Autonomous Mobile Gait Training Robot for Orthopedic Rehabilitation in a Clinical Environment*

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***Abstract*— Successful rehabilitation after surgery in hip endoprosthetics comprises self-training of the lessons taught by physiotherapists. While doing so, immediate feedback to the patient about deviations from physiological gait patterns during training is very beneficial. In the research project ROGER, a mobile socially assistive robot (SAR), which supports patients after surgery in hip endoprosthetics during their self-training, was developed. The robot employs task-specific, user-centered navigation and autonomous, real-time gait feature classification techniques to enrich the self-training through companionship and timely corrective feedback. This paper presents technical and usability results obtained during four weeks of user tests at our partner hospital "Waldkliniken Eisenberg" in Germany.**

I. Introduction

Patients recovering from hip endoprosthesis surgery often have to "relearn" a natural gait pattern. While professional hands-on physiotherapy is part of the process, repetitive practicing is in the responsibility of the patient itself. Consequently, the patients' motivation for self-training plays a crucial role in their rehabilitation process.

Against this background, self-training with socially assistive robots (SAR) bears medical as well as economic potential in rehabilitation care, since it allows to influence and document this important aspect of the process. Expected benefits of SAR-assisted self-training systems were already demonstrated in [1] and [2] with a robotic rehabilitation assistant for walking and orientation self-training of patients in late stages of the clinical post-stroke rehabilitation, practicing both mobility and spatial orientation skills. The results of these studies showed that the robot increases motivation for independent training and encourages patients to expand their training radius in the clinic [2].

Supporting patients by offering robot-assisted self-training is also the context and the core idea behind the research project ROGER (*RO*bot-assisted *G*ait training in orthop*E*dic *R*ehabilitiation, 2016 - 2019). Here, the focus is on guiding the patients through their gait training on top of their standard physiotherapeutic treatment and offering them real-time feedback about their walking movement and forearm crutch usage. Giving timely corrective feedback to the patient during the training is essential, as it helps to avoid adverse long-term effects on their gait [3]. Therefore, the objective of the project is to integrate real-time gait pattern analysis into a robotic application that patients can and want to use on a regular basis in an everyday clinical environment.

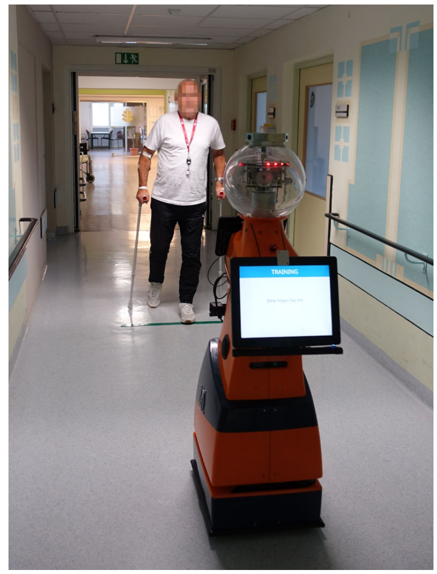

Fig. 1: Patient during SAR-assisted self-training where the robot drives in front of the user while observing his gait pattern and posture and giving immediate corrective feedback.

In this paper, the developed SAR for orthopedic gait training is presented with a technical overview of the robotic system and results from user tests. These results are part of two test campaigns evaluating (i) the effectiveness on the patient's gait in a comparative experiment with a treatment and control group each consisting of 15 patients, and (ii) the technical performance and usability of the robotic trainer with 20 patients. The results presented in this paper will only focus on the latter test campaign.

Hereafter, Sec. II first discusses related work in the field of mobile rehabilitation robotics with the focus of gait analysis and the sensors used for this purpose. Sec. III then describes the application scenario in our research project to outline the requirement, followed by the system architecture derived from those requirements. Sec. IV is describing the organizational framework for the real-world test campaign, whose results are then presented in Sec. V. We conclude the article in Sec. VI, and also provide an outlook to possible future work.

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II. Related Work

A. Mobile rehabilitation robotics in clinical environments

Although other gait training systems like exoskeletons and treadmills exist, this paper focuses on systems that are mobile and non-intrusive, because ROGER belongs to the field of socially assistive robots (SAR) [4], where systems have no permanent physical contact with its user.

