May I Keep an Eye on Your Training?
Gait Assessment Assisted by a Mobile Robot*

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***Abstract*— A successful rehabilitation after surgery in hip endoprosthetics comprises self-training of the lessons taught by physiotherapists. While doing this, immediate feedback to the patient about deviations from physiological gait patterns during training is important. Such immediate feedback also concerns the correct usage of forearm crutches in three-point gait. In the project ROGER, a mobile Socially Assistive Robot (SAR) to support patients after surgery in hip endoprosthetics is going to be developed. The current implementation status of the robotic application developed for the use in a real-world scenario is presented below.**

I. INTRODUCTION

Patients recovering from a minimally invasive surgery in hip endoprosthetics have to play an active role in their rehabilitation process to facilitate improvement of their gait. While therapists focus on hands-on therapy mainly, repetitive training is in the responsibility of the patients themselves.

Against this background, documented SAR-assisted self-training of patients is expected to have a promising medical as well as economic potential as a new trend in rehabilitation care. An example of a SAR-assisted self-training system was already demonstrated in [1], [2] with a robotic rehabilitation assistant for walking and orientation self-training of stroke 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 motivated the patients for independent training and encouraged them to expand the radius of their training in the clinic. So, a statement frequently repeated by many patients after training with the robot was: "I have never gone this far alone." [2]

Robot-assisted self-training is also the context and the motivation of the ongoing research project ROGER (RObot-assisted Gait training in orthopEdic Rehabilitiation) running from end 2016 till end 2019. Based on the already demonstrated ability to accompany patients under real clinical environment conditions, the focus of ROGER is the real-time analysis of the gait patterns together with the correct usage of forearm crutches in three-point gait (see Fig. 1). Giving corrective feedback to the patient already while doing training, gait deviations made once should not influence the patients gait in the long term [3]. A further focus is the integration of the real-time analysis of gait patterns in a real world robotic application that is supposed to be tested with patients in a clinical environment. In the ROGER project, the standard treatment by therapists stays unchanged, while the SAR-assisted gait training is only additional.

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

The remainder of this paper is organized as follows: 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. In Sec. III, our SAR-assisted training process is introduced. Based on this, Sec. IV presents the ROGER prototype with the used camera system and the essential human-robot interaction (HRI) and navigation skills required for a robot coach that can operate autonomously in such a challenging real-world environment like a clinic. Using these functionalities, in Sec. V important gait patterns and methods to analyze and assess them are introduced. Sec. VI presents the concept and results of first functional tests with 20 patients conducted under clinical everyday conditions at the Waldkliniken Eisenberg in October 2017 and March 2018. We also give an outlook on pending comparative user studies with volunteers from the group of hip endoprosthetics operated patients with and without using additional SAR-assisted training. So clinical impact can be reported at first after the studies are finished in October 2019.

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II. RELATED WORK

A. Mobile rehabilitation robotics in clinical environments

ROGER belongs to the field of SAR, which is defined as *"provision of assistance through social (not physical) interactions with robots. [...] A SAR system uses noncontact feedback, coaching, and encouragement to guide a user during the performance of a task"* [4]. Although other gait training systems like exoskeletons and treadmills also exists, this paper focuses on SAR systems which are mobile and non invasive.

Although SARs have shown promising results in a number of domains, including skill training, daily life assistance, and physical therapy [5], there is no SAR project known to us that aims in the same direction as ROGER - the development of a mobile robotic training companion which can accompany patients fully autonomously during their gait training within a clinical setting. The ROREAS project [6] addressed the walking and orientation self-training of stroke patients to improve their basic mobility skills and self-confidence but did not support gait training.

In [7] the CLARC project is presented, where a SAR helps clinicians perform comprehensive geriatric assessment procedures in clinical environments. While the geriatric assessment is a different focus than that of ROGER, both approaches base on similar basic robotic skills, like navigation in real environments, person perception by a Kinect2, HRI, and both approaches use the MIRA framework [8].

In [9] and [10] smart walkers were developed, which use a laser scanner for detection, and then record the motion trajectories.

B. Mobile gait analysis using a Kinect2

Using a laboratory system for gait analysis, e.g. a Vicon-System with 10 infrared cameras (Bonita 10), [11] a very accurate 3D motion analysis is possible. Because of it's high precision it is used by the biomechanic research and sport science community. But these laboratory systems are stationary, expensive, and markers need to be placed manually to build a gait model. They are therefore not usable for a gait training with a mobile robot.

