in radian).

	Left side lumber stretching	**Right side lumber stretching**	**Back strength**	**Upper arm stretching**
Left Shoulder Pitch	0.000	0.000	0.000	0.000
Left Shoulder Roll	0.000	0.022	0.005	0.060
Left Elbow Roll	0.000	0.049	0.014	0.000
Right Shoulder Pitch	0.000	0.000	0.000	0.000
Right Shoulder Roll	0.020	0.000	0.008	0.007
Right Elbow Roll	0.065	0.006	0.003	0.000
Left Hip Roll	0.105	0.036	0.025	0.060
Left Hip Pitch	0.195	0.109	0.208	0.138
Left Knee Pitch	0.109	0.293	0.173	0.194
Right Hip Roll	0.018	0.053	0.027	0.009
Right Hip Pitch	0.187	0.183	0.186	0.122
Right Knee Pitch	0.206	0.185	0.263	0.218

5.3. Evaluation of the Performance of Exercise Interventions with Robotic Fitness Coach

5.3.1. The First Experimental Study with Young Subjects

For the first experimental study, we tested our system with nine young people who are members of our department. Since our project targets providing assistance in elderly exercise, these experiments do not give information about the real performance of the system. However, they were useful in determining the shortcomings of the system.

In this initial study, 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 analyze how the subjects were synchronized with the robot and the performance of the subject in imitating the gesture accurately. Figure 5.2 shows the angles for two different tracked joints (for all subjects) during two different gestures. 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. Except for one subject (which is shown in red), the joint angle values of all subjects follow the same trajectory with the human demonstrator's angle values which means that they were able to follow and replicate the gestures of the robot successfully.

We have also assessed the interaction with a post-exercise study. The subjects were requested to fill out the first survey which is mentioned in Section 4.3 in detail. The survey is evaluated to measure the effects of the system. The results are given in Table 5.5. 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 5.5. The user evaluation results of the experiment with the young subjects.

Component	**Mean**	**Standard Deviation**
Positive Affect	3.63	0.72
Negative Affect	2.20	0.68
Flow	3.25	1.13
Immersion	3.68	0.37
Challenge	2.65	0.72

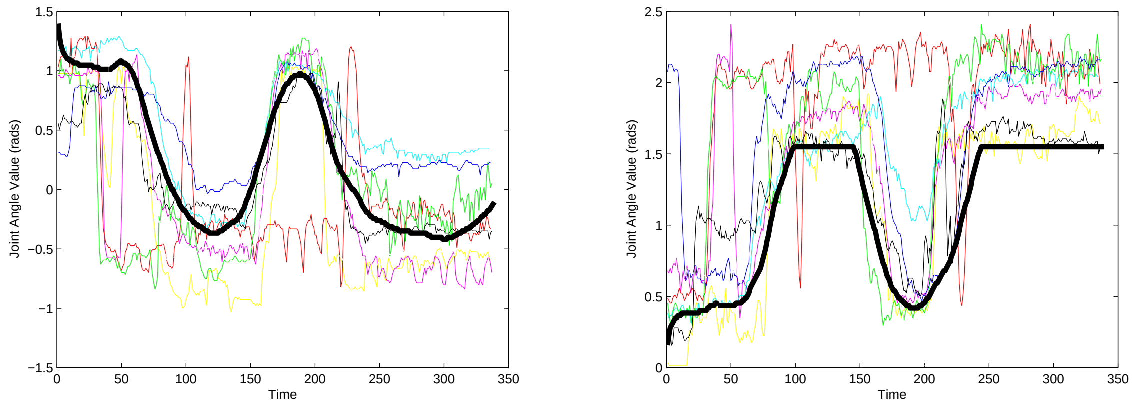


Figure 5.2. Left Shoulder Pitch (left) and Right Elbow Roll (right) joint angle trajectories of the subjects and the human demonstrator for one gesture.

5.3.2. The Second Experimental Study with the Elderly Subjects of the Nursing Home

In the experiment held in the nursing home, at the beginning of each exercise session, the robot gives an introduction of itself as “I am Erdal, I am here to assist you for the exercise session”. Afterwards, it gives a brief explanation of the system flow as “Now, I will display some exercise motions and request you to follow me. I will give vocal explanation for each gesture before starting performing the gesture”. We adopted again five exercise motions which are different from the ones selected for the initial study with the young subjects. These exercise motions were chosen from the exercise list performed in the exercise sessions held in the nursing home as mentioned in Table 5.1 and 5.2. The robot performs *side lumber stretching (to both side and three times for one side), upper arm stretching (five times)* and *back strength (five times)* in stand pose. Thereafter, it sits down and continues with the leg motions. The selected leg motions are *knee extensions (both knees and five times for one knee)* and *ankle exercise (both ankles and five times for one ankle).* All of the motions can be seen in Figure 5.3. The gestures performed in the standing pose are taught to the robot by imitation, while the leg motions are handcoded using the *Choregraphe* software. The robot gives vocal explanation for each gesture. On the other hand, *counting feedback* is provided only for the gestures learned by imitation in order to assist the motion.

Our aim is to test the performance of the combination of the gestures learned by imitation and *counting feedback* compared to the handcoded gestures performed without vocal assistant. Therefore, we also questioned the subjects to rate on the demonstration performance of the leg and the arm motions of the robot. Although eight subjects participated in our study, two of the subjects refused to fill out the survey applied after the exercise intervention. Hence, we evaluated the results of the six remaining subjects. Three subjects out of six said that the arm motions are easier to understand. Two subjects rated the same performance on both the leg and the arm motions. Only one subject preferred the leg motion demonstration to the arm motions.

The subjects were asked to rate over a *1-10* scale the performance of the robot on the explanation of the gestures by visual demonstration and vocal commands. The results are pleasing as shown in Table 5.6. The elderly people rated 7 points for visual and 7.5 for vocal performance on the average. This means that our system is powerful enough to express the exercise motions to the elderly. All of the subjects had also a common opinion in that the vocal explanations besides the visual demonstrations make the perception of the gestures easier. Figure 5.4 and Figure 5.5 show two different exercise motions demonstrated by the robot to an elderly subject in the experimental study held in the nursing home.

The second survey mentioned in Section 4.3 was applied to the subjects after the exercise session. We noted that, the interest in and the acceptance of the robot is high for the older subjects in this group. There may be some psychological effect so that the older people have a stronger sense of loneliness and a robotic companion can be perceived as a way of addressing such a need. On the other hand, our subject set is too small to comment on this claim.

