A Reuseable Framework for Designing Socially Assistive Robot Interactions

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Abstract

Robots are increasingly tested in different socially assistive scenarios. Future applications range from dieting, coaching, tutoring to autism therapy. In such applications the success of the system is commonly evaluated by the ability to encourage the user to keep up with a task. Hence, one important requirement for supportive systems is to have an interactional motivational model that formalizes the way how users can be assisted. In this paper we describe our framework for coordinating motivational interaction scenarios with socially assistive robots (SAR) in the context of sport assistance. We exemplify three different sport scenarios where we have used the same motivational interaction model. Furthermore, we show how this model can be used to systematically test the different aspects of motivation in the context of SAR in sport domains. Therefore, we have conducted an experiment to evaluate the importance of acknowledgement from SAR for human interaction partners. The results show that users exercise longer if acknowledgment is included into the motivational model.

Keywords: Human-Robot Interaction, System Design, Socially Assistive Robots

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1. Introduction

Research in Socially Assistive Robotics (SAR) targets scenarios where robots instruct people during tasks that benefit from some social assistance like rehabilitation, dieting or cognitive tasks [8, 13, 15]. Those systems are often built from scratch and implemented interaction patterns are hand-crafted for each scenario or new application. This leads to recurring implementations of interaction structures that are difficult to compare across different systems or use cases. If we take a closer look, we see commonalities between the different scenarios that require social assistance. In the examples mentioned above we see that in all scenarios users are working towards a task goal. While the tasks (e.g. dieting, rehabilitation, cognitive or engagement tasks) are different, all share common attributes (see Table 1). They have a beginning, measurable parameters and a goal. Thus, the social assistance relates to these values and the task goals and support (e.g. acknowledgment, feedback or reparation) can be triggered to help the user reach the goal. The question is if there are common motivational patterns that capture the interactional requirements neccessary to keep a user motivated to work on a task. And if so, can this concept help to systematically test the important aspects of social support?

In previous work we have developed a motivational interaction model which we have evaluated in an extended long-term study [25]. While the previous implementation focused on a single use case, we have now worked on the reusability of this model in the scope of a modular framework. In this work we describe a general formalized framework for SAR and introduce three scenarios that made use of it. Furthermore, we want to show that the modularization of the motivational interaction patterns allows to systematically test different aspects of interactional motivation.

We propose that re-usability of common motivational concepts and frameworks could help to systematically carry out experiments, measure the scientific progress and be reused in other domains.

The paper is organized as follows: First we will give a brief introduction of motivation as a key component for building SAR robots. Afterwards, we will explain our prior research efforts in this domain. In Section 3 we explain our current framework for designing SAR robotic scenarios. In Section 4 we will show the current usage of our framework as well as an evaluation on how this framework can be used to verify the importance of different interactional aspects of our modular motivational interaction patterns. In the last section, we will give a conclusion.

2. Related and Previous Work

2.1. Motivation: A Key Component for SAR

To develop a common concept of motivational support for SARs it is indispensable to identify the key components of motivation from an interdisciplinary perspective. There exists a wide variety of different motivational theories. For example, J. E. Barbuto [10] discriminates motivation in extrinsic and intrinsic motivation with further subdivisions. Motivation can also be influenced by the goals for a task [16] and the intention to show a certain behavior can be influenced by the expectations of a a significant other [1]. Lastly, motivation is varied by a person's high or low self-efficacy belief toward the behavior [2]. Besides the amount of different motivational theories that could be applied to SAR recent research has mostly incorporated intrinsic motivation (and specially the theory of flow [6]) for their task assistance to adapt the task difficulty to match the user's individual optimal challenge [7, 17]. The general definition claims that motivation is a force which drives human behavior but this perspective focuses mostly on the internal states of an individual person. However, in socially assisted scenarios one main goal is to collaboratively achieve a goal. Therefore, also a sociological and linguistic perspective which analyze the different multimodal cues during interactional processes have to be considered. Some form of communication which helps express one's desires and intentions has to be established. Therefore, future systems need to deal with miscommunication, need to have repair mechanisms and require a concept of when to trigger which kind of supportive feedback in a multi-modal manner in order to achieve a goal-oriented interaction [21].

In conclusion, the diversity and complexity of the different motivational theories show that it is a challenging task to apply one that could help to keep a trainee motivated to exercise. Depending on the task, the user group or the environment a different kind of theory might be suitable. Thus, it is difficult to implement a single theory of motivation into a SAR system because both a global and a local view on motivation are important. However, to narrow the current work we are focusing only on local motivation between a trainer and a trainee from an intstructional perspective.