Although SARs have shown encouraging results in several domains, including skill practice, daily life assistance, and physical therapy [5], there is no SAR project known to us that has the full set of features of ROGER - the development of a mobile robotic training companion which can accompany and correct patients fully autonomously during their gait training within a clinical setting.

The ROREAS project [6] addresses walking and orientation self-training of stroke patients to improve their mobility skills and self-confidence but did not support gait training. The CLARC project [7] developed a SAR to help clinicians perform comprehensive geriatric assessment procedures in clinical environments. While geriatric assessment is a different task than that of ROGER, both approaches base on similar basic robotic skills, e.g. navigation in complex environments and person perception by vision sensors.

In [9] a smart walker was developed, which uses a laser scanner to record and analyze leg motion trajectories. [10] and [11] followed a similar approach, but equipped their walker with two depth cameras to observe the upper and lower body simultaneously. This setup makes it possible to evaluate the overall posture of the person relatively to the walker.

B. Mobile gait analysis using depth sensors

Stationary multi-camera setups, e.g. *Vicon Bonita 10* with 10 infrared cameras [12], are able to perform a very accurate 3D gait and motion analysis. Because of their high precision, these systems are used in biomechanic research and sports science. They are, however, not suited for unsupervised everyday use, since they have to be set up and calibrated carefully, and usually require manual placement of reflective markers at predefined body keypoints.

In contrast, devices such as Kinect or Kinect2 are low-cost depth sensors and a suitable alternative to the expensive laboratory systems under the right conditions as shown in [13], [14], [15], [16]. In these studies, the sensors are mounted statically on a treadmill or in a laboratory environment for evaluating temporal parameters and joint angles, proving their ability to analyze the user's gait cycle in real-time.

In [17] a Kinect is used for fall detection of elderly people, however the authors note that movements near the wall, furniture or poorly reflective clothes complicate the detection. [18] also investigated a static Kinect2 for fall risk assessment of elderly people and therefore analyzed gait parameters like step length, step duration, cadence and gait speed. They found the Kinect2 to be a suitable low-cost alternative for this task.

A mobile version of a fall detector was developed by [19]. Their robot is able to follow the user, while the on-board Kinect can be used to evaluate the user's gait pattern in order to predict whether the user is about to fall. An obstacle-free environment is assumed for a smooth procedure. Similarly the authors in [20] describe a six-wheeled mobile robot with a Kinect2 mounted on-top, driving in front of the subject and evaluated parameters such as walking speed and step lengths. None of these systems is able to navigate autonomously and avoid obstacles or give an immediate acoustic or visual corrective feedback to the subject.

Fig. 2: (Top) Robot approaching the patient during break. (Bottom) Robot waiting on the hallway in a non-obstructing observation position for the training to continue.

In all cases, the spatio-temporal gait parameters obtained using a Kinect or Kinect2 were well in agreement with the reference system. Also, calculation of hip and knee angles is mostly unproblematical. However, the angles at the ankle joint pose an issue due the fact that skeletal point estimations in the foot area tend to be very inaccurate [16].

III. Mobile Robot as a Gait Coach

Sec. III-A is describing the scenario and outlines the distinct challenges a robot system faces during a training session. They are mainly caused by the interaction of the robot with its environment, the patient, and other persons in its immediate surroundings. Sec. III-B will consequently describe how the ROGER prototype intends to address these requirements using a wide variety of skills.

A. Scenario

The robotic gait coach assists patients who have received medical consent to walk alone on crutches with three-point gait, usually on the second day after the surgery. For more details on the training schedule, refer to Sec. IV.

To initiate the training, the patient has to go to the robot, log in by using a personalized RFID transponder, and take a seat on a nearby chair. The robot then approaches the sitting patient until it is at arms reach [21], and starts to interact using speech synthesis and its touchscreen. Before the training begins, the patient can watch a short video on how to use forearm crutches correctly during training. This is followed by a textual and spoken reminder that it's always possible to rest at one of the chairs placed along the hallway. After the dialog has finished, the robot generates an appearance model to re-identify its user among bystanders while driving to the starting position in the hallway.

During the training session, the robotic gait coach leads its current patient by a certain constant distance in order to continuously ensure sufficient sensor coverage of the patient [22] (see Sec. III-B). By analyzing the user's skeleton while walking, several gait features are extracted and rated by a rule-based classifier [23]. If a gait deviation is detected, the robotic coach gives speech- and GUI-based feedback to the patient. At the end of the hallway, the robot stops, turns around and waits. As soon as the patient gets behind the robot again, the training continues.