We also asked the subjects whether they have seen a robot before and interacted with it. We want to understand, whether the subjects who have never seen a robot before will be more interested in the robotic fitness coach or not. Only one of the subjects had a real experience with a robot during her lifetime. Hence, we do not have a diverse subject set, as we mentioned, to be able to test this claim.

The results of the survey questions related to the robot and interaction perception is also shown in Table 5.6. Although the subjects appreciated the performance of exercise demonstration of the robot, they did not prefer our robot as an exercise partner. The reason behind this can be two fold. First, our robot has low social skills while interacting with the subject. It is more like a *functional* robot. *Social presence* and *social attraction* perceptions of the robot by elderly subjects also have low scores 5.6. This may prevent the subjects to adopt our system. Second, the subjects in the nursing home were selected from people who attend the group exercise sessions held three times in a week under the supervision of a physiotherapist. They perceive these sessions as social events and say that this a social event which allows them to socialize with each other.

As a future work, we intend to extend our experiments by integrating new social skills to our system and apply the survey again to see the effect of social interaction on the percep-

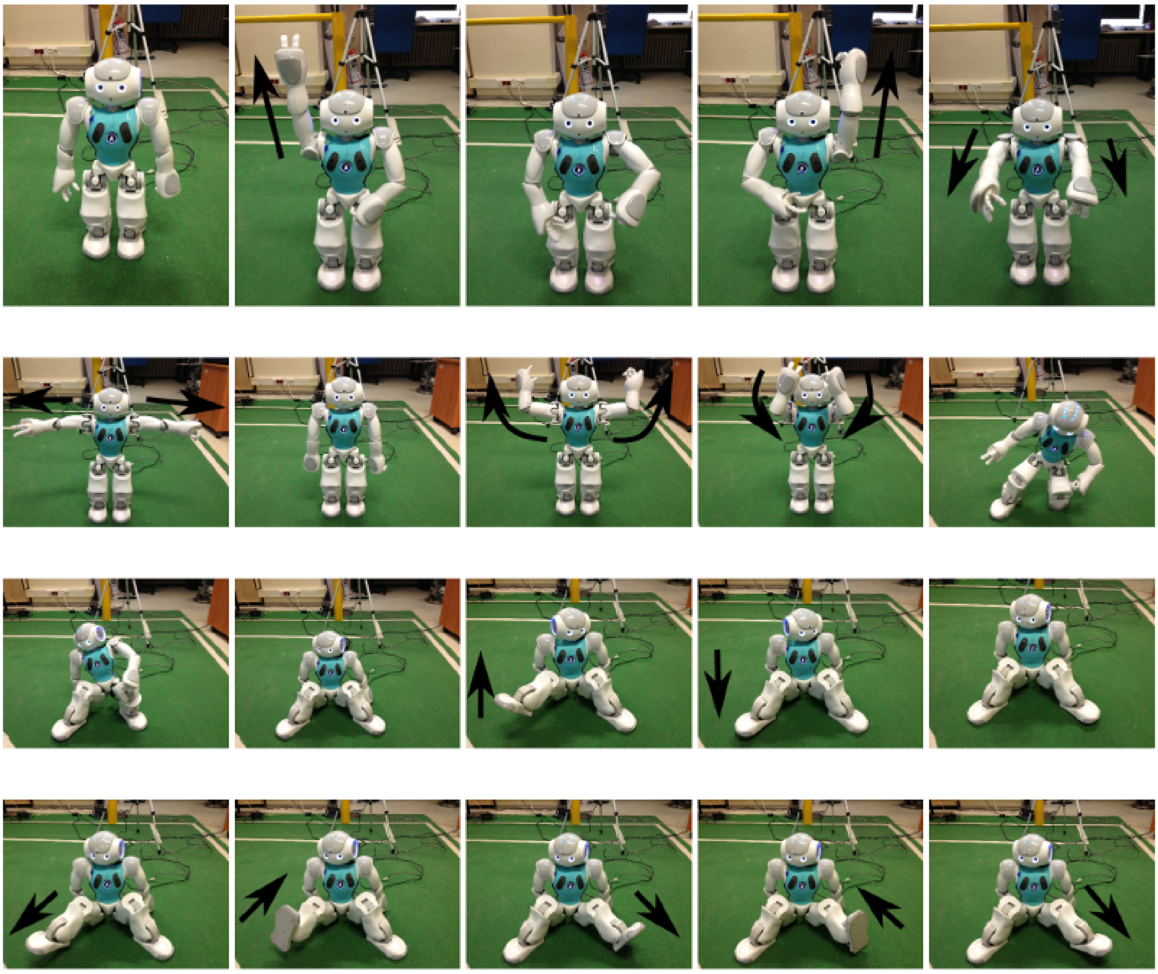


Figure 5.3. Gestures performed in the experimental exercise interventions held in the nursing home.

tion of our system as an exercise partner.

5.3.3. The Third Experimental Study with the Subjects who are Unfamiliar with the Gestures

The same exercise intervention scenario was carried out with the subjects of the third experimental study. The average age of this group was 58. The subjects have not attended any exercise activities previously. Hence, they were not familiar with the exercise motions performed in the experiment. They were able to repeat the motions after the robot demonstration (see Figure 5.6). However, for the motions where the *Nao* robot can only perform partially such as side lumber stretching, the direct replication of the robot by the subjects resulted in incorrect reproduction of the gestures. This observation shows that the previous

Table 5.6. The user evaluation results of the experiment held in the nursing home.

Interaction			
Component	*Mean*	*Standard Deviation*	*Scale*
Enjoyableness	4.8	1.38	1-10
Usefulness	4.3	2.24	1-10
Robot			
Component	*Mean*	*Standard Deviation*	*Scale*
Companionship	5.7	2.0	1-10
Intelligence	5.0	2.28	1-10
Helpfulness	4.16	2.63	1-10
Social Attraction	2.54	2.31	1-7
Social Presence	3.25	2.29	1-10
As Exercise Partner	3.91	2.92	1-10
Demonstration Performance of Robot			
Component	*Mean*	*Standard Deviation*	*Scale*
Visual Demonstration Performance	7.0	2.34	1-10
Vocal Explanation Performance	7.5	2.42	1-10
Providing Feedback Performance	2.0	0.89	1-3

Figure 5.4. The robot and an elderly person performing *right side lumber stretching* exercise.

Figure 5.5. The robot and an elderly person performing *upper arm stretching* exercise.

domain knowledge in exercising are important for the perception of the motions which the *Nao* robot can not perform completely.