2.2. Approaches in SAR Systems

How did other researchers tackle the problem of incorporating motivation in their work on SAR? Jayawardena et al. [11] propose a three layered architecture for rapid prototyping of SAR systems and easy to use behavior description for subject matter experts (SME). A similar approach was reported from Mead et al. [18]. However, both approaches focus on the realization of an architecture and not on a formalized behavior description for motivational instruction patterns robots could use to provide support. In these cases motivational instructions are designed by some experts. Others focus on reinforcement learning approaches to learn which behavior is motivating the user the most by e.g. reducing the user's stress or changing the user's valence [5, 14]. Leyzberg et al. [15] proposes the usage of bayesian models to provide a suitable assistance based on the user's task experience. Looking at these examples one could wonder whether there is no connection between the different scenarios and believe that there exists no common pattern that could model the motivational interaction. In Table 1 we have summarized the different tasks, measures and supportive behaviors of a selected number of publications. The most prominent supportive behavior those systems provide is offering suggestion (e.g. advises, corrections, help, repair). The second most offered support is giving encouragement and praise (e.g. positive feedback, acknowledgment). Hence, these systems observe the task parameters and trigger supportive behavior for the users. If the users fail on a task they provide encouragement and in case they succeed acknowledgment. However, in all of the publications it is not described how the transition from one behavior to the other is modeled and whether there is a formalized connection between the different assistive behaviors.

Table 1: Comparison of different tasks, measures and supportive behavior in SAR scenarios.

Reference	Task	Measures	Supportive Behavior
Kidd and Breazeal [13]	dieting task	daily calory income and exercising	suggestions, advices
Leyzberg et al. [15]	nonogram puzzle	puzzle state, time, skill assessment score	instructions, strategy lessons
Chan and Nejat [5]	pairs	puzzle state, stress	instruction, help, acknowledgment, encouragement
Leite et al. [14]	chess	winning, game state, getting better/worse, valence	encouragement, feedback, suggestions
Midden and Ham [19]	laundry	energy consumption	positive/negative social feedback
Fasola and Matarić [7]	exercise games	arm position	corrections, praise, guidance, encouragement
Schneider et al. [22]	mental rotations	correct answers, time	guidance, suggestions

In this work we want to expand the field by introducing a framework and motivational interaction patterns which can be used and reused to systematically study the motivational concepts that SAR require. However, at the current stage of our work we can not consider the whole range of different domains in which SARs can be used. Therefore, we restrict our work to the domain of sport assistance.

2.3. Previous Work

We have investigated the instructional structures and motivational strategies that trainers incorporate into everyday workout (i.e. indoor cycling) in real world Human-Human Interaction. During field investigations colleagues observed the interaction between a coach and an athlete during indoor cycling sessions. The goal of the investigation was to identify some common interactional patterns that coaches use to motivate and engage their athletes[24]. A

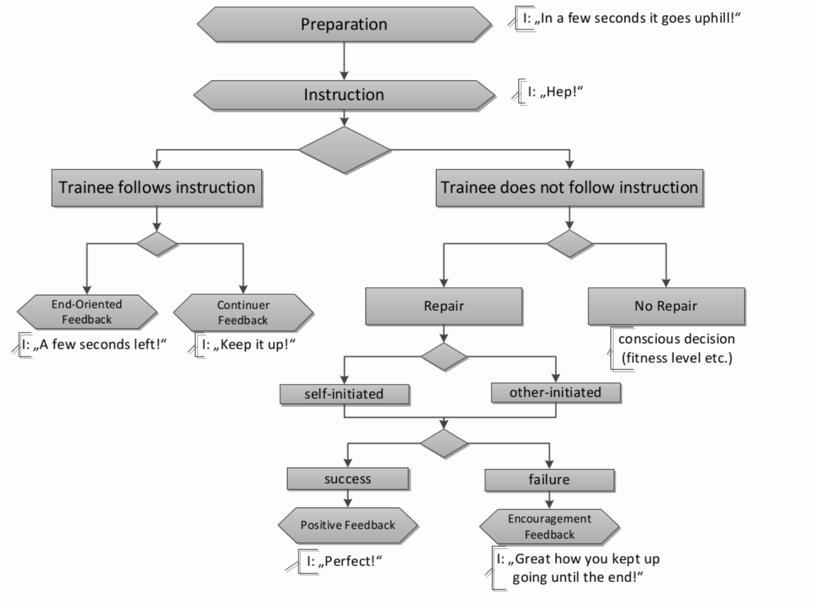

Figure 1: Interactive action-based motivation model [25].

qualitative analysis revealed a complex multi-modal structure of motivation-relevant processes that are fine-grained and sequentially . This model was reduced to an interactive action-based motivation model due to the limitations of current robotic systems (see Fig. 1). It captures the aspects of *preparation*, *instruction*, *acknowledgment*, *repair* and *feedback* (i.e. continuer-, encouraging-, positive-, end-oriented-feedback) in a systematic way for single exercise instructions/movements.

Concerning the five design principles for SAR from Fasola and Matarić [7] (i.e. motivation, fluid interaction, personalization, intelligent behavior and task driven behavior) this model captures some of them from a conceptual point of view. The model as a whole satisfies the requirements of fluid interaction by structuring exercises and guiding the user through the tasks in a formalized manner. The feedback fulfills the requirement for motivation by giving positive feedback if the user reaches the goal of an exercise or guidance and encouragement if the user does not reach the intended goal of an exercise. The reparation is adapted towards the user's activity and personalized by the user's fitness level. At last, the exercises need to be defined in a specified format including the exercise goals to match the requirement for a task driven behavior. This is fulfilled by the *preparation* which can incorporate the exact exercise goals.