Sensors such as Kinect or Kinect2 are low-cost sensors and an alternative to the expensive laboratory systems as shown in [12], [13], [14]. There, 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 [15] a Kinect is used for fall detection of elderly people. The Kinect's results are usable, however the authors note that movements near the wall, furniture or poorly reflective clothes complicate the detection. In [16] the author investigated a static Kinect2 for fall risk analysis of elderly people and, therefore analyzed gait parameters like step length, step duration, cadence, and gait speed. In the result, they inferred that the Kinect2 is an excellent low-cost alternative.

A mobile version of a fall detector was developed by [17]. Their robot is able to follow the user, and the 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 [18] describe a six-wheeled mobile robot with a Kinect2 mounted on-top to drive in front of the subject and evaluated parameters such as walking speed and step lengths.

In all cases, the temporal results of the Kinect or Kinect2 were well in agreement with the reference system. Also, the calculation of the angles at hip and knee joint is unproblematically. However, the angles to the ankle joint pose a problem due the fact that the skeletal point estimation in the foot area tends to be very inaccurate. None of these systems is able to navigate autonomously and avoid obstacles or give an immediate acoustic or visual feedback to the subject.

III. GAIT TRAINING SESSION

In the following, the phases of a ROGER-typical SAR-assisted gait training session are outlined, which is implemented as a statebased training application (see Sec. IV-A), and tested in a series of functional tests with users (see Sec. VI).

The robotic gait coach is planned to assist patients who have just received medical consent to walk with three-point gait on crutches at second day after operation. The duration of one session is 5 to 20 minutes, adjustable by the patient appropriate for their state of health or predefined by a physiotherapist. Training sessions take place each day until release from clinic, twice a day. It also always takes place at the same hallway in the clinic. To ensure the patient's privacy, the starting and ending dialogues of the training take place in a separate waiting room beside the training hallway.

To initiate a training, the patient has to go to the robot, log in by using a personalized RFID transponder and takes a seat at the hip chair. After that the robot turns until its display heads in direction of the sitting patient, approaches and starts to interact by speech e.g. *"Hello, I am your robotic gait coach! At first I'd like to remind you of the procedure and the focus of our training session."*. Furthermore, the right use of three-point gait on crutches and the correction of already known gait deviations of the patient are shown by video. At the end of the introduction, the patient is asked to rate their physical condition and choose the preferred duration of the training. After that, the robot asks, *"Are you ready? After confirming on my display I move to the hallway, and we are going start training."* While driving to the starting position in the hallway, the robotic gait coach generates a temporarily, non-identifying, color-based model of the patient's clothing (see Sec. IV-A) to recognize her or him among bystanders on the training hallway.

During the training session, the robotic gait coach leads the patient by a certain constant distance and keeps the patient at a suitable position in the sensoric field of view in order to continuously keep a good view on the patient during the training session [19] (see Sec. IV-A). By analyzing the gait and posture while training, several gait features are extracted (see Sec. V-A) which are rated by comparison with thresholds (see Sec. V-C). If a gait deviation has been detected, the robotic gait coach gives speech-based and GUI-based feedback to the patient, e.g. *"Take care of the same step length for both legs."*

At the end of the hallway, the robot stops, turns around and waits. As soon as the patient is sensed behind the robot again, the robot continues the training. Along the hallway hip chairs are set up providing resting places. After the recognition of the sitting patient, the robot starts approaching the patient, i.e. reducing the distance to her or him, to create the necessary distance to physically interact with the robot's touch display [20], while stating *"I notice you want to pause the training. Do you want to gather strength or rather finish the training?"*. Depending on the choice of the patient the training is continued after the patient stands up or is terminated by guiding the patient to the waiting room to do the closing dialogue, e.g. *"You walked 100 m very well. For the next training, please pay attention to the usage of crutches and straighten your upper body."*. After finishing the regular training time a similar dialogue appears, too.
Finally, physiotherapists are able to check the results of each training session, and may furthermore adjust the focus of the next training session. Depending on the way the robot is integrated into the clinic infrastructure the physiotherapists might also be able to follow the gait training session in real-time.