The second survey mentioned in Section 4.3 was applied to the subjects. The survey results of the study are given in Table 5.7. This group of subjects found the exercise system more useful and more enjoyable compared to the elderly people in the nursing home. The evaluation of the robot for social presence and as an exercise assistant are also better. Since the subjects do not have any other alternative for exercising, our system can be perceived as more valuable and useful. Furthermore, one of the subjects said that the arm motions are easier to understand. Two subjects rated the same performance on both the leg and the arm motions and one subject preferred the leg motion demonstration to the arm motions. All of the subjects had again a common approach in that the vocal explanations besides the visual demonstrations make the perception of the gestures easier.

5.3.4. The Gesture Replication Performances of the Subjects in the Exercise Interventions

The numerical evaluations of the replication performances of the subjects of the first, second and third user studies are shown in the Tables 5.8, 5.9 and 5.10 respectively. The mean and standard deviation over the absolute differences in the angle values of the human demonstrator and the subject for *gesture identifier joints* per frame are calculated for each exercise motion the subject performs. The results are assessed for each subject separately. Note that, due to some technical problems during the exercise intervention of the third user study, we could not record the skeleton data of one the subjects and evaluated the remaining three subjects.

The overall replication performance of the young subjects are relatively higher than the subjects of the second and third user group. According to our observations, the elderly people have some difficulties in performing the exercise motions due to their physical inabilities. Hence, worse replication performance compared to the first and third group of subjects is reasonable. The third group has nearly the same results with the elderly subjects of the nursing home except the second subject although our expectation was to obtain better results

Table 5.7. The user evaluation results of the third group of subjects.

Interaction			
Component	*Mean*	*Standard Deviation*	*Scale*
Enjoyableness	7.6	1.00	1-10
Usefulness	8.8	0.99	1-10
Robot			
Component	*Mean*	*Standard Deviation*	*Scale*
Companionship	7.25	2.7	1-10
Intelligence	8.5	2.38	1-10
Helpfulness	6.00	3.60	1-10
Social Attraction	4.81	3.31	1-7
Social Presence	5.62	2.81	1-10
As Exercise Partner	5.06	4.69	1-10
Demonstration Performance of Robot			
Component	*Mean*	*Standard Deviation*	*Scale*
Visual Demonstration Performance	7.66	2.51	1-10
Vocal Explanation Performance	8.25	2.36	1-10
Providing Feedback Performance	1.0	0.0	1-3

Figure 5.6. The subjects of the third user group are replicating the robot.

compared to the second group, since this group of subjects are relatively younger and capable of demonstrating all motions physically. However, the subjects had no prior domain knowledge on exercising and this may cause them directly replicating the robot for all motions. Since the robot performance shows differences for the motions which can be done partially, the final difference in the way of performing exercise of the subjects and the human demonstrator are higher than the first group of subjects and similar to the second group.

Since the skeleton tracking performance of the *OpenNI* software is not satisfactory for the postures other than the standing pose due to camera noise, we could not record the skeleton data of the subjects for the leg motions performed in the sitting pose in the second and the third user studies. Hence, we can not compare the replication performance of the upper body and lower body motions for these groups. For the first user study, we were able to test the leg motions in the standing pose with the young subjects. However, the results show that there is no significant difference in the replication performance of the arm and the leg gestures.

Another interesting finding in the experimental results of the elderly people is that the replication performance increases through the exercise session. Although the left side lumber stretching and the right side lumber stretching gestures are the same, all subjects replicated the second repetition of the gesture (stretching to the right side) more successfully. This shows that the recognition of the robot's physical structure and its way of motion may affect the replication performance. More promising results can be obtained with an increased number of user studies with the same subjects.

Table 5.8. The mean of absolute differences between the joint angles of the human demonstrator and the subject of first user study.

	Chest stretching 2 (Mean ± Std. Dev.)	**Upper arm stretching (Mean ± Std. Dev.)**	**Back strength (Mean ± Std. Dev.)**	**Hip side extension (Mean ± Std. Dev.)**	**Hip extension (Mean ± Std. Dev.)**
Subject 1	0.122 ± 0.122	0.156 ± 0.147	0.101 ± 0.071	0.097 ± 0.054	0.082 ± 0.092
Subject 2	0.113 ± 0.115	0.220 ± 0.136	0.270 ± 0.037	0.062 ± 0.081	0.119 ± 0.435
Subject 3	0.099 ± 0.109	0.157 ± 0.143	0.148 ± 0.049	0.071 ± 0.059	0.143 ± 0.141
Subject 4	0.097 ± 0.123	0.196 ± 0.189	0.129 ± 0.069	0.109 ± 0.063	0.181 ± 0.128
Subject 5	0.111 ± 0.108	0.132 ± 0.101	0.081 ± 0.072	0.085 ± 0.037	0.090 ± 0.087
Subject 6	0.112 ± 0.109	0.171 ± 0.133	0.268 ± 0.092	0.057 ± 0.059	0.104 ± 0.307
Subject 7	0.101 ± 0.142	0.135 ± 0.096	0.189 ± 0.052	0.101 ± 0.050	0.069 ± 0.320
Subject 8	0.094 ± 0.174	0.145 ± 0.145	0.105 ± 0.060	0.070 ± 0.040	0.100 ± 0.077
Subject 9	0.093 ± 0.151	0.132 ± 0.071	0.074 ± 0.048	0.111 ± 0.031	0.048 ± 0.038

Table 5.9. The mean of absolute differences between the joint angles of the human demonstrator and the subject of second user study.

	Left side lumber stretching (Mean ± Std. Dev.)	**Right side lumber stretching (Mean ± Std. Dev.)**	**Back strength (Mean ± Std. Dev.)**	**Upper arm stretching (Mean ± Std. Dev.)**
Subject 1	0.363 ± 0.380	0.185 ± 0.195	0.262 ± 0.288	0.102 ± 0.057
Subject 2	0.383 ± 0.354	0.171 ± 0.172	0.275 ± 0.272	0.118 ± 0.061
Subject 3	0.421 ± 0.420	0.194 ± 0.197	0.264 ± 0.301	0.119 ± 0.091
Subject 4	0.394 ± 0.382	0.196 ± 0.225	0.289 ± 0.286	0.055 ± 0.124
Subject 5	0.381 ± 0.370	0.175 ± 0.206	0.250 ± 0.281	0.054 ± 0.078
Subject 6	0.361 ± 0.353	0.168 ± 0.191	0.264 ± 0.259	0.106 ± 0.080

Table 5.10. The mean of absolute differences between the joint angles of the human demonstrator and the subject of third user study.