In case the patient chooses to sit down on one of the chairs along the hallway, the robot starts approaching the patient to reach the necessary distance for physical interaction with the robot's touch display (see Fig. 2). The patient can then select to either pause or abort the training session. If the patient chooses to pause, the robot will drive to a non-obstructive waiting position permitting a continuous observation of the patient such that the robot will not miss the moment the patient stands up again and continues the training. If the training is aborted, the robots guides the patient to the waiting room where a closing dialogue takes place. Physiotherapists are also able to check the results of each training session afterward and may adjust the focus and length of the next training session.

The following sections III-B and V provide more technical details on the functional requirements derived from this scenario.

B. System architecture

To manage the complexity of our application for SAR-assisted gait training, we designed our system hierarchically in multiple abstraction layers (see Fig. 4). Therefore, we relied on the robotic middleware MIRA [8], allowing us to decompose the application into modules, which can be developed and tested independently.

1) Hardware Layer: The base of our robotic system is a customized SCITOS plattform [24] with a height of $1.5\,\mathrm{m}$ and a footprint of $45\,\mathrm{cm} \times 55\,\mathrm{cm}$. The platform can reach a speed of up to $0.9\,\mathrm{m/s}$. For obstacle avoidance, person perception, and HRI, multiple sensors and actuators are mounted on the base platform (Fig. 3 and [23] for a detailed description).

As primary user interface, two touch displays are mounted at different heights allowing standing or sitting patients to comfortably interact with the robot.

To assess the patient's gait during training, we utilize a backward-directed Kinect2. Since the Kinect2 has a relatively narrow field of view of $70°$, it is mounted on a pan-tilt unit. With this configuration, we can actively keep the patient in view [22] even when the robot has to evade obstacles or persons encountered on the training track.

2) Skill Layer: The skill layer builds upon the sensor information and actuators of the hardware layer to provide the core functions of our robotic gait coach. These core functions can be categorized in modules for *person perception*, *gait analysis*, *navigation,* and *HRI*. Only the main modules are discussed in the following. For more technical details and experimental evaluation, refer to the given references (see Fig. 4).

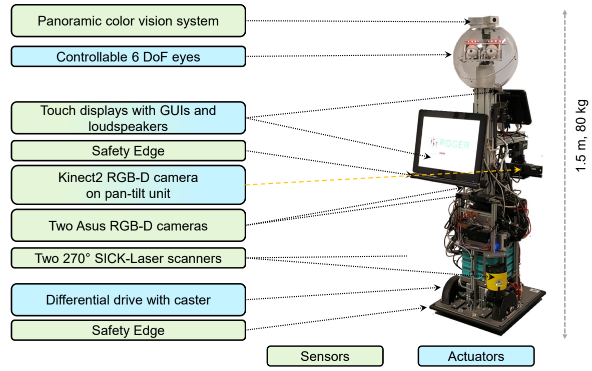

Fig. 3: Sensors and actuators of our robot platform. A detailed description can be found in [23].

Navigation: The core of our navigation system consists of the motion planner and pose finding skills for determining poses to approach and observe the patient when s/he takes a break at a chair. These skills depend mainly on the input of the localization and obstacle detection module providing the current pose and the location of obstacles in the robot's vicinity. Both localization and obstacle detection can process 2D laser and 3D information [32], [33]. Since we are operating on the hallway of a hospital where we may encounter other persons, the robot's movement must be able to adapt to the current situation. To account for these dynamics, the motion planner and the pose finding modules use a multi-objective optimization approach. While the motion planner uses an evolutionary algorithm to find safe trajectories which also keep the patient at a predefined distance to the robot, so that the patient is fully visible by the Kinect2 [22], [35], the pose finding modules uses particle swarm optimization to calculate the best poses to approach and observe the patient [36], [21].

Person Perception: We use a multi-modal person tracking framework [25] which is not only capable of estimating the positions and velocities of persons in the robot's vicinity, but also to re-identify the patient among all detected persons. This is crucial for our training application since on the hallways other persons (e.g. hospital staff or guests) may cross the robot's path. To track position and velocity, a multivariate Kalman filter is utilized. As detection modules, we use OpenPose [26] and a laser-based detector able to detect persons' legs, even with mobility aids [27], i.e. crutches, walkers or wheelchairs. For re-identification, we rely on face features [30] and the patient's overall appearance by using a metric-learning approach with color and texture features [29].