IV. MOBILE ROBOT AS A GAIT COACH

Based on the scenario in Sec. III, there is a set of distinct challenges a robot system has to tackle to make a successful training session possible. Sec. IV-A will focus particularly on the challenges imposed by the requirement of an autonomous SAR. In Sec. IV-B specific results to demonstrate the autonomy obtained from function tests in clinical environment are presented.

A. System architecture

An application for a SAR-assisted gait training has an inherently complex nature, and we therefore use a hierarchical system structure consisting of multiple abstraction layers (see Fig. 3) in combination with the robotic middleware MIRA [8].

1) Hardware Layer: Consisting of various sensors and actuators for obstacle avoidance, person perception, and HRI, the hardware layer resides at the bottommost level. Sensors and actuators are mounted on a customized SCITOS platform [21] with a relatively small footprint of $45\,\mathrm{cm} \times 55\,\mathrm{cm}$, a height of $1.5\,\mathrm{m}$ and a maximum driving speed of up to $0.9\,\mathrm{m/s}$ (see Fig. 2 and [19] for a detailed description).

As the main sensor for gait assessment, we use a backward-directed Kinect2, to observe the patient during gait training. While guiding, unconcerned persons can be encountered, too, and have to be treated with great care in order to not violate the person's comfort zone [22]. In these situations, it would be possible to lose sight on the patient if the camera was mounted at a fixed position. This especially appears if cameras have a relatively narrow field of view, like the Kinect2 with a vertical field of view of $70°$. To compensate this, our robot is equipped with an actively controlled pan-tilt unit in order to counter this movement [19].

The major interfaces for interaction with the robot are two touch displays mounted at different heights. This setup allows the standing or sitting patient to comfortably use the robot.

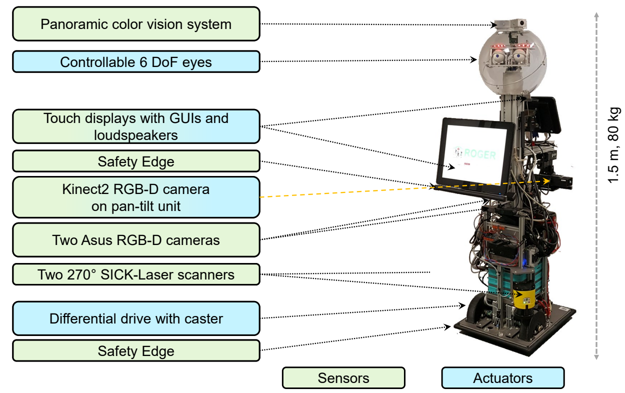

Fig. 2: Sensors and actuators of our robot platform.

2) Skill Layer: By using the raw sensor information and the actuators of the hardware layer, the skill layer realizes the core functions of our robotic gait coach. The skills can be categorized in modules for *person perception*, *gait analysis*, *navigation,* and *HRI*. In the following, we will discuss the main modules only and refer to the given references (see Fig. 3) for more technical details and experimental results.

Person Perception: The person perception is comprised of a joint person tracking and re-identification module [26]. Since hospital staff and guests can also move in the hallways during training, the re-identification is a crucial skill and is used to distinguish the patient among detected bystanders. The tracker is based on a multivariate Kalman filter and is able to estimate the positions and velocities in 3D. As detection module, a body part detector [24] is employed. Additionally, generic distance-invariant laser-scan features detect legs and persons even with mobility aids, i.e. crutches, walkers and wheelchairs [25]. With these detection modules, we are able to track persons up to a distance of $8\,\mathrm{m}$. For re-identification, a metric-learning approach with color and texture features is utilized [27]. This person perception module was already benchmarked in the ROREAS project [6] with results showing the suitability for this application.

Gait Analysis: For gait analysis, the estimation of 3D skeletons is essential. Based on the skeleton representation of a patient, features for assessment can be extracted in a straightforward manner. The Kinect2 is our sensor of choice, since in conjunction with Microsoft's SDK [28] we can make use of an already fully functioning 3D skeleton tracker which robustly estimates a 25-joint-skeleton in real-time ($30\,\mathrm{fps}$). Thus, we were able to concentrates on the core of the ROGER project, the extraction of gait features from the skeleton obtained by the Microsoft's SDK and their assessment to distinguish pathological from physiological gait patterns. This approach sped up the project by avoiding