	Left side lumber stretching (Mean $\pm$ Std. Dev.)	**Right side lumber stretching (Mean $\pm$ Std. Dev.)**	**Back strength (Mean $\pm$ Std. Dev.)**	**Upper arm stretching (Mean $\pm$ Std. Dev.)**
Subject 1	0.317 ± 0.411	0.160 ± 0.203	0.242 ± 0.360	0.136 ± 0.081
Subject 2	0.269 ± 0.333	0.329 ± 0.183	0.146 ± 0.188	0.106 ± 0.037
Subject 3	0.363 ± 0.307	0.133 ± 0.156	0.251 ± 0.194	0.120 ± 0.023

6. CONCLUSION

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.

We have compared 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.

We have carried out three experimental studies with three different user groups which are young subjects, elderly people who reside in the nursing home and a small middle aged population who have never experienced an exercise activity during their lifetimes. The young subjects found the movements of the robot too slow and recommended to speed up the exercise motions. They also stated that the system is interesting and enjoyable. The subjects of the second group with an average age of 75 were the residents of the nursing home who attend the exercise sessions held in the nursing home three times in a week. According to the our observations and tracking results, the subjects were able to replicate the exercise motions with the robot successfully. However, the four subjects were bored and uninterested to the system after the exercise intervention. They stated that the robot lacks of sufficient social aspects to motivate them to exercise with a robot. The childish appearance of our robot may prevent them to take it seriously. Moreover, we beheld that as the subjects get older their interest in the system also increases. The eldest two subjects enjoyed the system and said that they can benefit from such a system for exercising in their room without waiting for the collective exercise sessions held in the nursing home. For the third group of subjects, the important outcome is that the domain knowledge in exercise activities affects the perception of the exercise motions performed by the robot. They performed the motions in the same way as the robot does which causes incorrect replications of the motions the robot can perform partially. On the contrary, the subjects of the other two groups were not affected this mismatch. This group of users also find the system useful. The reason behind this may be that they have not had an opportunity to attend such an ongoing exercise activity which may be an alternative to our system.

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 [75]. We work with an elderly care facility, where the robotic fitness coach was warmly received by the inhabitants. Our plans for near future include enriching the robotic system with various social abilities and assessing interaction aspects for perceived usefulness, perceived ease of use, and for variables that relate to social interaction [47].

6.1. Contributions

We can list our contributions to the literature of fitness coach robot systems as follows:

- None of the currently developed system adopts a learning mechanism for exercise motions. They require preset joint angle values which can be inconvenient for each new gesture added to the exercise session. We develop a system which allows us to teach new gestures by demonstration. Hence, the motions are closer to the human's than the designed ones considering directly the embodiment of the robot. We investigate the perception shortcomings of these exercise motions which can not be performed as observed by the human demonstrator due to the inabilities of the robot. We integrate feedback mechanism and vocal explanations to fill the gap originated from the inabilities of the robotic system.

- We form a list which contains a number of senior exercise motions with their descriptions. A feasibility study on realizing these gestures on the *Nao* robot is also carried out and the results are included in the form. These gestures are selected from the exercise sessions held in a nursing home so our system is convenient to create a real world scenario.
- We also evaluate our system with the elderly residents of a nursing home who attend the exercise sessions which are supervised by a physiotherapist. We consult the physiotherapist for the motions which should be performed in a short exercise intervention in order to converge our experimental studies to a real world scenario.
- We have written two conference papers, one was presented and published [76] and the other one is accepted to be presented and will be published in the proceedings [77].

6.2. Future Work

As a future work, we aim to develop a robot with further cognition capabilities. Gesture recognition plays significant role in order to make the imitations more robust and smooth. Developmental learning can also be consulted if the robot can extract and identify motion primitives of the gesture performed by the human demonstrator. A set of primitive motions can be composed from the existing ones and new primitives can be added to this set as they are recognized from new posture sequences of the demonstrator. Gesture recognition also allows to compose text messages autonomously which is used to explain the gesture verbally.

Feedback mechanism can be developed to give feedbacks not only considering the last posture of the motion but also whole joint sequences which compose the motion. Cognition of intention of the user during exercise session and avoidance from extensive verbal feedbacks which may result in annoyed subjects are also another future challenges which are planned to realize in the project.

We did not put human-robot interaction performance of the robot in our central focus for this project. On the other hand, social abilities of robot affect his perception as an exercise coach which in turn changes the perceived usefulness of the system. In order to analyze the success of the system in making the subject imitate the gestures correctly and motivate on exercising, HRI factors which may prevents the subject to benefit from the system as it should be, should be considered and implemented in the system.

We plan to continue our user studies in five different sections in order to control the effects of various hidden factors on the performance of the system. The scenarios considered are as follows:

- The elderly is observed when he exercises with a human exercise coach. This study is required in order to determine on the physical capabilities of the elderly. The performance of the system should be evaluated upon this base.
- The *Nao* robot guide the elderly only providing vocal commands to explain the gestures. No visual performance is realized. This study is required to analysis the effect of providing vocal commands besides visual demonstrations on the perception of gestures.
- The *Nao* robot performs gestures besides providing vocal commands.
- The system is controlled remotely by applying the Wizard of Oz methodology. This study may be helpful to compare the autonomous robot to its best performing, interactive version.
- The virtual *Nao* robot displayed on a screen is used as an exercise coach. This study is required to measure the effect of the physical embodiment on the overall performance of the system.

APPENDIX A: KINEMATIC MODEL OF THE NAO HUMANOID ROBOT

A.1. Joint Information of the Nao Humanoid Robot

Table A.1. Joint limits of the *Nao* robot.