Gait Analysis: The Kinect2 is the primary sensor for our gait analysis algorithm. By using it in conjunction with Microsoft's SDK [31], we can utilize a fully functioning 3D skeleton tracker which robustly estimates a 25-joint-skeleton in real-time ($30\,\mathrm{fps}$). To describe the patient's gait, we extract

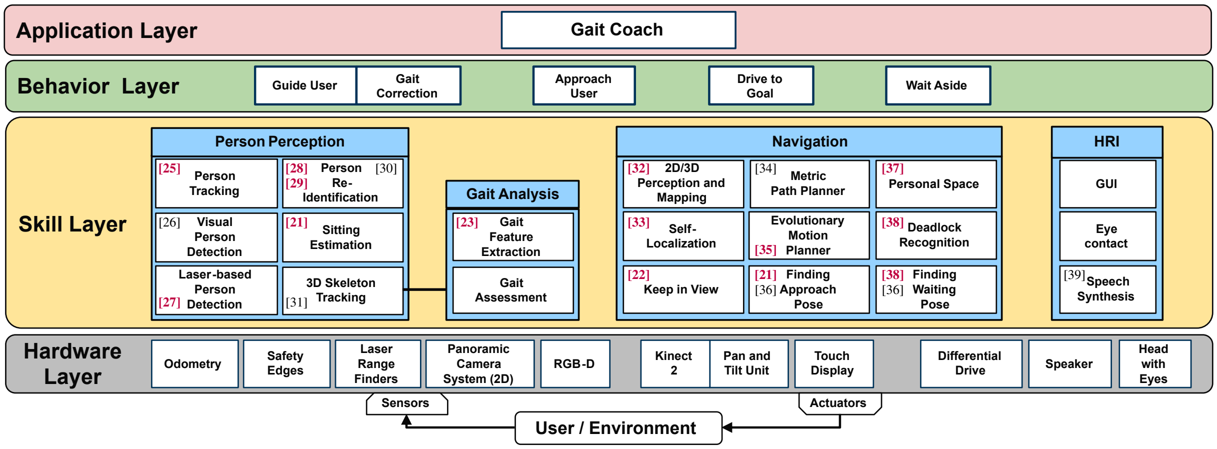

Fig. 4: Hierarchical architecture of the robot's functional system. A detailed description of the skills developed within the ROGER and ROREAS [6] projects together with the results obtained from functional tests can be found in the red highlighted references.

the step length, step width, stance duration, trunk lean, and flexion/extension of knee and hip from the 3D skeleton. Since the correct execution of the three-point gait is also an important factor for the healing progress, we extract the crutch position in reference to the patient's feet from the point cloud.

In collaboration with physiotherapists, we developed an heuristic approach to detect pathological gait patterns. In a previous study we performed training sessions with patients where the robot did not actively analyze and correct the gait movement but filmed their walks and captured their skeletons provided by the Kinect2 at the same time. Subsequently, a subset of videos was selected to be annotated by four physiotherapists. Since the gait training robot should be able to detect gait errors concerning step length, stance duration, step width, upper body lean, flexion/extension of hip and knee joints as well as the correct usage of the crutches, the physiotherapists used an annotation tool to label the stored video sequences with the predefined error labels. From the labeled data, error and non-error classes were created and thresholds by means of the F1-score were determined. For some gait parameters, such as step width and knee flexion, absolute values are appropriate to describe the patients' motions, whereas in other cases calculating the ratio between two values leads to more understandable gait features, e.g. ratio between left and right stance duration as a measure for gait symmetry. For further details on the extracted gait features and assessment algorithms, refer to [23].

HRI: The HRI modules consist of skills for displaying graphical user interfaces on the robot's touch displays and a text to speech system [39] (TTS). The TTS can generate spoken language in real-time, allowing us to customize the gait correction instructions to the patient's needs.

3) Behavior Layer: Basically, behaviors can be regarded as small state machines, parameterizing and coordinating the activation and deactivation of skills. Each behavior realizes a directly observable function of the robot by managing the interplay of the required modules in the skill layer. The training application mainly uses the behaviors "Guide User" (using the skills, e.g. "Evolutionary Motion Planning", "Keep in View") and "Gait Correction" (using the skills, e.g. "Gait Feature Extraction" and "Gait Assessment") for analyzing the patients' gait while guiding them through the clinic hallways.