Since our previous implementation was tailored for a single use case we will describe how we model the conceptual requirements in a framework that suits a variety of sport scenarios.

3. A Formalized Framework for Socially Assistive Robots

Our framework (see Fig. 2) consists of four main components that communicate over the Robotic Service Bus (RSB) middle-ware [26]. The communication between the components is based on a publish-receive pattern and on remote-procedure calls. The messages can include different RSB Data Types (RST[1]). The framework is composed of a state-machine based scenario description, a decision server that triggers state changes based on the sensor input, data pipelines receiving sensor information, and dialog acts. We illustrate our framework by going through the different parts using a simple example scenario (i.e. a user is asked to raise an arm and hold it for some seconds).

3.1. Motivational Instruction Patterns

As outlined in Section 2.3, we have identified recurring patterns that describe motivational instructions. They represent sequences of states that characterize a socially assistive task and provide a reusable solution for scenario implementations. It is a graphical model that captures the interaction between a trainee and a trainer as well as the system level. Thus, it serves as a guideline for developers and as internal interaction model.

We distinguish two types of interaction patterns: A *static movement pattern* which represents tasks requiring to do some static exercises (e.g. cycling with predefined speed, see Fig. 3; And a *cyclic movement pattern* which represents

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[1] `http://docs.cor-lab.de//rst-manual/trunk/html/data-types.htmll`

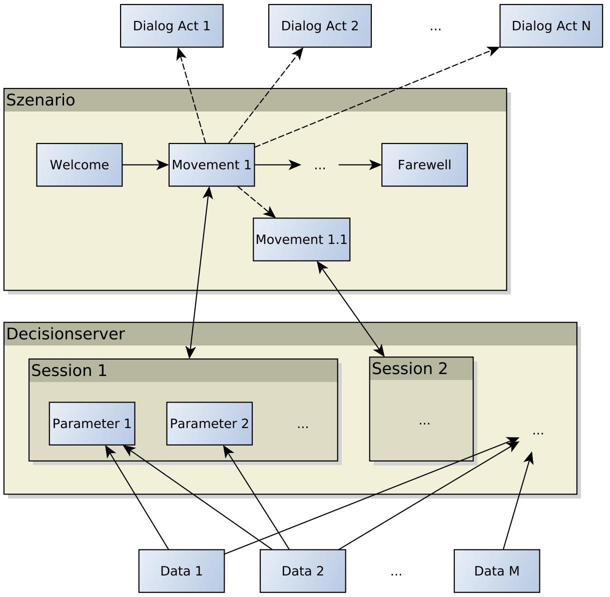

Figure 2: Framework for a socially assistive scenario implementation.

tasks where the user has to follow a cyclic path (e.g. doing squats, see Fig. 4). Considering our example scenario raising an arm and holding it for some time is a static movement. Pattern instances require a variable context with dynamic as well as static information that are provided by a configuration in XML format. This includes the utterances for each state, parameters for the decision component specifying exercise targets, configurations for the evaluation and ending of movement. Table 2 summarizes the different states of the patterns. We incorporated a high flexibility and modularization in our implementation so that a variety of scenarios can be realized. For example, teaching and coaching scenarios require to trigger exercises that can correct a wrong exercise execution (i.e. the system can help the user to reach a specific pose required for an exercise or to start a correcting exercise). Thus, it is important that each state can also activate other state machines or instruction patterns in a hierarchical way:

1. Hierarchy States can trigger simple utterances, dialog acts and also new movement pattern (see Fig. 2, *Movement 1* initiates *Movement 1.1*).

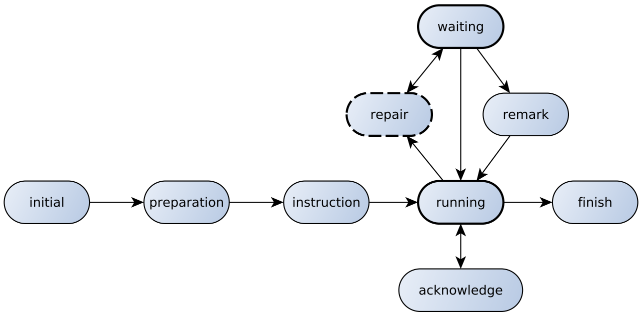

Figure 3: Static Movement Instructions.

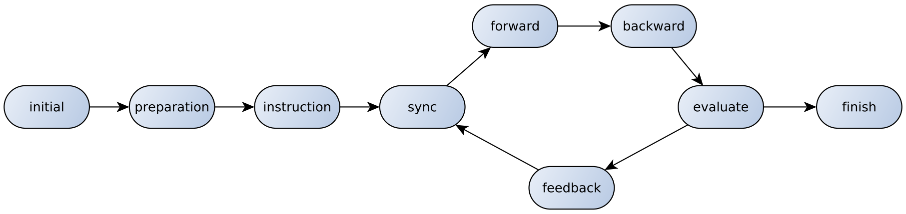

Figure 4: Cyclic Movement Instructions.