Part	Joint Name	Range (in radians)
Head	HeadYaw	[-2.08 , 2.08]
	HeadPitch	[-0.67 , 0.51]
Left Arm	LShoulderPitch	[-2.08 , 2.08]
	LShoulderRoll	[-0.31 , 1.32]
	LElbowYaw	[-2.08 , 2.08]
	LElbowRoll	[-1.54 , -0.03]
	LWristYaw	[-1.82 , 1.82]
Left Leg	LHipYawPitch	[-1.14 , 0.74]
	LHipRoll	[-0.37 , 0.79]
	LHipPitch	[-1.77 , 0.48]
	LKneePitch	[-0.09 , 2.11]
	LAnklePitch	[-1.18 , 0.92]
	LAnkleRoll	[-0.39 , 0.76]
Right Arm	RShoulderPitch	[-2.08 , 2.08]
	RShoulderRoll	[-1.32 , 0.31]
	RElbowYaw	[-2.08 , 2.08]
	RElbowRoll	[0.03 , 1.54]
	RWristYaw	[-1.82 , 1.82]
Right Leg	RHipYawPitch	[-1.14 , 0.74]
	RHipRoll	[-0.73 , 0.41]
	RHipPitch	[-1.77 , 0.48]
	RKneePitch	[-0.10 , 2.12]
	RAnklePitch	[-1.18 , 0.93]
	RAnkleRoll	[-0.78 , 0.38]

Table A.2. DH parameters for the left arm of the *Nao* robot.

i	$\boldsymbol{\alpha_i}$	$\mathbf{a}_i$	$\boldsymbol{\theta_i}$	$\mathbf{d}_i$
1	-π/2	0	β_1	L_1
2	π/2	0	π/2+β_2	0
3	π/2	0	π+β_3	L_1
4	-π/2	0	β_4	0

A.2. Forward Kinematics for the Nao Humanoid Robot

A.2.1. DH Parameters for the Left Arm of the Nao Humanoid Robot

DH parameters for the left arm of *Nao* are shown in Table A.2 and transformation matrix from the base coordinate system to that of the end effector is as follows:

$$NaoT = \begin{bmatrix} T_{11} & T_{12} & T_{13} & T_{14} \\ T_{21} & T_{22} & T_{23} & T_{24} \\ T_{31} & T_{32} & T_{33} & T_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{A.1}$$

$T_{11} = cos(\beta_4) \times cos(\beta_1) \times sin(\beta_2) \times cos(\beta_3) - cos(\beta_4) \times sin(\beta_1) \times sin(\beta_3) - cos(\beta_1) \times cos(\beta_2) \times sin(\beta_4)$

$T_{12} = -sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) \times cos(\beta_3) + sin(\beta_4) \times sin(\beta_1) \times sin(\beta_3) - cos(\beta_1) \times cos(\beta_2) \times cos(\beta_4)$

$T_{13} = -cos(\beta_1) \times sin(\beta_2) \times sin(\beta_3) - sin(\beta_1) \times cos(\beta_3)$

$T_{14} = cos(\beta_1) \times cos(\beta_2) \times L_1$

$T_{21} = -cos(\beta_2) \times cos(\beta_3) \times cos(\beta_4) - sin(\beta_2) \times sin(\beta_4)$

$T_{22} = cos(\beta_2) \times cos(\beta_3) \times sin(\beta_4) - sin(\beta_2) \times cos(\beta_4)$

$T_{23} = cos(\beta_2) \times sin(\beta_3)$

$T_{24} = sin(\beta_2) \times L_1$

$T_{31} = -cos(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times cos(\beta_3) - cos(\beta_4) \times cos(\beta_1) \times sin(\beta_3) + sin(\beta_1) \times cos(\beta_2) \times sin(\beta_4)$

$T_{32} = sin(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times cos(\beta_3) + sin(\beta_4) \times cos(\beta_1) \times sin(\beta_3) + sin(\beta_1) \times cos(\beta_2) \times cos(\beta_4)$

$T_{33} = sin(\beta_1) \times sin(\beta_2) \times sin(\beta_3) - cos(\beta_1) \times cos(\beta_3)$

$T_{34} = -sin(\beta_1) \times cos(\beta_2) \times L_1$

$\beta_1 = LeftShoulderPitch, \beta_2 = LeftShoulderRoll, \beta_3 = LeftElbowYaw, \beta_4 = LeftElbowRoll, L_1 = UpperArmLength$

A.2.2. DH Parameters for the Left Leg of the Nao Humanoid Robot

Table A.3. DH parameters for the left leg of the *Nao* robot.

i	$\boldsymbol{\alpha_i}$	$\mathbf{a}_i$	$\boldsymbol{\theta_i}$	$\mathbf{d}_i$
1	-$\frac{3\pi}{4}$	0	$\beta_1 - \pi/2$	0
2	$\pi/2$	0	β_2	0
3	$-\pi/2$	0	β_3+$\pi/4$	0
4	0	0	β_4	-L_1
5	0	0	β_5	-L_2
6	-$\pi/2$	0	β_6	0
7	0	0	0	-L_3

DH parameters of the left leg of *Nao* are also shown in Table A.3 and transformation matrix from the base coordinate system to that of the end effector is as follows:

$$NaoT = \begin{bmatrix} T_{11} & T_{12} & T_{13} & T_{14} \\ T_{21} & T_{22} & T_{23} & T_{24} \\ T_{31} & T_{32} & T_{33} & T_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{A.2}$$

$T_{11} = -cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} - 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times 2^{1/2} \times sin(\beta_3) - cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times 2^{1/2} \times sin(\beta_3) - cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + sin(\beta_6) \times sin(\beta_3) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times sin(\beta_6) \times sin(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} - 1/2 \times sin(\beta_6) \times sin(\beta_1) \times 2^{1/2} \times cos(\beta_3)$

$T_{12} = sin(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times 2^{1/2} \times sin(\beta_3) + sin(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + cos(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times 2^{1/2} \times sin(\beta_3) - cos(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2}$

$T_{13} = -sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} - 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times 2^{1/2} \times sin(\beta_3) - sin(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times sin(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times$

$cos(\beta_1) \times sin(\beta_2) + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times 2^{1/2} \times sin(\beta_3) - sin(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - cos(\beta_6) \times sin(\beta_3) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times cos(\beta_6) \times sin(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_6) \times sin(\beta_1) \times 2^{1/2} \times cos(\beta_3)$

$T_{14} = -L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} - 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times 2^{1/2} \times sin(\beta_3) - L_3 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2\, times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times 2^{1/2} \times sin(\beta_3) - L_3 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + L_3 \times sin(\beta_6) \times sin(\beta_3) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times L_3 \times sin(\beta_6) \times sin(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} - 1/2 \times L_3 \times sin(\beta_6) \times sin(\beta_1) \times 2^{1/2} \times cos(\beta_3) - L_2 \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times L_2 \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} - 1/2 \times L_2 \times cos(\beta_4) \times sin(\beta_1) \times 2^{1/2} \times sin(\beta_3) - L_2 \times sin(\beta_4) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times L_2 \times sin(\beta_4) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - L_1 \times cos(\beta_3) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times L_1 \times cos(\beta_3) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} - 1/2 \times L_1 \times sin(\beta_1) \times 2^{1/2} \times sin(\beta_3)$

$T_{21} = 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) - 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_2) - 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4)\, times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_2) + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_2) - 1/2 \times sin(\beta_6) \times sin(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_6) \times sin(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times sin(\beta_6) \times sin(\beta_3) \times cos(\beta_2) -$

