# Please ASTRO, can you follow me? Design of a social assistive robot for monitoring gait parameters

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Abstract

This paper proposes an alternative strategy for the analysis of the gait activity using a socially assistive robot. This solution aims to be less invasive while guaranteeing an accurate evaluation of the rehabilitation performance. In this work, we implemented a follow-me module to enable ASTRO robot to detect, track, and follow the patient during walking, adapting to his/her walking speed. The robot detects the person through a 2D laser sensor and an RGB-D camera. To follow the user at a predetermined distance, the implemented follow-me module integrates two controllers for handling the linear and angular velocities, respectively. The controllers' gains were set according to the maximum speed attainable by the robot. The extracted gait parameters were compared with the parameters extracted by an inertial sensor placed on the feet (SensFoot) and analyzed to characterize the best robot configuration for the task of the gait assessment. Eleven participants were recruited to perform the tests with 3 different values of the robot's maximum speed. For each test, 4 parameters were extracted from the laser and 10 parameters from the wearable sensors. The best configuration was found to be the one with the highest maximum speed, 0.7 m/s, whose gains from the two linear and angular controllers are $K_p$ = 1.0, $K_d$ = 0.4, and $K_p$ = 1.0, respectively. Qualitative results collected at the end of the test also confirm the 0.7 m/s as the optimal perceived maximum velocity.

**Keywords**

follow-me, gait parameters, socially assistive robot

## 1. Introduction

Nowadays, socially assistive robotics applications are extensive and cover the human life cycle spectrum of needs and want. It ranges from the field of physical and cognitive disorders in children [1, 2], to the care and assistance of people suffering from cognitive decline and associated complications [3, 4]. This wide and complex range of applications foresees the presence of different stakeholders, i.e. professional caregivers, social service providers, medical services, etc. Due to recent advances in the field of socially assistive robots, the range of potential applications has greatly expanded, becoming one of the most promising emerging technologies devoted to helping and assisting citizens in daily activities at home but also in relevant healthcare settings. Particularly, overall last few years, several researchers focused

*ALTRUIST workshop, held at International Conference on Social Robotics, December 2022, Florence, IT*
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also on the use of social robots for promoting active aging and for being used as a support in clinical [5] and residential contexts [6, 7, 8]. Indeed, thanks to the embedded sensors, social robots can "percept" information related to human movements, body postures, and emotions – among others – that can be linked to the clinical status of the humans thus providing decision support for the clinicians. For instance, they can use social robots to acquire information while the patients are doing some commonly used cognitive or physical exercises (e.g. walking). The current gold standard for clinical motion analysis is represented by optical motion capture systems performed in the laboratory. Unfortunately, economic, as well as environmental and time constraints prevent the continued collection of these high-quality data. In addition, motion data collected in the laboratory may not be able to describe the natural movements of an individual as in the home environment [6].

Technologies based on non-wearable sensors (e.g. cameras, footpads) or wearable sensors (or a combination of both types) are also being used to obtain information about the motor condition of the patient. However. sometimes they are cumbersome or considered too invasive also from a privacy perspective. For instance, in [9], machine learning models were developed to predict clinical gait parameters from the trajectories of 2D poses of the body extracted from videos using OpenPose [10] thus predicting the gait parameters and clinical decisions relying on machine learning classifiers (i.e. CNN, Random Forest, and Redge Regression). In [11] a real-time gait analysis is developed using a Kinect v2 sensor and measuring variables such as step length and angles between joints. In [12] the approach proposed relied on a deep learning technology (i.e. Mask R-CNN) to recognize a human subject in a 2D image, then combining 3D data to measure walking parameters such as the stride length and the walking speed. However, all the proposed solutions are based on a fixed camera installed in the environments, but what if the users won't perform the exercise in front of the camera or the workspace requested by the exercises is bigger than the camera workspace (e.g. if the user is walking)? The acquired parameters can have low accuracy, so the clinician can't rely on them. From the clinical perspective, the monitoring of gait parameters represents a core point; indeed, alteration in walking can be linked with some neurological disorders. In this sense, the information acquired by the robot can be used as biomarkers for monitoring the progression of the disease or for predicting some abnormal status.