4) Application Layer: Top layer of the hierarchical system architecture is the application as interface for guiding the patient through the whole training. The application is implemented as a state machine realizing the described training procedure (see Sec. III-A).

IV. User Tests

In August and September 2019, the main study was conducted with a focus on evaluating usability and user acceptance as well as the technical performance of the robotic gait coach over four weeks within a clinical environment. The tests took place at Waldkliniken Eisenberg, an orthopedic hospital located in Thuringia, Germany. For the sake of comparability, we only included patients in our study, who met the requirements of having a hip total endoprosthesis, being in a reasonable physical and psychological condition otherwise, and were between 55 and 75 years old.

To avoid scheduling conflicts when two patients would want to train at the same time, every user had preset time slots of $30\,\mathrm{min}$. The actual training time within a single session lasted from $5\,\mathrm{min}$ to $10\,\mathrm{min}$, predefined by a physiotherapist. Training sessions for a single patient took place twice a day each day until the patients were released from the clinic and were scheduled so that there is a rest period of not less than three hours in between. Limited by the daily routine at the hospital and the robot's battery capacity, a maximum of six patients per day could take part in the tests.

At the first training, a physiotherapist was present, supervising the right usage of the crutches, giving useful hints and monitoring the patient for signs of exhaustion or other severe problems. From the second up to the last training the patients practice on their own. Usually, the patients are released at noon on the 6th day after operation, so they had the possibility to use the SAR-assisted training up to eight times during their stay (see Fig. 5). Since the robot

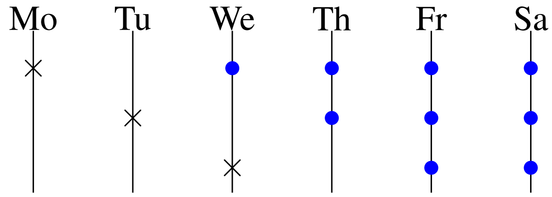

Fig. 5: Possible training days (•) for patients with surgery (×) at different days

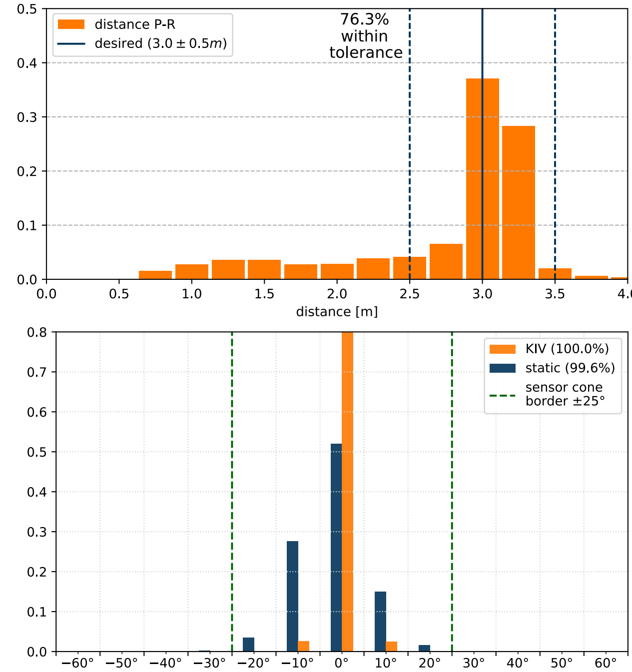

Fig. 6: (Top) Distance between user and robot over all training sessions (Bottom) Angular position of the user in the Kinect2 sensor cone (*static* would be without the actively controlled PTU)

could not operate on Sunday, because of legal restrictions for the observing staff, we could only guarantee two days of successive training for all patients taking part in the study. Hence, only the results from these first two days are used when judging usability and user acceptance. However, reported results on robot functionality include all training sessions.

Prior to the first training, the patients were asked to provide a short self-assessment questionnaire regarding their attitude towards technical innovations. Later on, they answered a relatively short questionnaire immediately after each SAR-training. The questions varied slightly between each session and covered aspects of the patients' attitude towards the robot, their satisfaction with what happened during the training, as well as system usability. Those questions regarding usability also included the set widely established by the System Usability Scale (SUS) [40]. Each question could be answered using one of five response options, ranging from *Strongly Disagree* to *Strongly Agree*. The last questionnaire also asked the participants to provide some biographical data, such as year of birth, gender, as well as their highest school degree.