$1/2 \times sin(\beta_6) \times cos(\beta_3) - 1/2 \times sin(\beta_6) \times cos(\beta_3) \times cos(\beta_1)$

$T_{22} = -1/2 \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_2) + 1/2 \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_3) + 1/2 \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_3) \times cos(\beta_1) - 1/2 \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} - 1/2 \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_2) - 1/2 \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_2) + 1/2 \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_3) + 1/2 \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_2)$

$T_{23} = 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) - 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times sin(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times sin(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_2) - 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4)\ times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_2) + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times sin(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_2) + 1/2 \times cos(\beta_6) \times sin(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times cos(\beta_6) \times sin(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times cos(\beta_6) \times sin(\beta_3) \times cos(\beta_2) + 1/2 \times cos(\beta_6) \times cos(\beta_3) + 1/2 \times cos(\beta_6) \times cos(\beta_3) \times cos(\beta_1)$

$T_{24} = -1/2 \times L_1 \times sin(\beta_3) \times cos(\beta_1) - 1/2 \times L_3 \times sin(\beta_6) \times cos(\beta_3) + 1/2 \times L_1 \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times L_2 \times sin(\beta_4) \times sin(\beta_2) + 1/2 \times L_2 \times sin(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times L_1 \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times$

$sin(\beta_3) \times cos(\beta_1) + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_2) - 1/2 \times L_3 \times sin(\beta_6) \times sin(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times L_3 \times sin(\beta_6) \times sin(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times L_2 \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times L_2 \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) - 1/2 \times L_1 \times sin(\beta_3) - 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_2) - 1/2 \times L_3 \times sin(\beta_6)\ timessin(\beta_3) \times cos(\beta_2) - 1/2 \times L_3 \times sin(\beta_6) \times cos(\beta_3) \times cos(\beta_1) + 1/2 \times L_2 \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times L_2 \times cos(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times L_2 \times sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times L_1 \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times L_2 \times cos(\beta_4) \times sin(\beta_3)$

$T_{31} = 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_2) + 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) - 1/2 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_2) - 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4)\ timescos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_2) - 1/2 \times sin(\beta_6) \times sin(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_6) \times sin(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times sin(\beta_6) \times sin(\beta_3) \times cos(\beta_2) + 1/2 \times sin(\beta_6) \times cos(\beta_3) - 1/2 \times sin(\beta_6) \times cos(\beta_3) \times cos(\beta_1)$

$T_{32} = -1/2 \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_3) + 1/2 \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_3) \times cos(\beta_1) -$

$1/2 \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} - 1/2 \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_2) - 1/2 \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_3) + 1/2 \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_2$

$T_{33} = 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_2) + 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) - 1/2 \times sin(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times sin(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times sin(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_2) - 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4)\ timescos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times sin(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_2) + 1/2 \times cos(\beta_6) \times sin(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times cos(\beta_6) \times sin(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times cos(\beta_6) \times sin(\beta_3) \times cos(\beta_2) - 1/2 \times cos(\beta_6) \times cos(\beta_3) + 1/2 \times cos(\beta_6) \times cos(\beta_3) \times cos(\beta_1)$

$T_{34} = -1/2 \times L_1 \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times L_3 \times sin(\beta_6) \times cos(\beta_3) - 1/2 \times L_1 \times cos(\beta_3) \times cos(\beta_2) + 1/2 \times L_2 \times sin(\beta_4) \times sin(\beta_2) + 1/2 \times L_2 \times sin(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times L_1 \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times sin(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times sin(\beta_5) \times cos(\beta_4) \times sin(\beta_2) - 1/2 \times L_3 \times sin(\beta_6) \times sin(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} + 1/2 \times L_3 \times sin(\beta_6) \times sin(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times L_2 \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) \times sin(\beta_2) \times 2^{1/2} - 1/2 \times L_2 \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times$

$cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times sin(\beta_1) sin(\beta_2) \times 2^{1/2} - 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) - 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) + 1/2 \times L_1 \times sin(\beta_3) - 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times cos(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_1) \times cos(\beta_2) \times 2^{1/2} + 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) + 1/2 \times L_3 \times cos(\beta_6) \times cos(\beta_5) \times sin(\beta_4) \times sin(\beta_2) + 1/2 \times L_3 \times sin(\beta_6) \times sin(\beta_3) \times cos(\beta_2) - 1/2 \times L_3 \times sin(\beta_6) \times cos(\beta_3) \times cos(\beta_1) - 1/2 \times L_2 \times cos(\beta_4) \times cos(\beta_3) \times cos(\beta_2) - 1/2 \times L_2 \times cos(\beta_4) \times sin(\beta_3) \times cos(\beta_1) + 1/2 \times L_2 \times sin(\beta_4) \times cos(\beta_1) \times sin(\beta_2) - 1/2 \times L_1 \times cos(\beta_3) \times cos(\beta_1) \times cos(\beta_2) + 1/2 \times L_2 \times cos(\beta_4) \times sin(\beta_3)$

$\beta_1 = HipYawPitch, \beta_2 = HipPitch, \beta_3 = HipRoll, \beta_4 = KneePitch, \beta_5 = AnklePitch, \beta_6 = AnkleRoll, L_1 = ThighLength, L_2 = TibiaLength, L_3 = FootHeight$

APPENDIX B: INFORMED CONSENT FORM USED IN THE EXPERIMENTS

Table B.1. Informed consent form used in the experiments.