In this context, this work proposes an alternative solution for gait analysis using a social robot, equipped with an RGB-D camera and a 2D laser. The idea was to develop a follow-me module where the robot acquires information on the human's gait while they are walking together, so as to be sure that the users will be always in the optimal field of view of the sensor. This solution allows the person to avoid wearing additional sensors - which can create discomfort in the patient - while providing the assessment during the rehabilitation activities, which can be carried out both in hospital facilities and in patient's homes. Particularly, the aim of this work was to design, develop and characterize a robot control module to be used for acquiring reliable gait parameters during the walking activity, without interfering with the user's "normal" walking speed and measuring his/her level of technology's acceptance. Within this aim, we implemented a follow-me software module that allows the robot to detect, track, and follow the patient during the walking activity. The RGB-D camera, together with the laser, is used to locate the person in the environment. The presented work tends to answer to main research hypothesis:

(a) RQ1: What should be the optimal robot velocity that the robot should keep guaranteeing a reliable gait assessment?

(b) RQ2: How is the optimal combination perceived by the user in terms of acceptability?

# 2. Materials and Methods

## 2.1. ASTRO Robot

The robot used in this study is ASTRO robot, a robotic platform designed to promote the user's mobility within ACCRA project [13]. The robot is mounted over a SCITOS-G5 platform, developed by Metralabs[1]. SCITOS-G5 is a differential drive mobile platform with a base of dimensions 582x7537x617 mm, equipped with two drive wheels and one caster wheel, an EC motor with high torque, and a bumper sensor with a mechanical emergency stop. The platform is equipped with a Sick-s300 laser sensor placed at the bottom, and an Astra Orbecc RGB-D camera placed at the height of the "neck" of the robot, as visible in 1. Since ASTRO is a ROS-based robot, the CogniDrive module, developed by MetraLabs GmbH, represents the middleware to receive and send velocity commands at the motors of the SCITOS platform.

## 2.2. Follow-me module

The follow-me module is composed of a perception and a controller block, respectively. The perception part is responsible for identifying and tracking the person along the path, by using the data stream recorded by the camera and the laser. To locate the person using the camera, the RGB image is fed into the YOLOv3 network [14], which returns the coordinates of the bounding box of the detected person, i.e. (x,y) coordinates (pixels). The information is then combined with the camera calibration information to project the centroid of the person on the depth image, i.e. z coordinate (meters). The centroid is computed as the center of the bounding box. To properly locate the legs of the person, the leg-tracker ROS package is used to process the laser data in real time. The data returned at the end of the process belongs to the (x,y) position of the left and right leg's centroids, respectively [15].

The controller part is made of two controllers, for handling the linear and angular velocity of the robot separately. The former is a Proportional-Derivative (PD) controller that takes as input the distance of the robot from the person to be followed, defined as the difference between the actual distance and the ideal distance (i.e. input error). The output of the PD controller represents the linear velocity to be imparted to the robot to keep it at a fixed distance from the person. In this study, the fixed distance has been set to 1.5 m, which represents the distance at which the camera can detect the full body of the person, as well as a proxemic value that lies outside the personal space of the user [16]. To provide an answer to RQ1, we tuned the PD controller to guarantee three different maximum linear velocities: 0.3 m/s (lowest velocity); 0.5 m/s (an intermediate velocity); 0.7 m/s (highest velocity). The gains used in this work are $K_p$=1 for every velocity, while varying the derivative gain $K_d$, namely: 0.2 for the lowest velocity, 0.3 for the intermediate velocity, and 0.4 for the highest velocity.