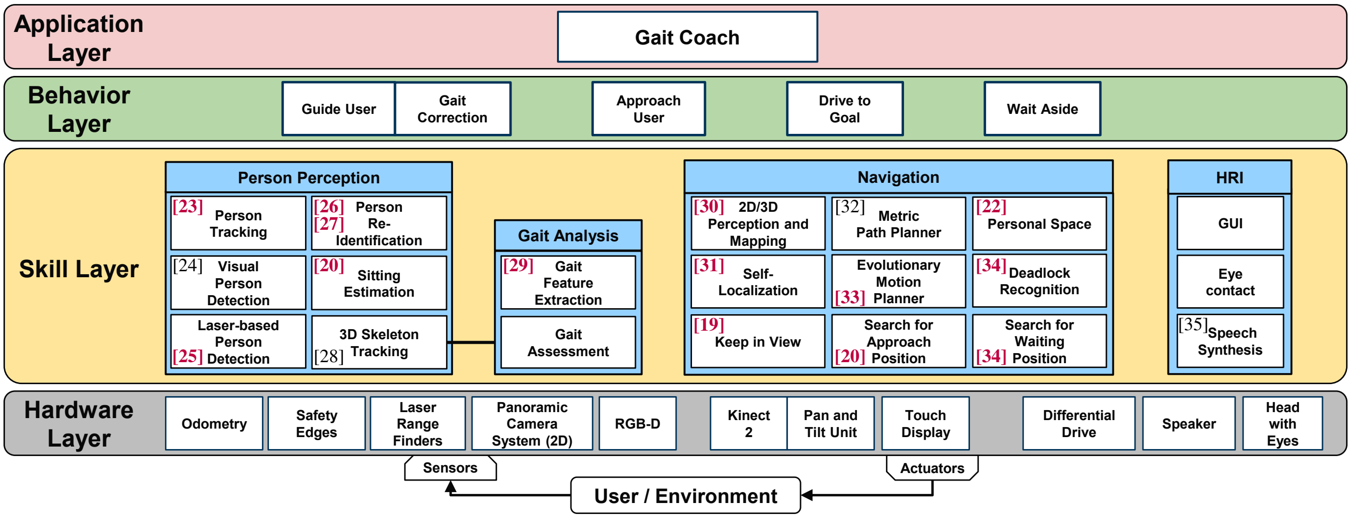

Fig. 3: Hierarchical architecture of the robot's functional system. A detailed description of the skills developed within the ROGER and ROREAS [6] projects together with the results obtained from functional tests can be found in the red highlighted references.

the tedious development of our own skeleton estimation system. Further details on the extracted gait features and assessment algorithms are presented in Sec. V.

Navigation: To assure a safe navigation in a dynamic environment, the problems of localization, obstacle detection, and motion planning have to be solved. Our localization system is based on an adaptive Monte Carlo approach, and detecting obstacles is performed through an occupancy grid mapping approach. Both systems for localization and obstacle detection are generically designed to process both 2D laser scans and 3D information [30], [31]. Based on the estimated robot pose and obstacles in the vicinity, we generate motion commands with a multi-objective motion planner which utilizes evolutionary algorithm for optimization [33]. To guarantee the best conditions for estimating the skeleton of the patient by the Kinect2 during training, we take advantage of the versatile properties of our motion planner to keep the patient in an optimum distance and angle relative to Kinect2.

HRI: Since touch displays are our major interface, the HRI modules simply encompasses modules for displaying graphical user interfaces. Furthermore, a speech synthesis system generates [35] spoken language in real-time, making it possible to customize the gait correction instructions to patient's needs.

3) Behavior Layer: Each behavior realizes a directly observable function of the robot by managing the interplay of the modules in the skill layer. Basically, behaviors can be regarded as small state machines, parameterizing and coordinating the activation and deactivation of skills. The mainly used behaviors of the applications are "Guide User" (using the skills, e.g. "Evolutionary Motion Plannning", "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).

B. Environment and functional tests for the robot's autonomy

The typical environment for SAR-assisted self-training in clinic buildings are hallways. In general, clinic hallways are stretched-out and straight which contributes to a good view on the exercising patient. However, there are often situations where the robot needs to navigate around bystanders or obstacles, e.g. carts with medical supplies. As SAR-assisted self-training aims to be seamlessly integrated into the usual clinical day-to-day activities, the robot will subsequently also operate in this environment.