Katılımcı Bilgi ve Onam Formu
Araştırmacıyı destekleyen kurum: Boğaziçi Üniversitesi **Araştırmanın adı:** Yaşlı Kişilere Günlük Egzersiz Aktivitelerinde Yardımcı Olacak Egzersiz Eğitmeni Robotunun Geliştirilmesi **Proje Yürütücüsü/Araştırmacının adı:** Prof. Dr. H. Levent Akın , Binnur Görer **Adresi:** Boğaziçi Üniversitesi, Bilgisayar Mühendisliği ETA37, 34342 Bebek İstanbul **E-mail adresi:** akin@boun.edu.tr, binnur.gorer@boun.edu.tr **Telefonu:** +90 212 359 7096 Sayın Katılımcı, Boğaziçi Üniversitesi Bilgisayar Mühendisliği Bölümü öğretim üyesi Prof. Dr. H. Levent Akın'ın danışmanlığında yürütmekte olduğum yüksek lisans tezi kapsamında yaşlı kişilere günlük egzersiz hareketlerinde yardımcı olacak bir egzersiz eğitmeni robotu geliştirmekteyim. Bu çalışmanın amacı yaşlı kimselerin ikamet ettikleri yerlerde bir insan gözetmenine ihtiyaç duymaksınız günlük egzersiz aktivitelerini bir robot yardımı ile yapmalarını sağlamaktır. Günlük egzersiz hareketlerinin yaşlı kişilerin kas ve kemik sağlığını korumasının yanında idrak ve algılama yeteneklerinin de kullanılmasına yarar sağladığı bilinmektedir. Ayrıca robotun yaşlı kişiye eşlik etmesi yalnız yaşayan bireylerin psikolojik olarak kendilerini iyi hissetmelerini de sağlayabilmektedir. Bu çalışma ile yukarıda bahsedilen amaçlara uygun olarak geliştirilmeye çalışılan bir robot egzersiz eğitmeninin performans değerlendirilmesi yapılması istenmektedir. Bu araştırmaya katılmayı kabul ettiğiniz takdirde robotumuz size bir dizi egzersiz hareketleri gösterip sizden onu taklit etmenizi isteyecektir. Hareketi gösterme esnasında sesli olarak da size hareketi anlatacaktır. Bir hareket bittikten sonra, bir sonraki harekete geçmeden önce size mevcut hareketi doğru ya da yanlış yaptığınızla ilgili geri bildirimde bulunarak egzersiz hareketini en doğru biçimde tekrar etmenize çalışacaktır. Egzersiz boyunca robotun sizinle herhangi bir fiziksel teması bulunmayacaktır. Robot belirli bir alanda hareket edecektir, bu açıdan herhangi bir tehlike oluşturmamaktadır. Bir egzersiz dizisinin 20-25 dakikada tamamlanması düşünülmektedir ve bu seanslar sizin ikamet ettiğiniz yerde gerçekleştirilecektir.

Table B.1. Informed consent form used in the experiments (cont.).

Egzersiz seansı boyunca robot size geri bildirimlerde bulunabilmek ve sizinle senkronize bir şekilde seansa devam edebilmek için derinlik algılayıcı kamera ile sizi izleyecektir. Bu kamera ile herhangi bir görüntü alma ya da kaydetme işlemi yapılmayacaktır. Sadece vücudunuzun duruş pozisyonu ve eklemlerinizin açı değerleri hesaplanarak kaydedilecek ve sizin hareketi tekrar etmedeki başarınıza göre robotun hareketi gösterme ve anlatmadaki performansı değerlendirilecektir. Bu kayıtlarda kimlik bilgisi yerine numara kullanılacaktır. Seçilmiş bazı örnekler kimlik belirtilmeden bilimsel nitelikteki sunumlarda kullanılabilir.

Son olarak, sizden egzersiz seansını ve robotun performansını değerlendirmenizi isteyeceğiz. Bunu herkes için standart bir hale dönüştürebilmek adına 8 soruluk bir anketimiz olacak. Anketimizin öncesinde sistemimizin başarısına olan etkisini incelemek adına yaş ve cinsiyet bilgilerinizi de öğrenmek isteyeceğiz.

Bu araştırmaya katılmak tamamen isteğe bağlıdır. Katıldığınız takdirde çalışmanın herhangi biraşamasında herhangi bir sebep göstermeden onayınızı çekmek hakkına da sahipsiniz. Bu araştırmada sağlığınıza zarar verecek herhangi bir durumun oluşmayacağını ve şahsi herhangi bir bilginizin kullanılmayacağını hatırlatmak isteriz. Araştırma projesi hakkında ek bilgi almak istediğiniz takdirde lütfen Boğaziçi Üniversitesi Bilgisayar Mühendisliği Bölümü Araştırma Görevlisi Binnur Görer ile temasa geçiniz (Telefon: +90 212 359 7096, Adres: Boğaziçi Üniversitesi, Bilgisayar Mühendisliği Bölümü ETA 37, 34342 Bebek, İstanbul).

Ben, (katılımcının adı) ...., yukarıdaki metni okudum ve katılmam istenen çalışmanın kapsamını ve amacını, gönüllü olarak üzerime düşen sorumlulukları tamamen anladım. Çalışma hakkında soru sorma imkanı buldum. Bu çalışmayı istediğim zaman ve herhangi bir neden belirtmek zorunda kalmadan bırakabileceğimi ve bıraktığım takdirde herhangi bir ters tutum ile karşılaşmayacağımı anladım.

Bu koşullarda söz konusu araştırmaya kendi isteğimle, hiçbir baskı ve zorlama olmaksızın katılmayı kabul ediyorum.

Formun bir örneğini aldım / almak istemiyorum (bu durumda araştırmacı bu kopyayı saklar).

Katılımcının Adı-Soyadı:..........................
İmzası:..
Adresi (varsa Telefon No, Fax No):................
Tarih (gün/ay/yıl):...............................

Katılımcının Vasisinin Adı-Soyadı:................
İmzası:..
Tarih (gün/ay/yıl):...............................

Table B.1. Informed consent form used in the experiments (cont.).

Araştırmacının Adı-Soyadı:........................ İmzası:.. Tarih (gün/ay/yıl):...............................

APPENDIX C: QUESTIONNAIRES

C.1. Questionnaire Applied in the User Study with Young Subjects

Table C.1. Questionnaire applied in the user study with young subjects.