[1] https://www.metralabs.com/en/mobile-robotscitos-g5

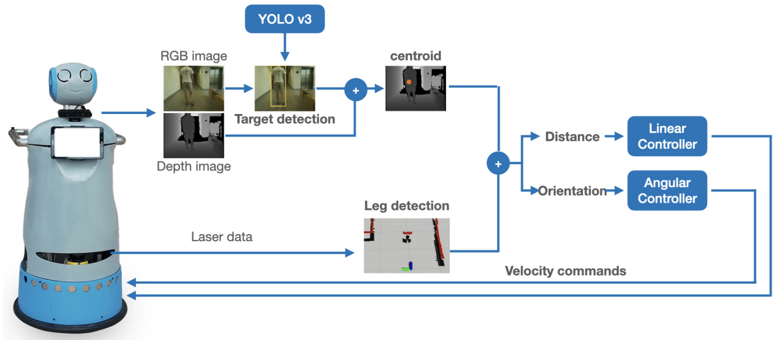



**Figure 1:** System Architecture.

The latter is a Proportional (P) controller, in which the error concerns the distance between the center of the camera and the centroid of the person (distance intended along the x-axis, i.e. the one parallel to the camera) and the output signal represents the angular velocity to be imparted to the robot so as to keep the centroid of the person always in the center of the camera's field of view. To guarantee this behavior (i.e. correct the orientation of the robot with respect to the person to follow), the angular controller was tuned with $K_p$=1. Both linear and angular controllers have been implemented with the simple-PID python API[2].

## 3. Experimental protocol

The goal of this experimentation is to define the optimal follow-me robot configuration, intended as the velocity configuration of the robot, that allows to correctly measure the gait parameters (RQ1) while avoiding the "disturbance" factor introduced by the presence of the robot (RQ2), that may affect the way in which the patient walks (i.e. naturalness). The "10 meters" clinical protocol was chosen for this experiment since it is widely used in clinical practice. Within the test, the user is requested to walk ten meters along a straight path. At the beginning of the experimental protocol, the user was asked to wear SensFoot on both feet [17], as shown in Figure 2. These sensors were used only for data comparison, without including them in the final prototype. The experimental setup was composed of 4 trials, each one dedicated to a particular combination of robot velocities and controller's gains (reported in Table **??**), as follows:

1. NM (*Not Move*): The robot remains stationary at the starting position.
2. LS (*Low Speed*): The robot follows the user with a max linear velocity of 0.3 m/s.
3. MS (*Medium Speed*): The robot follows the user with a max linear velocity of 0.5 m/s.
4. HS (*High Speed*): The robot follows the user with a max linear velocity of 0.7 m/s.

During each trial, the participant was asked to walk in front of the robot. At the end of each trial, each participant evaluated how the presence of the robot affected his walk on a 10-Likert

[2]https://pypi.org/project/simple-pid/

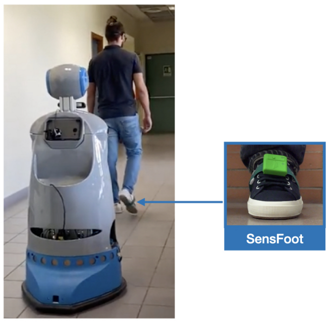



**Figure 2:** System Architecture.

scale for evaluating (where 1 meant that the presence of the robot did not affect the walking, a value of 10 meant the robot affected walking a lot). The gait assessment was performed offline by considering the data recorded by the laser and the SensFoot worn by the participant.

## 4. Participants

For this experimentation, a total of 11 young participants were recruited from Ph.D. students and researchers employed at the Department of Industrial Engineering of the University of Florence. The cohort was composed of 6 men, and 5 women (avg age: 31.27; std: ±8.78). All the participants signed the informed consent before entering into the study. The tests were performed in accordance with the Declaration of Helsinki and the data storage is compliant with the GDPR regulation.