To assess the performance of our navigation skill, we performed several functional tests, first in our lab building and after that in the clinical environment. Since our robot enhances the system of our previous project ROREAS, we refer to [1] for a summary of previously conducted tests. In the following paragraphs, we will only present the results of the navigational skill "Keep in View" which is specific to the project ROGER.

We determined the performance of the obstacle avoidance and the ability to keep a polite distance to bystanders when driving to a specific position (still not guiding a patient). This test took place on two floors of the clinic during a work day and comprised the robot commuting between both ends of a floor. To assess the performance, we counted the number of collisions with obstacles which would force an emergency stop and the number of close encounters with persons in a radius of $0.6\,\mathrm{m}$ to evaluate if the robot proactively avoided obstacles and kept a polite distance to bystanders. The total mileage driven by the robot was $2\,800\,\mathrm{m}$, while the robot encountered 44 persons in a radius of $3\,\mathrm{m}$. During this test, no collisions occurred but 8 close encounters with persons which were primarily caused by clinic staff intentionally moving close to overtake the robot and missing detections of the person tracker because of adverse light conditions.

To assess the performance of keeping the patient at an optimum distance and angle relative to Kinect2 while guiding, additional tests were conducted in our lab. For these tests, a $140\,\mathrm{m}$ long track resembling the clinic environment was set up. On this track eight test subjects were guided from start to end and back at a distance to the robot of $2.5\,\mathrm{m}$ ($\pm 0.5\,\mathrm{m}$). In total, 30 test runs were recorded resulting in a overall mileage of $4\,200\,\mathrm{m}$. With the combination of motion control of the robot's drive and the camera tracking of the pan-tilt unit, we could keep the test subject in the Kinect2's field of view in $99\,\%$ of the time [19].

All integrated robotic skills, e.g. the person tracker or the re-identification module have significant influence on the working SAR-assisted training. But during the development of the application, most skills are also still under development. So, we utilize a control interface on a tablet computer (control tablet), which was specifically developed for this purpose in order to provide an interruption-free testing process. Using this control tablet during the functional tests, the observer was able to make real-time adjustments to skills, e.g. person detection, and compensate erroneous decisions of those skills. This way, the functional tests including those with users were enabled to start much earlier than this would have been possible by the readiness level of the respective skills. Moreover, the developers got objective and situation-specific feedback about the function of their algorithms.

V. GAIT ASSESSMENT

A. Gait Features and their Extraction

Besides the aforementioned requirements on hardware and basic robotic skills, detection and evaluation of gait features are crucial in the scope of a mobile robot which is designed for SAR-assisted gait training. Therefore, a group of physiotherapists was asked to recommend a set of typical gait pattern related anomalies they usually pay attention to. On the basis of this list, together with the results of conducted accuracy investigation for a static Kinect2 setup [29], a subset of gait features was defined the robot needs to be able to detect in a reliable way. The subset is made up of *step length*, *stance duration*, *step width*, *trunk lean*, *flexion/extension* of knee and hip joints as well as the crutch position which is not supported by the Kinect2 SDK.

In continuation to the investigations on the accuracy between Kinect and Vicon made with a static setup [29], further investigations were also done in the gait laboratory with a Kinect2 mounted on the robot and a Vicon system simultaneously. The Vicon system which was used in the static as well as in the dynamic setup is a static marker based motion capture system. The results gathered for the dynamic setup are depicted in Fig. 4 for the joints of the lower body. Considering the dynamic setup the comparison of the Vicon as reference system with the joint positions estimated by the Kinect2 showed, that the standard deviations of the errors are between 3 and $5\,\mathrm{cm}$ (see Fig. 4). So the Kinect2 sensor can also supposed to be appropriate for gait feature assessment on a mobile platform.

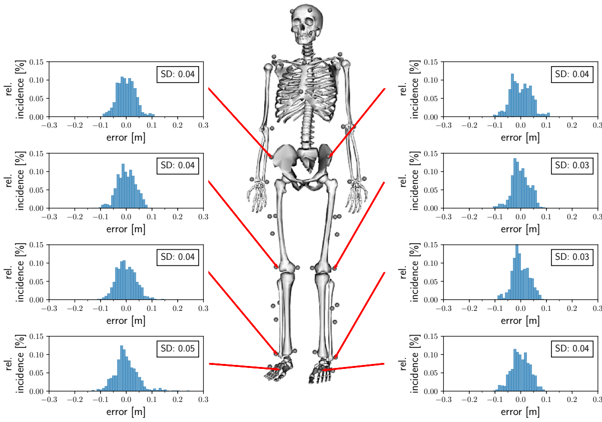

Fig. 4: Histograms of the errors between Kinect2 and Vicon system and their standard deviations (SD) for the lower body joints.