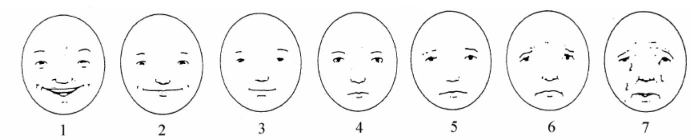
Egzersiz Robotu Değerlendirme Anketi		
Mesleğiniz: **Cinsiyetiniz:** **Yaş Aralığınız:**		
1. Dikkatim dağılmış hissettim.	☐	1 (doğru değil) - 5 (doğru)
2. Sıkıldım.	☐	1 (doğru değil) - 5 (doğru)
3. Eğlendim.	☐	1 (doğru değil) - 5 (doğru)
4. Oldukça konsantre olmuş hissettim.	☐	1 (doğru değil) - 5 (doğru)
5. Uygulamanın konusu ile ilgiliydim.	☐	1 (doğru değil) - 5 (doğru)
6. Güldürücüydü.	☐	1 (doğru değil) - 5 (doğru)
7. Benim için zengin bir deneyim olduğunu düşünüyorum.	☐	1 (doğru değil) - 5 (doğru)
8. Zorlayıcı bir görev gibi hissettim.	☐	1 (doğru değil) - 5 (doğru)
9. Egzersiz hareketlerini yapmaya teşvik edilmiş hissettim.	☐	1 (doğru değil) - 5 (doğru)
10. Seans boyunca çevremle olan bağlantımı oldukça azalttığını hissettim.	☐	1 (doğru değil) - 5 (doğru)
11. Mutlu hissettim.	☐	1 (doğru değil) - 5 (doğru)
12. Zihnimde başka şeyler vardı.	☐	1 (doğru değil) - 5 (doğru)
13. Kendimi iyi hissettim.	☐	1 (doğru değil) - 5 (doğru)
14. Tüm dikkatimi bir şeye yoğunlaştırdığımı düşünüyorum.	☐	1 (doğru değil) - 5 (doğru)
15. Dış dünya ile bağlantımı kopardığımı düşünüyorum.	☐	1 (doğru değil) - 5 (doğru)
16. Uygulamanın amacı benim için sıkıcıydı.	☐	1 (doğru değil) - 5 (doğru)
17. Seans süresince oldukça efor sarfettiğimi düşünüyorum.	☐	1 (doğru değil) - 5 (doğru)
18. Estetik açıdan hoşa giden bir yanı vardı.	☐	1 (doğru değil) - 5 (doğru)
19. Zor olduğunu düşünüyorum.	☐	1 (doğru değil) - 5 (doğru)
20. Uygulamayı yaratıcı buldum.	☐	1 (doğru değil) - 5 (doğru)
21. Zamanı çok takip edemedim.	☐	1 (doğru değil) - 5 (doğru)
22. Bir şeyler öğrendiğimi hissettim.	☐	1 (doğru değil) - 5 (doğru)
23. Yorucu olduğunu düşünüyorum.	☐	1 (doğru değil) - 5 (doğru)
24. Memnun oldum.	☐	1 (doğru değil) - 5 (doğru)
25. Yeni şeyler keşfettiğimi düşünüyorum.	☐	1 (doğru değil) - 5 (doğru)

C.2. Questionnaire Applied in the User Study with Elderly Subjects

Table C.2. Questionnaire applied in the user study with elderly subjects.

Egzersiz Robotu Değerlendirme Anketi		
Adınız: **Yaşınız:** **Mesleğiniz:**		
1. İlk defa mı bir robot görüyorsunuz? Hayırsa daha önce gördüğünüz robotu biraz anlatır mısınız? (Sizinle iletişime geçebilen bir robot muydu?)		
2. Egzersiz seansını ne kadar ...		
eğlenceli	☐	1 (hiç değil) - 10 (oldukça fazla)
ilginç	☐	1 (hiç değil) - 10 (oldukça fazla)
tatmin edici	☐	1 (hiç değil) - 10 (oldukça fazla)
sıkıcı	☐	1 (hiç değil) - 10 (oldukça fazla)
heyecan verici	☐	1 (hiç değil) - 10 (oldukça fazla)
kullanışlı	☐	1 (hiç değil) - 10 (oldukça fazla)
faydalı	☐	1 (hiç değil) - 10 (oldukça fazla)
değerli	☐	1 (hiç değil) - 10 (oldukça fazla)
buldunuz?		
3. Robotu ne kadar ...		
sevimli	☐	1 (hiç değil) - 10 (oldukça fazla)
arkadaşça	☐	1 (hiç değil) - 10 (oldukça fazla)
sıcak	☐	1 (hiç değil) - 10 (oldukça fazla)
kendinize yakın	☐	1 (hiç değil) - 10 (oldukça fazla)
akıllı	☐	1 (hiç değil) - 10 (oldukça fazla)
kabiliyetli	☐	1 (hiç değil) - 10 (oldukça fazla)
yardımsever	☐	1 (hiç değil) - 10 (oldukça fazla)
buldunuz?		
4. Böyle bir robot arkadaş ister miydiniz?	☐	1 (hiç istemem) - 7 (çok isterim)
Robotla iyi vakit geçirebileceğinizi düşünüyor musunuz?	☐	1 (hiç sanmam) - 7 (kesinlikle)
Kişisel bir iletişim kurabilecek kadar yakın hissettiniz mi?	☐	1 (hiç sanmam) - 7 (kesinlikle)
Robotla daha çok vakit geçirmek ister miydiniz?	☐	1 (hiç istemem) - 7 (çok isterim)
5. Robotla iletişim halinde iken onu sosyal bir varlık olarak düşündünüz mü?	☐	1 (hiç sanmam) - 10 (kesinlikle)
Robotun sizinle gerçekten iletişim kurduğunu düşünüyor musunuz?	☐	1 (hiç sanmam) - 10 (kesinlikle)
Robotu ne kadar sosyal buldunuz?	☐	1 (hiç) - 10 (çok)
Size ne kadar bir makine izlenimi verdi?	☐	1 (hiç) - 10 (çok)

Table C.2. Questionnaire applied in the user study with elderly subjects (cont.).

6. Egzersiz hareketlerini robotla yapmaktan hoşlandınız mı?	☐	1 (hiç sanmam) - 10 (kesinlikle)
Tanıdıklarınıza da tavsiye eder misiniz? Ne kadar?	☐	1 (hiç sanmam) - 10 (kesinlikle)
Gelecekte bir robot egzersiz eğitmen ile egzersizlerinize devam etmeyi düşünür müsünüz?	☐	1 (hiç sanmam) - 10 (kesinlikle)
Robotla egzersiz yaparken kendinizi ne kadar motive olmuş hissettiniz?	☐	1 (hiç) - 10 (çok)
7. Robotun, egzersiz hareketini görsel olarak anlatmadaki başarısını değerlendiriniz.	☐	1 (çok başarısız) - 10 (çok başarılı)
8. Robotun, egzersiz hareketini sesli olarak anlatmadaki başarısını değerlendiriniz.	☐	1 (çok başarısız) - 10 (çok başarılı)
9. Robotun egzersiz hareketini görsel olarak anlatmasının yanında sesli olarak da açıklamasını da faydalı buldunuz mu?	☐	Evet - Hayır
10. Robotun kol ve bacak hareket gruplarından hangisini daha başarılı bir şekilde gösterebildiğini düşünüyorsunuz?	☐	Kol - Bacak
11. Robotun size verdiği geri bildirimleri ne kadar başarılı buldunuz?	☐	1 (başarısız) - 3 (başarılı)
Bugünkü mutluluk durumunuzu aşağıdaki hangi resimle ilişkilendirirsiniz? 	☐	1 - 7

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