## 5. Data analysis

Data from the laser and inertial sensors were processed offline, using Matlab®R2020b (The MathWorks, Inc., USA). Data from the wearable sensors were pre-processed using a fourth-order low-pass digital Butterworth filter with a 5 Hz cut-off frequency for eliminating high-frequency noise. Custom-made algorithms [17] were then applied to extract parameters reported in Table 1. The acquired laser data were transformed from the robot's moving reference system to a fixed reference system, coincident with the initial position of the robot. This step guarantees the exact measurement of the gait parameters with a moving system. Then, to properly identify the centroids of the left and the right legs, the laser data were then separated according to a threshold along the y-axis (i.e. axis perpendicular to the direction of motion). Finally, the laser data are segmented from the inertial data, thus identifying the various phases of the walk, as in [18]. At the end of the feature extraction process, a total of 14 gait-related parameters were extracted (as shown in Table 1), namely: 4 parameters were extracted from the laser and 10 from SensFoot data.

To answer RQ1 and RQ2, we compared three different follow-me configurations (i.e. varying velocity), considering a reference configuration. We considered the stationary condition (NM)

**Table 1**
Gait parameters extracted from the laser and inertial sensors for gait assessment. Each parameter is computed for the left and right foot, separately.

| Parameter | Acronym | Description | Devices |
|---|---|---|---|
| Step number | GSTRD | Number of steps | Laser/SensFoot |
| Step Length | StL | Average of step lengths | Laser |
| Gait Swing Time | GSWT | Average duration of Swing phase | SensFoot |
| Gait Stance Time | GSTT | Average duration of Stance phase | SensFoot |
| Gait Stride Time | GSTRDT | Average duration of the Stride phase | SensFoot |
| Foot lift | GAngExc | Average of the angular excursion of the ankle | SensFoot |

as a reference for undisturbed gait performance. When stationary, the robot can not disturb the patient in any way. However, this condition may affect the reliability of the parameters' measurements when the user is too far from the robot. In this case, the gait parameters extracted with the inertial sensors were used as references. To properly identify the differences between the parameters computed within the moving robot configurations and the stationary robot, the absolute relative error between the two configurations has been computed as:

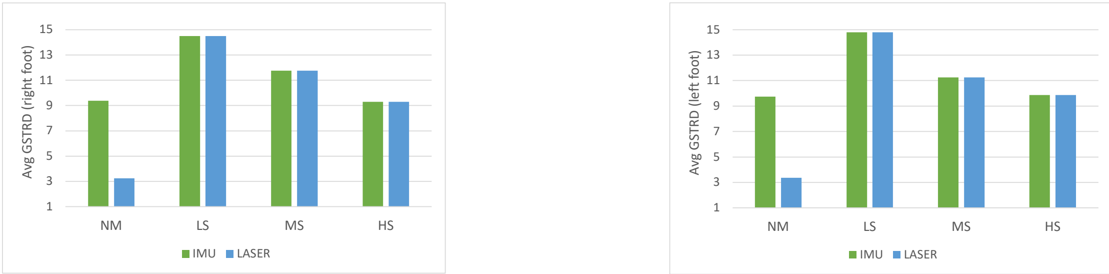
$$e_{PAR\_i} = |\frac{\mu_i - \mu_{NM}}{\mu_{NM}}| \quad (1)$$

Where PAR is the parameter of interest, and $\mu$ is the average value of the parameter of interest computed among the trials of the follow-me configuration $i$ (i.e. $i = [LS, MS, HS]$).