Most gait parameters are defined by the spatio-temporal heel and tip movement respectively. Although the investigations showed that the accuracy of the foot position estimation is comparable to the ankle position accuracy, it also showed that the Kinect2 SDK had issues with stable tracking of the foot positions. Since the whole gait feature tracking depends on a stable estimation of the foot position during the gait phases, the presented gait feature assessment uses the ankle positions due to their more accurate estimation instead the more error-prone foot positions.

Following this assumption, the *step length* is defined as the Euclidean distance between the ankles during one gait cycle. A gait cycle consists of swing phase and a stance phase of each leg. The consecutive gait cycles of both legs are a stride. In addition to the step length the *stance duration* for the foot is defined as the time between two consecutive maximum step lengths while the respective foot stands on the ground and the opposite foot is swinging. Unlike the step length, the *step width* is the minimum norm distance between the left and right ankle. Fig. 9 shows the step length and stance duration during a sequence of four gait cycles for a patient with a total hip replacement of the right hip joint.

Although the Kinect2 skeleton does not provide the pose of body parts, the poses can be obtained by linking adjacent skeleton joints. Thus, the *angle of the knee joint* is defined by the direction vectors between knee to hip skeleton point and knee to ankle skeleton point. In order to determine the flexion and extension for both *hips joints*, corresponding shoulder and knee points are used. In contrast to the joint angles, the *forward lean of trunk* is defined to be the angle between the line from mean hip joint to mean shoulder joint and the line perpendicular to the mean hip joint (see Fig. 5, right).

B. Forearm Crutches and their Detection

Since the robotic gait coach's focus are patients shortly after their endoprosthesis operation, forearm crutches are mandatory to avoid overstressing the joint. Before receiving medical consent for self-training, a physiotherapist gives an

[1]https://bit.ly/2RUGbcz

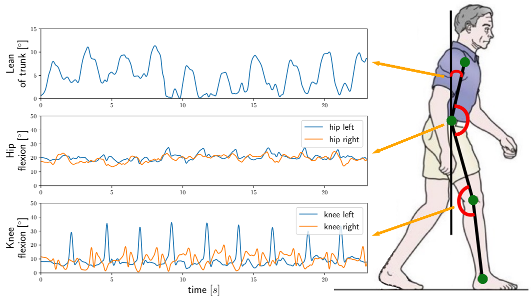

Fig. 5: Sequence of lean of trunk, hip flexion, and knee flexion over a period of 23 s for a patient with a total hip prosthesis (right hip)[1]. The gait impairment results in the unequal progression of the knee flexion curves.

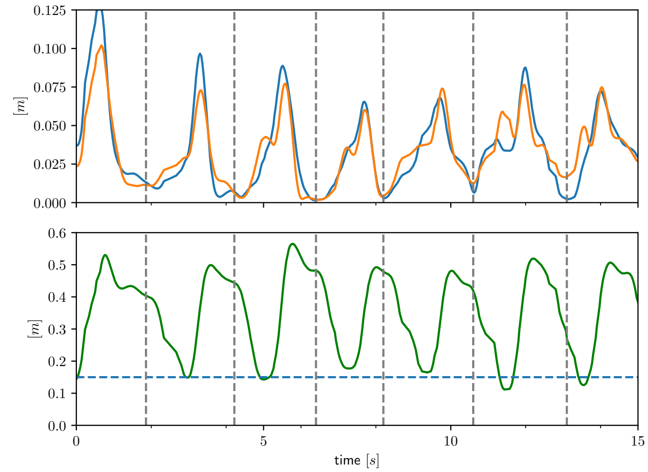

Fig. 7: **Top:** Vertical height of the estimated crutch tips (left: blue, right: orange) and initial contact times with the ground plane (dashed) **Bottom:** Distance of the foot (operated side) to the connection line of both crutch tips. For three-point gait the dashed horizontal line would be ideal, and distance minima should be close to crutch-ground contact markers.