In some scenarios it might be necessary to synchronize the actions between the system and the user.

2. Synchronization *Cyclic movements* include a synchronization point and a waiting task.

During the wait task the decider verifies if the user has reached the desired position. If the user does not comply, the system can continue with the execution of the next cycle or it can start a reparation. For certain exercises the order of different states is important and one synchronization point is not sufficient.

3. Ordering *Cyclic movements* can have forward and backward actions with multiple synchronization points (see Figure 5).

As seen in the related work, it is not necessary to always include every state of the pattern. In some cases acknowledgment is sufficient in other cases only reparations might be useful.

4. Modularization States are modular and can be omitted.

Table 2: Overview and explanation of the different states.

static pattern	explanation (*example utterance*)
preparation	Preparation for the next exercise (*Next we will do an arm raising exercise. Please sit down.).*
instruction	Instructions for the next exercise (*Now copy my movement for 20 seconds.).*
running	Observation of the exercise targets
repair	User does not reach the target (*Raise the arm a little bit higher*).
waiting	Evaluation of the reparation (*Still a little bit higher*).
remark	The user is not able to reach the target (*Good try!*).
acknowledge	User reaches the target (*You are doing it right.*).
finish	Finishes the exercise after a specified termination parameter (*We are done. Nice work.*).
cyclic pattern	**explanation**
sync	Synchronizes the action of the user and the system (e.g. the system waits for the user to finish a cycle)
forward-backward	Ensures a correct ordering of the cyclic path. 5
evaluate	After a cycle the performance of the user is evaluated.
feedback	Based on the evaluation the system can give a feedback.

Technically, the movement patterns are modeled in a Domain Specific Language (DSL), which is translated into statecharts [23] in the SCXML format and executed by a scenario coordination that uses the Apache Commons SCXML engine[2].

3.2. Dynamic Decision Component

On movement initialization the scenario coordination starts a new session on the decision server. This server manages three aspects: A data-processing

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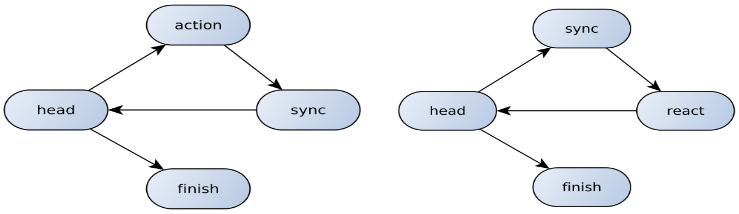
[2] `https://commons.apache.org/proper/commons-scxml/`



(a) The act-action. (b) The react-action.

Figure 5: Two possible actions for the *forward-backward* states of the cyclic movement. In **act-actions** the robot starts the exercises and waits for the user to follow. During **react-actions**, the robot follows the user's lead.

pipeline, local-global decisions and evaluation-finishing strategies. Based on the configuration the server makes decisions during movement run time (see Figure 2). Those decisions trigger a transition between the different states in the movement pattern.

As seen in Table 1 the assistance is either based on data representing a task state or a measurement of the user (e.g. strings, numbers, classification results). Because the values to decide on are inherently different between scenarios we have implemented a *data-processing* pipeline that defines input- and output data slots.

3.2.1. Configurable Data-Processing Pipeline

The pipeline consists of three main blocks: *data sources*, *transformations* and *deciders*. *Data sources* are input-slots that receive specific data types on a predefined scope. The *transformation* components transform data types into a required format (e.g. skeleton data to vector objects and joint angles) or calculate descriptive statistics on the incoming values (e.g. running median or means). At last, *deciders* transform in-slots to decision results or filter decisions of other components (i.e. in-range decider, entropy decider).

How would this be configured in our example case? Figure 6 shows an example pipeline. Skeleton data are received from a RSB data source and transformed into a joint angle format on which a descriptive statistic can be calculated. A decider evaluates whether the incoming data is in a specified range and, in the case we don't care which arm is raised, the last decider can evaluate whether one of the deciders provided a positive evaluation.

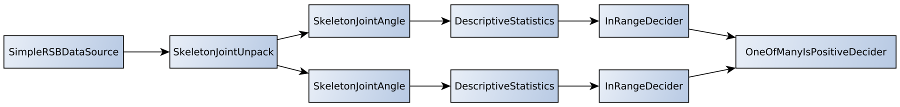


Figure 6: Processing pipeline for the use case scenario.

3.2.2. Local and Global Decisions

Local decisions are represented as a *decision reason* including the name of the parameter, the local decision, a time stamp and a boolean variable showing whether a goal is reached. In our use case this could be the name of the parameter (e.g. “shoulder angle), the local decision could be ”too low“ if the value is below a specified threshold (”too high“ or ”equal“ respectively) and false (or true) for the goal violation. They are collected into a *decision bag* (see Fig. 7) which is verified by a global decider. This decider can trigger a specific supportive behavior based on the collected decisions. Current implemented deciders are a *simple decider*, a *hierarchic reaching decider* and a *hierarchic monitoring decider*. The *simple decider* evaluates the *decision bag* for errors. If an error is found, a *repair* advice is sent and the guidance is set to *failed*. If there is no error, an *acknowledge* is sent. Decisions on multiple concurrent parameters can be handled by the *hierarchic reaching decider*. Lastly, the *hierarchic monitoring decider* is similar to the *hierarchical reaching decider*, but it observes the specified parameters for a longer range of time.