Student assistants of our lab were present during the tests to observe the robot. They also assisted the patients with the post-experiment questionnaires if necessary, but were instructed not to interfere otherwise. Situations where the robot could not resolve a major issue on its own, such as system crashes or severe application failures, were exempt from this rule. However, the patients were not informed about this beforehand in order to not influence their initial expectations towards the system.

V. Results

This section is to presenting the results obtained during the tests as described in the previous section.

A. Navigation

1) Guiding and Keep-in-View (KIV):

Guiding is the most crucial behavior to facilitate a successful gait training. The requirements that have to be fulfilled during this task can directly be derived from choosing the Kinect2 as sensor and Microsoft's Kinect SDK as skeleton estimator to be used for gait assessment. With a field-of-view of $60° \times 70°$ (vertical $\times$ horizontal) and a maximum range of $4.5\,\mathrm{m}$ of the skeleton tracking algorithm, the following criteria where chosen:

- distance between robot and user: $3.0\,\mathrm{m} \pm 0.5\,\mathrm{m}$
- user within $\pm 25°$ relative to the camera center

As can be seen in Fig. 6, the distance requirement was satisfied $76.3\,\%$ of the time. Closer analysis suggests that situations where the distance was too short regularly occurred at turning points at the end of the hallway, or when restarting the training after a break. These situations are not critical since the gait's initial phase was not of special interest in our application. Furthermore, a few patients were able to walk faster than the robot was able to drive and followed the robot at a relatively close distance. This can be seen at the slight peak at around $1.25\,\mathrm{m} - 1.5\,\mathrm{m}$ measured from the robot's point of origin, which is approximately $0.75\,\mathrm{m}$ away from where the PTU and camera are mounted. If those fast patients are excluded from the evaluation, the distance criterion is met in $84.9\,\%$ and the second peak is no longer visible.

Results of the camera tracking algorithm can also be found in Fig. 6 (lower graph). Since the robot's operation environment was a mostly straight hallway, the expected gain from using a PTU-mounted camera is relatively low. Therefore it's not surprising, that even without a PTU, the patient would be within the angular constraints defined above most of the time ($99.6\,\%$). The active camera control is nevertheless able to reduce the angular deviation significantly.

2) Approaching sitting Users:

Approaching the user is another core skills the robot has to manage in order to provide a seamless training experience for the patient. The robots performance in this task was judged using the following criteria:

- distance to user, measured from midpoint of front display to users' center of mass
- deviation from the optimal orientation relative to the direct line of sight

During all tests, the robot had to approach patients a total of 267 times. The success of an approach maneuver was evaluated afterwards by looking at the recorded camera images. In case of a success, the patient was able to comfortably reach the touch screen without leaning and the deviation from the optimal orientation was less than $30°$, otherwise it was counted as unsuccessful. This lead to the following results based on the points outlined above:

- average distance to user: $0.66\,\mathrm{m} \pm 0.11\,\mathrm{m}$
- average orientation deviation: $10.1° \pm 8.7°$
- successful: $86.5\,\%$

The suitability of the found pose is strongly dependent (a) on how well the obstacles in the user's vicinity are perceived and (b) how accurate the position of the sitting user is estimated. The unsuccessful maneuvers were mainly caused by violation of these two factors. (a) The used ASUS RGB-D cameras for 3D obstacle perception have a limited field of view and need a appropriate observation pose to fully perceive the obstacle configuration. For a seamless training, we had to trade off the waiting time for the approach maneuvers such that a fast but sometimes suboptimal observation pose was accepted which lead to some unsuccessful cases. (b) The accuracy of the estimated position of the patient is dependent on our person detectors. Since we use visual detectors operating on RGB images, we can encounter positional inaccuracies when projecting the detections from the image plane back into 3D world coordinates.

3) Observing Users at Waiting Positions: Whenever the patient takes a rest at one of the chairs in the hallway, the robot has to determine a suitable, non-obstructive waiting position near the patient. That also covers the requirement to be able to observe the user during breaks in order to detect the user standing up, and also possibly leaving the training hallway. Reported results therefore cover the following aspects:

- distance to wall
- alignment of robot to the wall (robot's driving direction should be parallel to the wall)
- do not stand in front of doors
- observability of the user (so that the PTU can center the user in the Kinect2).