## 6. Results

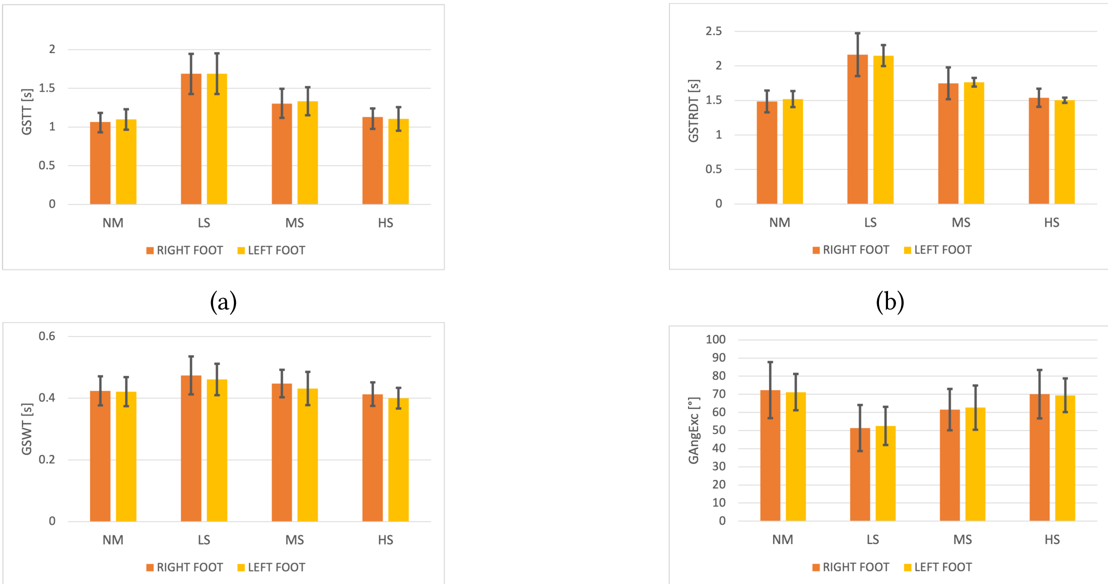
Due to the presence of misclassified laser data, the performances of some participants were excluded. In the end, the analysis included 8 participants for the trial with the stationary robot (NM), 10 for the trial with low speed (LS), 8 for the medium speed (MS), and 7 for the high speed (HS). Comparing the number of steps extracted from the laser with the measurements estimated by the inertial sensors, it emerged that there was a loss of laser data in the stationary configuration (NM). Namely, after a certain distance (c.a. 4m), it is not possible to identify the legs of the users from the laser data. As shown in Figure 3, this phenomenon did not happen in the remaining trials, where the number of steps coincided with the two devices' measurements. This result validates the idea of integrating a follow-me module to perform a valid gait assessment, directly using the data recorded by the robot's sensors.

Considering the gait parameters extracted from the inertial data, the results returned that the higher is the velocity of the follow-me robot, the closer the parameters extracted with the moving robot configuration and the stationary configuration are. As shown in Figure 4(a)-(b), the stance and stride duration computed during the HS trials are the closest to the stance and stride duration estimated during NM. Namely, the measurement error of the stance time between NM and HS is 0.01, and it increases while considering MS ($e_{ST\_MS}$=0.17) and LS ($e_{ST\_LS}$=0.43). Similarly, the error of the stride time is lower considering the HS trials, and it increased in other cases, as reported in Table 2. Regarding the swing phase (see 4(c)), high-velocity configuration




(a) (b)

**Figure 3:** Graph plot of the GSTRD parameter extracted with the two devices: (a) for right foot, (b) for left foot.




(c) (d)

**Figure 4:** Graph plots of the gait parameters measured within each robot configuration: (a) stance time; (b) stride time; (c) swing time; (d) ankle excursion.

reported measurements closer to the stationary configuration ($e_{SW\_HS}$= 0.03), with respect to the MS and LS trials ($e_{SW\_MS}$= 0.22;$e_{SW\_LS}$= 0.56). Considering the step length, it emerged that as the velocity increased, the step length increased as well. As shown in Figure 5, the average step length was 0.29 m for LS, 0.505 m for the MS, and 0.695 m during HS. Especially for the high speed, it emerged a very high standard deviation for the step length. It may be due to a small dataset and/or because the difference in the step length between a taller and a shorter person, is more noticeable at high velocities than at lower ones.