3.2.3. Evaluation and Finishing Strategies

Finally, we have implemented strategies to finish a movement or to start the evaluation of the *decision bag*. They are separated into distinguished strategies to meet the different requirements of varying scenarios (see Fig. 7). The movement can be evaluated or finished manually, after a certain amount of time,

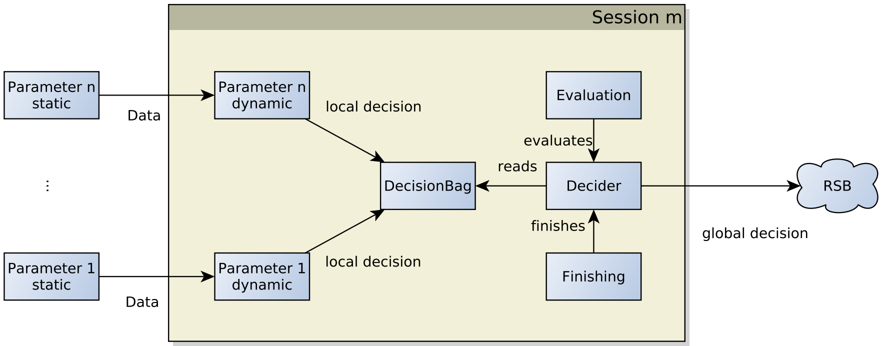


Figure 7: Overview of the decision system.

after a number of events or by a external component. Regarding the use case scenario, the evaluation strategy could be set to 10 seconds and the finishing strategy to 20 seconds. Thus, if the user is able to reach the required arm position and can hold it s/he will receive an acknowledgment after ten seconds and the movement finishes after twenty seconds have passed.

The evaluation strategy can give five different types of guidance: *continue*, no reason for a change in the current situation; *repair*, reasons make a reparation necessary; *acknowledge*, reasons favor a praise; *finished*, last known state was accurate and *failed*, last known state required a reparation.

3.3. Scenario Coordination

The scenario coordination is a state machine in which the whole interaction flow can be modeled. This includes generic robot behaviors (idle behavior, greeting, farewell, robot navigation) and task related movement patterns. To help non-expert users to create a SAR scenario state machine and robot programming are implemented in a Domain Specific Language (DSL) which is automatically transformed to SCXML. It eases the process of handling the middleware communication between the different parts of the system and therefore simplifies the programming effort (for details regarding the middle ware see Section V of [20]). Additionally, DSLs have the benefit of providing specified input format and suggestions on how to program a scenario for the user. Moreover, it reduces errors by including auto-completions and constraints. As implementation tool we use the Meta Programming System developed by JetBrains[3].

While the scenario and movement patterns are modeled in a DSL the configuration of the movements are in XML format. The configuration includes the dialog acts that are triggered in the different states of a movement, the exercise targets (e.g. joint angle configuration of the user, speed or number of repetitions of exercises) and which deciders and strategies should be used.

3.4. Movement Pattern as Building Blocks for Socially Assistive Interactions

How can this framework be used to create a work flow that helps to build new scenarios? Designers need to ask themselves the following questions: Does the user perform a static task or a cyclic task? If it is a cyclic task, how many steps does a cycle have? What measures exists to detect a correct transitioning through the different states? What values need to be observed? Are reparations or acknowledgments necessary? If yes, what kind of reparation should be given based on input? When does an exercise finish? After a specified amount of time, after a number of correct cycles or after the user stops?

If these aspects are considered, the interaction design is only a concern of right configuration and implementation of a suited detection or recognition system. In the following we describe our attempts to create different assistive scenarios with the same framework and describe where we needed to implement some extensions.

4. Usage and Model Evaluation

Indoor Cycling. In this scenario (see Fig. 8a) the robot is instructing the user to cycle at different speed, resistance and in different positions (e.g. standing, sitting or doing push ups on the bike). Each movement is finished after a specific time which is based on the length of a song that is played during the indoor cycling session. An earlier version of our framework and the motivational

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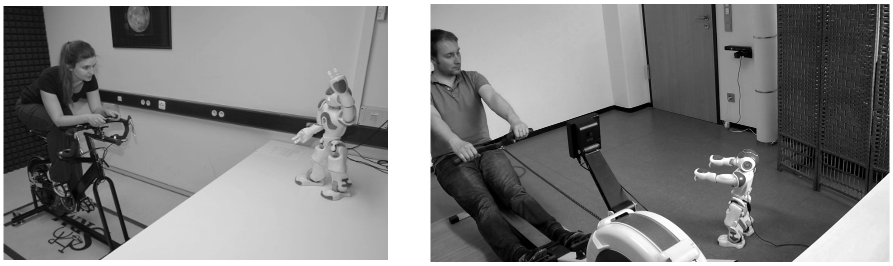
[3] `https://www.jetbrains.com/mps/`



(a) Nao as spinning instructor.