In 103 cases, the robot had to autonomously determine and drive to a observing position. Similar to V-A.2, the recorded data was used to determine whether or not the position taken by the robot fulfilled the criteria. We did not set a fixed thresholds for the quantifiable factors, but instead looked at possible obstructions for other persons using the hallway as well as blocked doors. In addition, we looked at the Kinect2 camera image to make sure that a clear line of sight did persist. That lead to the following results:

- average distance to wall: $0.34\,\mathrm{m} \pm 0.09\,\mathrm{m}$
- average deviation from optimal orientation parallel to the wall: $1.5° \pm 8.4°$
- successful: $95.1\,\%$

In the unsuccessful cases, the robot was misaligned to the wall or partly covered a door but always kept the user in view. The robot did not block the hallway or the door completely, but made it more difficult to enter the door or pass the hallway.

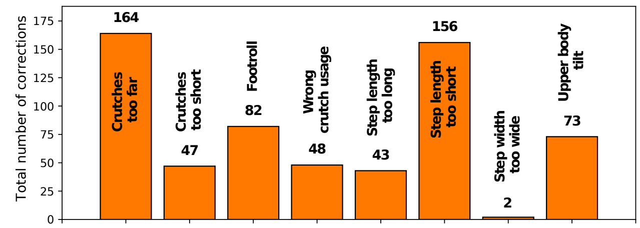

Fig. 7: Total number of correction given by the robot during 91 trainings with 20 patients. In total the robot gave 615 gait error related corrections. In comparison, during the same period the robot gave 647 motivation increasing encouragements.

B. Gait Assessment

Besides the autonomous navigation, the ability of gait assessment is the fundamental part of our presented SAR-assisted training. During the usability study, 20 patients took part in a total number of 91 trainings on 16 days. Thereby, each patient did 4.6 trainings within total time of $35\,\mathrm{min}$ on average during her or his stay.

The robotic gait coach was configured to avoid trainings without any feedback or, however, giving to much gait improvement suggestions could cause a high level of frustration. Therefore, a positive feedback was triggered automatically if no gait error was detected within the last $30\,\mathrm{s}$. In case of detecting multiple gait errors within one period, the most important error was selected and the corresponding correction comment was triggered. In total, the robot delivered 615 corrections and 647 positive responses during all training. This leads to an average amount of 6.7 corrections and 7.0 praises per patient and training. Fig. 7 shows the distribution of all feedback given to the patients during their training. Since gait errors concerning the usage of crutches as well as asymmetric step lengths were rated as errors with high priorities, their related outputs are preferred over other gait errors detected at the same time. Therefore, they occurred more often compared to the other errors. In a clinical setting, the gait error distribution can be used to verify the correct configuration of the error priority module as well as the individual training progress. Comparing the number of corrections with the number of motivating output, it can be noticed that the ratio between these types is quite balanced. Since we assumed positive effects for a successful and joyful training, we configured our SAR-assisted gait robot to reach a good balance of both types of outputs. As stated in Sec. V-C this configuration led to a high level of user acceptance and motivation during the training.

Following the usability study in September 2019, we asked three physiotherapists to re-evaluate the quality of corrections given by the robot. They used an annotation tool to watch video snippets and marked the robot given corrections they could confirm. The snippets were created from the video footage which was captured by the Kinect2 camera during the patients' training sessions. The end of each

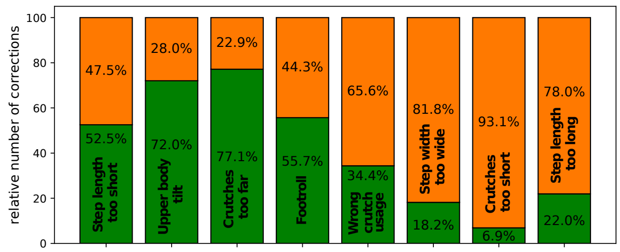

Fig. 8: Evaluation of the quality of robot given corrections. Columns show the proportion physiotherapists agreement (green) on the occurrence of the specific gait error and their disagreement (orange) respectively. The higher the percentage of physiotherapists agreement the greater the ability to recognize specific gait errors properly.

video snippet is determined by the time a new correction was given to the user. In order the get a video of sufficient length, the start time is chosen to get a total video length of at least 20 s. Start and end timestamps were utilized to select the gait errors the robot had recognized within this time span. During the annotations every therapist watched 702 videos and rated 1399 proposed gait errors. Subsequently, the ratio of agreement between the gait errors as recognized by the physiotherapists with those detected by the robot was computed. The results of this evaluation are shown in Fig. 8. It can be seen that there are some gait errors the three physiotherapists mostly agreed with, whereas other gait errors were rarely seen by the therapists.