Analyzing the user feedback at the end of each trial (Table 3), it resulted that as speed increases, the perceived naturalness of walking increases as well. Namely, the participants felt the presence of the robot was a disturbing factor during the LS and MS trials. On the contrary,

**Table 2**
Mean relative error between the left foot and the right foot of the inertial data versus reference test with the robot stationary.

| Configuration | GSTRDT | GSTT | GSTWT | GAngExc |
|---|---|---|---|---|
| LS (0.3 m/s) | 1.37 | 0.43 | 0.56 | 0.28 |
| MS (0.5 m/s) | 0.53 | 0.17 | 0.22 | 0.13 |
| HS (0.7 m/s) | 0.11 | 0.01 | 0.03 | 0.03 |

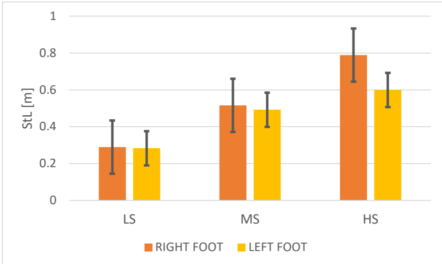



**Figure 5:** Step length parameter of the right and left foot with the standard deviation.

**Table 3**
Average user feedback for the 4 robot configurations.

| Configuration | Average Score ($\pm$ standard deviation) |
|---|---|
| NM | 1 ($\pm$ 0.76) |
| LS (0.3 m/s) | 8 ($\pm$ 0.73) |
| MS (0.5 m/s) | 6 ($\pm$ 0.75) |
| HS (0.7 m/s) | 3 ($\pm$ 0.80) |

the participants did not perceive the robot as a disturbance, during the stationary condition and the follow-me configuration with high speed. In these two configurations, the average user's feedback was 1 and 3, respectively, implying that the presence of the robot did not influence the walking activity.

## 7. Conclusion

This work proposed an alternative method for performing gait assessment by using a mobile robotic platform that follows the patient during the walking activity. This solution represents a not-invasive choice since the gait parameters could be directly extracted by the sensors mounted over the robotic platform. Furthermore, it represents a plug-and-play choice since the robot could be easily moved from one clinical environment to another. The main innovation of this work relies on the adoption of a follow-me module which increases the autonomy of the robot while guaranteeing a correct gait assessment. This module has been implemented by integrating the current state-of-the-art tools for people detection. The multi-modality of the robot's perception assures the robustness of the implemented system. The results of the preliminary tests with 11 participants highlighted that the follow-me module that better fits the needs of the gait assessment (RQ1) is the one with high velocity (i.e. HS). In fact, the analysis returned that the configuration characterized by the highest speed most closely approaches the gold standard configuration, represented by the stationary robot in terms of accuracy of gait parameters. Considering the user's feedback, it was found that the HS configuration is also one that does not compromise the naturalness of the walking performance (RQ2). In fact, it is the closest to the reference stationary configuration in terms of the perceived experience of walking at natural velocity. This was a fundamental step to verify before using the robot in a clinical setting since all the parameters of the robot controller should be properly set up. Using a mobile robot for gait assessment permits the exploitation of the computation of additional gait parameters. In this work, we estimated additional spatial parameters (i.e. step length) which could not be computed by using common wearable sensors, which are used to extract with high accuracy only temporal parameters (e.g., Stride, Swing, and Stance time).

In future works, we also would like to increase the number of parameters that could be extracted with the sensors mounted over the ASTRO robot, by also exploiting the information coming from the camera, like in [19]. Furthermore, other tests will be planned to verify the accuracy of the extracted parameters with an optical system, also increasing the number of participants. This solution has some limitations, mainly related to the context of use. In fact, this solution is robust only in controlled environments, where only one person is present in front of the robot. It may need further tuning for crowded environments, where there are more people in front of the robot, or for clinical tests involving not straight paths. To overcome these limitations, it will be necessary to integrate the capability of recognizing the target person in crowded environments and a navigation module to avoid possible obstacles on the path.

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