introduction on how to use crutches in three-point gait and accompanies the patients during their first training. As noted above, it is consequentially highly favorable to also cover the aspect of correctly performing a three-point gait in SAR-assisted gait training. Given the capabilities of our platform, a possible approach is to use depth data obtained from the Kinect2's 3D-sensor. To make best use of existing and mature libraries, the depth image is first converted to a point cloud suitable for processing using the *Point Cloud Library* [36] (PCL). The converted point cloud is then roughly segmented in smaller point clouds based on the patient's skeleton since we know that crutches ought to be near its forearms/hands. This allows the efficient use of standard segmentation and fitting algorithms on a reduced subset of points. For example, using RANSAC [37] allows segmentation of the crutch-candidate point clouds in real-time (30 fps) while giving reasonable accuracy and robustness (see Fig. 6).

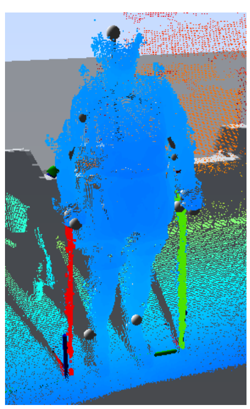

Fig. 6: Sample image of a crutch detection (left: green, right: red) in a Kinect2 point cloud.

After the crutches are found in the scene, further analysis is now possible. An example can be seen in Fig. 7 where the height of the crutch tips over the ground (top) as well as the distance of the foot (operated leg) to the line connecting both crutch tips is shown (bottom). Because patients in our scenario are asked to walk in three-point gait, the distance should be relatively constant over time since one of the requirements in three-point gait is to always support the implant with two crutches during stance phase. High distances at the marked contact points with the ground and noticeable peaks in the distance curve in contrast provide a strong hint that the patient moves and sets its crutches before actually lifting the heel and thereby offloading the body weight to the healthy leg. In this situation, the operated hip is unsupported and often still under the pressure, possibly causing discomfort or instabilities in the patient's gait.

C. Assessment of Gait Features

In addition to the gait feature extraction, the mobile gait training robot should be able to distinguish pathological from physiological gait patterns. Furthermore, the classification has to be executed in real-time while the patient walks behind the robot.

To classify whether detected step lengths, stance durations, step widths, trunk leans or joint flexions are within the physiological ranges, thresholds will be determined by physiotherapists.

For this purpose, semi-automatic trainings with patients with hip endoprosthetics were performed in order to film their walks and capture the patients skeleton movements provided by the Kinect2 at the same time. Subsequently, a subset of videos were picked out to be annotated by four physiotherapists.

When an error occurred, the sequence was labeled and timestamps corresponding to the beginning and end of the sequence were marked. Simultaneously, the gait features were extracted from the previously captured skeleton information and were also stored with their timestamps. In several iterations the physiotherapists watched the selected videos of six patients (approximately 1 h of video footage in total) and each time focused on an other gait error from the predefined list which should be detectable by the robot afterwards. In

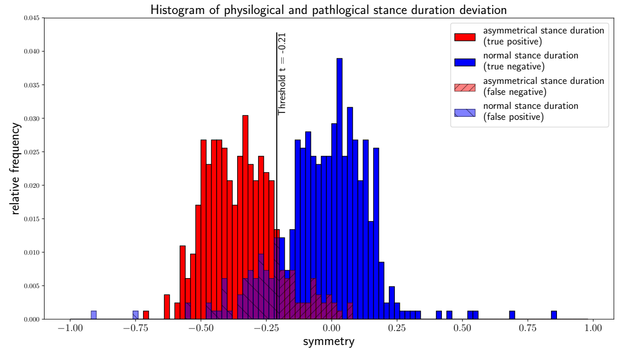

Fig. 8: Histograms show the distributions of pathological (error class) and physiological (no-error class) step length symmetries. A symmetry of 0.0 means perfect symmetry between left and right leg, whereas symmetries of ± 1.0 indicates that one leg makes twice the step length of the other leg respectively. By evaluating the F1 score a threshold can be found which separates both classes most suitable. In this case the best symmetry threshold is -0.17 (precision: 0.85, recall: 0.88, F1 score: 0.87), which means that step lengths with symmetry values less than -0.17 can be considered as a pathological deviation from the normal gait and needs to be corrected.

a consecutive evaluation, gait feature values of sequences in which all physiotherapists confirmed the gait error are considered to be part of the error class. In contrast, values of sequences without any annotations belong to the no-error class. For assigning the physiotherapists annotations with the gait feature values the timestamps are used.