C. Usability and Acceptance

Of all patients who matched the criteria outlined in Sec. IV during that four week period, 20 volunteered to take part in the tests. Two participants did not complete the final questionnaire, so some biographical data about them are unknown. They were assigned to the female group based on their clinical records. Of the remaining 18 participants, nine identified themselves as women and nine as men. Their average age was 64 years. The participants had a significantly higher education level than typical for their age group [41]. Nevertheless, their general affinity for technology only was slightly above average [42]. Therefore it's unlikely that this factor would positively bias their view on the robotic gait trainer. Eight, respectively three patients, had already experienced "a robot" in person or did own one. Even though this was not explicitly asked for in the questionnaire, these are likely vacuuming robots or similar appliances.

During pauses as well as when the training begins or ends, the robot has to operate very close to the patients to allow for a comfortable interaction with its touchscreens. Still, most of the patients $(18/20)$ felt very safe when interacting with the robot in these and other situations and provided positive feedback $(20/20)$ on the robot approaching and waiting for them whenever they take a break. Although this is a remarkable result, further experiments will be required to examine how the staff that was present during the tests influenced this rating.

Inspired by the experience of physiotherapists, two aspects were discovered which are expected to make a training effective. On the one hand, the robot needs to recognize when gait errors occur and correct them by giving appropriate instructions. On the other hand, the robot should give positive feedback if the patient walks without gait errors or puts the robot's feedback into practice. Occasional praises are considered to keep up the patients motivation and joy while training. The results showed, that all users felt motivated by the robot and thought they'd train more often with the robot than on their own (*"I'd never be this fit without him [the robot]!"*, *"I'd really like to train with him again tomorrow."*). When asked for the reasons of this increased motivation, all said they enjoyed being positively encouraged by the robot, while still 17 of 20 also felt motivated by the correction hints they got. Three users would like to get even more positive feedback, while 14 felt that on some occacions they were being corrected although they did walk properly. Seemingly neutral quantitative feedback, e.g. about their average walking speed and the distance covered during training, was put into perspective by the users themselves and provided another source for self-motivation, e.g. *"I was very happy to see, how I walked a little faster each time."*. In general, there seems to be a generous level of trust in the SAR regarding the correctness of what is proposed by the robot $(19/20$ users).

In general, the participants found the robot easy to handle in most cases, with only one individual disagreeing after the first two training sessions. All individual factors combined lead to a very favorable overall rating of 90.7 ± 7.27 points on the SUS (range: 0-100). Interestingly, older participants were more positive in their view towards the robot-assisted self-training.

VI. Conclusion

The project ROGER aimed to develop a mobile Socially Assistive Robot (SAR), which supports patients with hip endoprosthesis during their self-training to relearn a physiological gait. To reach this goal, three aspects are considered to be important for a successful training with a robotic coach. First, a robust collision avoiding and user-centered navigation, which guides the user along the hallway and reacts when the user slows down or takes a seat in order to have a rest. Secondly, a reliable person perception, which is able to keep the patient in view and distinguish him/her from bystanders. Finally, for a successful and motivating training a real-time gait analysis with gait error recognition and immediate corrective response is crucial. To investigate the benefit of robotic self-training, we conducted a user study over four weeks with 20 patients in "Waldkliniken Eisenberg" (Germany). The technical investigations were accompanied by a sociological study on usability and acceptance. Both investigations showed promising results. Almost all patients felt safe and motivated using the robot, indicating that the performance of our user-centered navigation and user perception reached a level where an autonomous training is possible most of the time. Concerning navigation and person perception, further improvements are still needed for a fully autonomous training, such as increasing the positional accuracy of the 3D obstacle and person detection, especially during situations where the robot is very close to the user. In terms of the given robot corrections the results showed that not all corrections were confirmed by consulted physiotherapists. Generally, the physiotherapists rated the robot as being potentially helpful and supportive if becoming an additional part of the therapy, because it would lead to more time for hands-on therapy within their narrow schedule. Further investigations could be done to tweak the gait correction module on base of a larger set of annotated gait errors. Another promising approach could be the exploitation of deep leaning methods due to their proven ability to recognize patterns in spatio-temporal sequences.

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