(b) Nao as rowing instructor.

Figure 8: Example scenarios.

instruction model have been evaluated during a 18-days long-term study [25]. In our revised version of this scenario we have used as decider *hierarchic reaching* and *hierarchic monitoring* on the parameter cadence, power and resistance. We added a new transformation in the data-processing pipeline to unpack the data from the bike. The usage of the instruction model led to the question whether it can also be used to teach a new motor movement to users. We have investigated this question in a rowing scenario.

Rowing. In this scenario the robot explains different positions of a rowing stroke (see Fig. 8b). We reused the *static* and *cyclic movement patterns* to implement the instruction of the rowing strokes. The *static movement* is used to instruct each part of a rowing stroke and the *cyclic movement* models the complete cycle of a rowing stroke. A *data-processing pipeline* receives data from a Kinect and the rower computer. The data represents the values for the position of the arms, legs and back as well as the rowing speed. We used the *hierarchic reaching decider* to repair wrong stroke execution in a hierarchical manner (i.e. legs, back, arms). If one of the parameters is violated the system goes to the reparation state of the movement pattern and starts a movement which explains the correct execution of an exercise. Thus, this scenario uses the concept of hierarchy. We reused the data-processing pipeline, the scenario coordination and the decision server in this scenario. However, we needed to implement new activity recognition systems to evaluate the position of the back and legs of the

(a) Nao as bodyweight workout instructor. (b) Toy scenario: Nao teaching colours.

Figure 9: Example scenarios.

user. Until now, we have evaluated the system only in an unpublished prototype study with six participants. Our preliminary result show that the participants were evaluating the robot's instruction as useful for learning a rowing stroke.

Besides teaching and instructing, we investigated if the framework can be used to exercise synchronously with a robot. Therefore, we have implemented a body weight workout scenario.

Body Weight Training. In this scenario the robot and user are co-actively working out together 9a. Also in this scenario we could reuse the *scenario coordination*, *decision server* and the *data-processing* pipeline. We configured *cyclic* and *static movements* for the different exercises (e.g. squats, push ups, squat hold, etc.) and the necessary parameters using the *data-processing* pipeline (e.g. angle between lower and upper leg) for the decision server. It was possible to reuse the different *evaluation* and *finishing strategies* (e.g. finishing an exercise after 10 repetitions or seconds, giving an acknowledgment after a certain amount of time or repetitions). The *cyclic movement pattern* was extended with a feature to count the current number of repetitions so that this information can be feedbacked to the user. For the cases where the user is leading the exercising we implemented a new dialog act that allows the robot to ask the user whether s/he wants to quit.

For all scenarios we used the same robot (i.e. Nao) in order to exclude effects due to the embodiment or appearance of the robot. Furthermore, we used the same decision system and scenario coordination as well as similar perceptive systems (skeleton tracking, heart rate, depth image of the user). Besides the extensions mentioned above we only needed to configure the explicit instructions, data-processing pipeline and decision criteria. In all scenarios we could reuse the basic structure of the same motivational interaction patterns and the same framework. However, to give a final conclusion whether the framework and the motivational model can be reused we need to implement more scenarios in different domains (cognitive, industrial or play tasks) and with different user populations (e.g. elderly, children). Therefore, we present a simple use case where Nao is teaching different colours (see Fig. 9b) to show that this framework is also applicable for other domains.

Teaching Colours. This toy scenario consists of a *static movement* and a *cyclic movement*. In the *static movement* the systems asks to show it a colour (e.g. "Show me something blue.“), gives a repair when the presented colour does not match the queried color (e.g. "This is green and not blue. Try again.“), and acknowledges if the user does it correctly (e.g. "Very good! This is blue“). The *cyclic movement* is a rehearsal task where the system asks to show the different colours repetitively. To realize this scenario we needed to implement a colour detector and configure a data-processing pipeline, a static movement and a cyclic movement. While this is just an illustrative example it exemplifies the possibility of creating a variety of different scenarios. Furthermore, it could be easily extended to create a full interactive system that could help e.g. children to learn colours.

Still, a detailed analysis of the applicability is needed and in the future we will implement and evaluate more scenarios.

4.1. Towards a Systematic Model Evaluation

While we can not give a quantitative evaluation on the applicability of our framework, we can show how this model can be used to systematically test different motivational aspects.

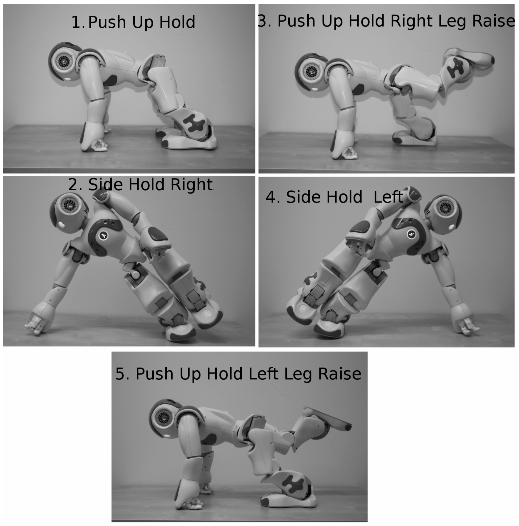
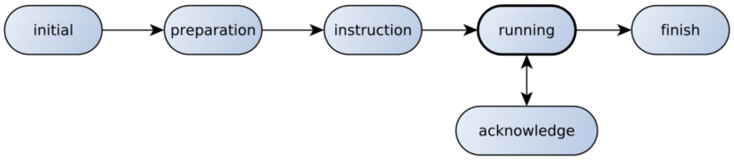


Figure 10: Five isometric exercises from the body weight training.