Since the physiological gait feature deviation covers a wide range, comparing absolute values with thresholds is not an expedient approach. In some cases a more reasonable way is evaluating the gait similarity between both legs during one cycle. The similarity is defined by the ratio of lengths, durations or angles between the leg with and that without hip endoprosthesis respectively.

In Fig. 9 a sequence of four consecutive strides of a patient with total prosthesis of the right hip is shown. It can be seen that the step length of the not operated leg is shorter than that of the operated leg with prosthesis. During a gait cycle, the patient tried to reduce the time standing on the operated leg to avoid discomfort. This is the reason the stance duration of the not operated leg is greater compared to the stance duration of the leg with prosthesis. Thus, the ratio between step length and stance duration of both legs is an appropriate instrument to classify whether the patients' gait is physiological or pathological and needs to be corrected during training.

The ability to separate both classes was evaluated by the F1 score which was computed for different threshold values. The most suitable threshold corresponds to the highest F1 score. In Fig. 8 histograms of the error class and the no-error class for physiological step length and the best fitting classification threshold are shown.

Current work concentrates on the evaluation of thresholds to separate pathological gait errors from physiological deviation as prerequisite for coming functional tests with users.

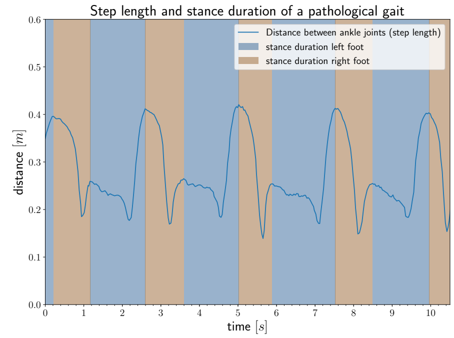

Fig. 9: Sequence of stance durations of a patient with a total hip prosthesis (right hip). To avoid pain, the patient acquires a pathological gait pattern which manifests in differing stance durations (different width of orange and blue areas) and step lengths (blue line).

VI. FUNCTIONAL TESTS WITH USERS

Before evaluating the gait coach performance with patients in a clinic, it must be assured that all required robotic skills and behaviors for HRI and human-aware navigation (see Fig. 3) do work as expected in a clinic setting. So we performed several functional tests, first in the hallways of our lab building [20] and after that in the clinic with volunteers (staff members, no patients) [19], [29].

In addition to these tests, in October 2017 and March 2018 we performed functional tests especially to develop methods to assess the gait patterns of 20 patients under real world conditions. Typical trials with patients had durations of about $10\,\mathrm{min}$ (including short pauses if needed) where the patients each walked $200\,\mathrm{m}$ on average. While being guided by the robot, the patients were recorded by the onboard Kinect2 observing the patient. As described in Sec. V-C, physiotherapists were able to establish thresholds for important gait features based on these videos. These tests were accompanied by technical staff using a control tablet to compensate erroneous decisions of those skills which were still under development.

In the last project phase beginning in May 2019, the final prototype of a robotic gait coach is going to be evaluated within further field tests with a sample size of 60 patients (30 getting robot training, 30 in the control group). The goal is to investigate the effect of additional SAR-assisted gait training with corrective feedback for a faster achievement of a physiological gait pattern. Besides of this, socio-emotional factors like safety, joy of use, and co-experience [38] play an important role for the acceptance and success of a SAR-assisted training. Thus, sociological studies will be run in parallel to evaluate the acceptability and user-friendliness of the robotic gait training by the patients.

VII. CONCLUSIONS AND OUTLOOK

Up to now, in our ongoing ROGER project we developed a robotic gait coach, which can navigate in clinic hallways accompanying and observing the self-training of patients. By recognizing gait deviations the robot will be able to give corrective feedback immediately under real clinic environment conditions. Giving this feedback in an objective way and being patiently, the robot is supposed to motivate the patient and promote its self-confidence. The feasibility and the advantages of self-training with a robotic accompaniment shall be further investigated in succeeding studies. By doing further real world tests, we can also improve our navigation and person recognition methods to enhance the autonomy of the robot. Also, the process of training can be further enhanced by integrating the robot into the clinic information system to yield improved interfaces to physiotherapists for evaluating and adjusting the training plans.

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