The modularization of the different states of the interactional model allow to systematically test the importance of different social support states (e.g. repair, acknowledgment). To evaluate the different parts of the instructional model we have implemented a SAR system that instructs users to do five isometric exercises (see Fig 10). To evaluate the importance of the acknowledgment state on people's motivation to hold these exercises we have conducted a study where we compare the *static movement* pattern including only the acknowledgment and one where we also excluded acknowledgment (see Fig. 11).



(a) *Static movement* including only acknowledgment.

(b) *Static movement* with no repair and no acknowledgment.

Figure 11: The two *static movement* configurations for the study design.

4.1.1. Study Design

Participants had to do two blocks of five isometric exercises each (see Fig. 10). They were instructed to hold each exercise once as long as possible. If they can not persist the exercises anymore they were told to stand up, wait for thirty seconds and then start the next exercise. In each condition the participants did not know that they have to do a second exercise block. In the first block the participants did the exercises alone and in the second block either alone or with the humanoid robot Nao[4]. During the robot instructor (RI) condition the robot was announcing the exercises the user had to do, as well as how long the break is. In the robot instructor feedback (RIF) condition the robot was additionally giving an acknowledgment to the user based on their performance from the first block. After three quarters of the time they held the exercises during the first block the robot gave the user an acknowledgment to encourage them to keep holding the exercises. As measurements of the importance of acknowledgment for the motivation to exercise we have used the Godspeed questionnaire [3] as well as the duration how long they persisted the exercises compared between the first and the second block. This study design was inspired and adopted by [9].

4.1.2. Experimental Design and Participants

Participants (n=50) were assigned to one of three conditions (17 in independent condition (IC), 17 in robot instructor condition (RI) and 16 in robot instructor feedback condition (RIF)). Participants were mostly students (male: 32, female: 24 , age M=26.05 years, SD=6.12) from our university. They received seven Euros as monetary compensation.

4.1.3. Procedures

The participants arrived at the lab individually, read and signed a consent form which informs them that they will be recorded during the experiment.

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[4] `https://www.aldebaran.com/en`

They watched a short video of Nao demonstrating the five exercises. They were guided to the lab and told to start after they have waited for a short time, so that the experimenter can check that the recording is working properly. Then the participants did each exercise alone in the lab while the experimenter observed them from a different room and took the times of each exercise. The participants completed Block 1 (each exercise once). Afterwards, the participants had a ten minute break where they were offered a glass of water. After the break participants in the IC condition were told the average time they held the planks and that they would complete the same set of exercises again (Block 2). In every condition the participants were not told that they had to do a second block of exercises until they had finished the first block. During the robot conditions participants were told that they will do the same set of exercises again but that this time a robot will be present. They were instructed to follow the guidance of the robot through the session. Participants were told the average time they held the planks, but received a false information on how long the robot can persist the exercises. They were told a number which is forty percent higher than their average time. This unfavorable comparison is in line with previous research and leads to greater effects [9]. Again the experimenter did not enter the room together with the participant. In both robot conditions, participants and robot had a short introduction phase where they shared their name (Nao), their hometown (Paris) and their hobbies (gardening, reading). This was done due to prior research which showed that people treat agents more like humans when there was an initial verbal interaction between them [4]. After Block 2 the robot thanked the participants for their participation, told them that they are allowed to leave the room, that it needs to rest a bit and powered itself down. After leaving the room the participants completed a questionnaire, were debriefed and received a monetary compensation. The whole procedure took about 45 minutes to one hour.

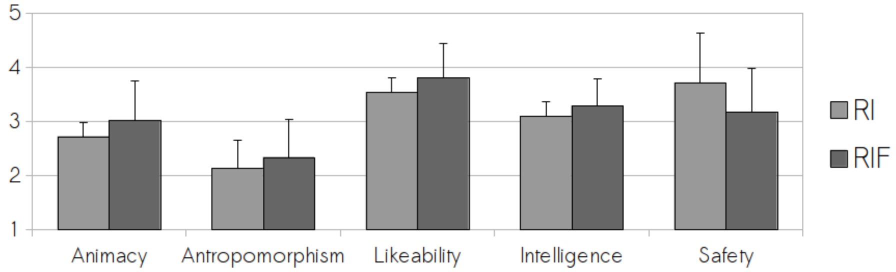

Figure 12: Godspeed scales and training enjoyment.

4.1.4. Measures

Persistence. Persistence was the number of seconds a plank was held from the moment participants moved into position until they quit. Block scores were calculated using total average seconds held on all five exercises.

Godspeed Questionnaire. In order to asses different perception of the robot between the conditions we asked the participant to rate the robot based on the Godspeed questionnaire (5 point-based differential scale, [3]).

Physical Training Enjoyment. We assessed the physical training enjoyment the users had using the Physical Activity Enjoyment Scale ([12]). We used the average value of all items as overall enjoyment score. Furthermore, we asked them about their intention to train tomorrow for at least 30 minutes.

4.1.5. Results

The results of the Godspeed questionnaire are depicted in Figure 12. A Multivariate Analysis of Variance (MANOVA) revealed no difference between the conditions on the Godspeed Questionnaire ($F_{1,32} = 0.45, p = .50$).

As a primary dependent variable we used the average difference persistence time in seconds between the two blocks (Block 2 - Block 1). This approach controls for individual differences in strength and fitness and shows possible changes in persistence. The results obtained for the average block score of Block 2 subtracted with the average block score of Block 1 are shown in Figure

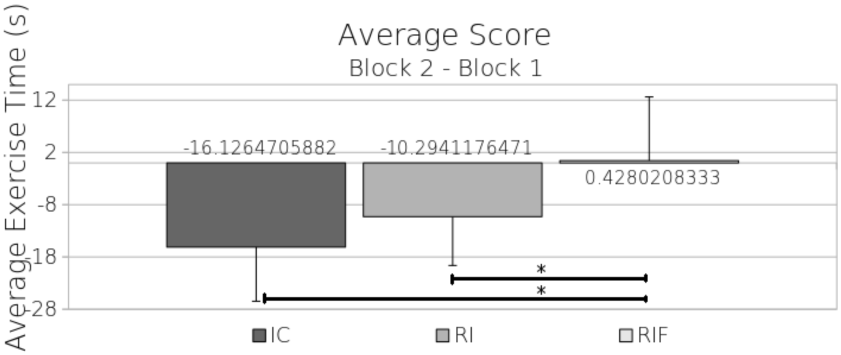

Figure 13: Block scores

13. An Analysis of Variance (AOV) on the difference score showed a significant main effect for the conditions ($F(2, 51) = 11.33, p < 0.001$). A Tukey's pairwise comparison revealed the significant differences between RIF (M=0.42, SD=12.2) and IC (M=-16.12, SD=10.35) ($p < 0.001$), and between RIF and RI (M=-10.3, SD=9.34) ($p < 0.05$). Additionally, we found no differences in the average Block 1 scores (F(2,51)=1.13,n.s). Thus the results are not due to any general higher fitness level in the RIF population.

An AOV also showed no differences in training enjoyment (F(2,51)=1.837, n.s.) and sport per week (F(2,51)=0.13,n.s.). However, we found a difference for the intention to exercise ($F(2, 51) = 1.93, p < 0.05$). A Tukey's pairwise comparison revealed a significant difference between the RI and IC condition ($p < 0.05$).

4.1.6. Discussion

First of all, the results show that the framework allows to systematically test the importance of different motivational aspects for SAR. The implementation of both interactive behaviors was fairly easy and only included to dynamically change the acknowledgment time of each exercise suited to each user. Therefore, we were able to verify a new important research question. The results show that acknowledgment is an essential part of the instructional model and should be included in every implementation of an SAR system. Even though the subjective ratings did not differ significantly, the objective task performance shows that the motivation to exercise is higher in cases where the system gave acknowledgment compared to a system which did not give acknowledgment and to the IC condition.

A significant difference in performance was measured but no differences for intention and enjoyment were found (at least between the RIF and all other conditions). Participants persisted longer without any effects on enjoyment and future exercise plans. These results show that it is possible to extend exercising time without negative effects.

To further investigate the importance of different social support states we will conduct a follow-up study testing whether users have an additional motivational boost when the system is repairs wrong exercise execution.

5. Conclusion

In this paper we have presented our proposed framework for designing and coordinating sport scenarios for socially assistive robot based on motivational instruction patterns. We have introduced the key concepts and components that will help to guide the design of scenarios across different application domains. Furthermore, we have presented three different sport scenarios where we already use our proposed framework. We hope that in the future our approach can be applied to evaluate different scenarios using different robots which are based on the same underlying interaction models. Using some standard measures (i.e. Godspeed Questionnaire and task measures) it might be possible to a) either evaluate different robots (i.e. comparing Nao and iCub) instructing on the same task using the same model, b) evaluating the same robot with different configurations of the instructional model (i.e. including reparation or acknowledgment), or c) using the same robot and the same instructional model in different domains (i.e. indoor cycling, rowing, body weight training). By implementing a structured approach of evaluating different interaction configurations, robot platforms or domains we will gain a better insight in the underlying psychological and interactional concepts that shape HRI. Thus, it might ease the task to implement a suited SAR to assist people on rehabilitation or everyday tasks. We have taken the first steps to systematically investigate the different aspects of interactional motivation that SAR can incorporate by showing that a simple acknowledgment by the robot can lead to higher motivation for the user which is promising for future applications of SARs.

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