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Towards a User-Adaptive Context-Aware Robotic Walker with a Pathological Gait Assessment System: First Experimental Study

Georgia Chalvatzaki, Xanthi S. Papageorgiou and Costas S. Tzafestas
School of Electrical and Computer Engineering, National Technical University of Athens, Greece
{gchal,xpapag}@mail.ntua.gr, {ktzaf}@cs.ntua.gr

***Abstract*— When designing a user-friendly Mobility Assistive Device (MAD) for mobility constrained people, it is important to take into account the diverse spectrum of disabilities, which results to completely different needs to be covered by the MAD for each specific user. An intelligent adaptive behavior is necessary. In this work we present experimental results, using an in house developed methodology for assessing the gait of users with different mobility status while interacting with a robotic MAD. We use data from a laser scanner, mounted on the MAD to track the legs using Particle Filters and Probabilistic Data Association (PDA-PF). The legs' states are fed to an HMM-based pathological gait cycle recognition system to compute in real-time the gait parameters that are crucial for the mobility status characterization of the user. We aim to show that a gait assessment system would be an important feedback for an intelligent MAD. Thus, we use this system to compare the gaits of the subjects using two different control settings of the MAD and we experimentally validate the ability of our system to recognize the impact of the control designs on the users' walking performance. The results demonstrate that a generic control scheme does not meet every patient's needs, and therefore, an Adaptive Context-Aware MAD (ACA MAD), that can understand the specific needs of the user, is important for enhancing the human-robot physical interaction.**

I. INTRODUCTION

Mobility problems are common in the elderly, as older adults have to cope with instability and lower walking speed, [1]. Medical experts commonly use the Performance-Oriented Mobility Assessment (**POMA**) tool to assess the mobility status of patients, [2], in order to propose a proper rehabilitation treatment. Certain pathologies are responsible for changes in stride length and in walking phases, [3], while it seems that basic gait parameters of normal subjects are affected with aging, [4]. Medical studies for past-stroke patients establish the significance of evaluating the gait parameters for rehabilitation purposes, [5]. Fall prevention of elders is equally important and researches associate gait speed with the functional independence and mobility impairment of the elderly, [6].

Robotics seems to fit naturally to the role of assistance, since it can incorporate features such as posture support and stability, walking assistance, health monitoring, etc. These goals closely interweave; while the ethical goal is to increase the user mobility, its constrain leads to user dissatisfaction, anxiety and frustration, and finally rejection of the system.

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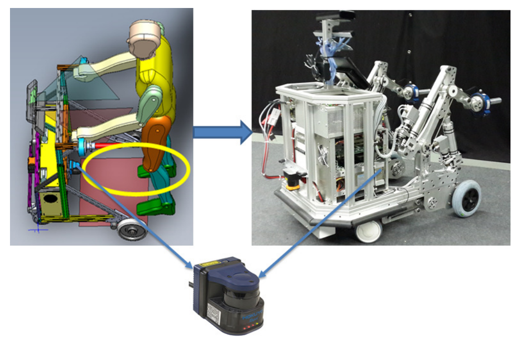


Fig. 1: On the left: a CAD representation of a robotic MAD. On the right: a robotic platform, constructed with financial support of EU project MOBOT, equipped with a Hokuyo Laser Sensor aiming to record the experimental gait data of the user (below knee level).

The development of MADs for elders that provide physical, sensorial and cognitive assistance is a common research topic in recent years [7]. The automatic classification and modeling of specific physical activities of human beings is very useful for the development of smart walking support devices, aiming to assist motor-impaired persons and elderly in standing, walking, as well as to detect abnormalities and to assess rehabilitation procedures [8], [9]. Recent control architectures for mobile robots include adaptive admittance control schemes, [10]. In [11], the authors developed an admittance control for a passive walker with servo brakes and used a fall-prevention function considering the position and velocity of the user, utilizing measurements from a laser range finder. A control strategy for a robotic walker is presented in [12]. The control parameters are the linear/ angular velocities and the orientation of the human and the walker; those define a desired distance and angle in the human-robot formation. An adaptive shared control for a mobility assistance robot is presented in [13], which was developped for the MAD of Fig. 1.

For extracting gait motions, different types of sensors have been used, from gyroscopes and accelerometers to cameras, e.g. [14], [15]. The development of a low-cost pathological walking assessment tool was presented in [16], where the user is followed by a robotic platform equipped with a Kinect sensor that detects targets placed on the subject's heels and estimates the stride length.

Gait analysis can be achieved by using Hidden Markov Models (**HMM**s), which can model the dynamic properties of walking. HMMs are currently used for gait modelling

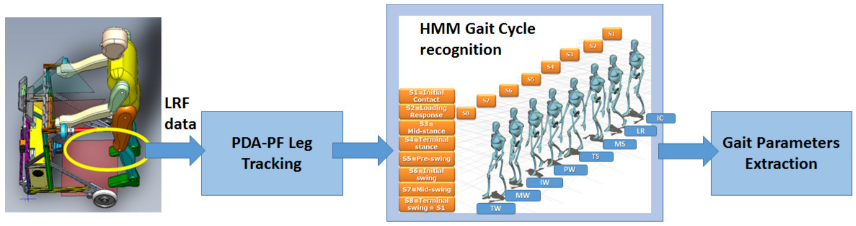


Fig. 2: Gait recognition system: from left to right: a CAD representation of a user walking with physical support of the MAD while the laser sensor records the legs motion; the laser data are fed into the gait tracking module; the estimated legs states are the observations of the HMM gait cycle recognition system;for each gait cycle we extract the respective gait parameters.

employing data from wearable sensors, like gyroscopes mounted on human's feet, [17]. In our previous work, we have analyzed extensively the properties of our HMM system and its applications for modeling normal human gait, [18], as well as for pathological human gait recognition, [19]. Finally, we have validated the extraction of gait parameters from the range data based on HMM in [20].

Our aim is to use intelligent MADs (Fig.1), which can monitor and understand the patient's walking state and will autonomously reason on performing assistive actions regarding the patient's mobility and ambulation. For a robotic walker that aims to support patients of different mobility status and also assist their rehabilitation progress, a generic control architecture will not affect the same way all patients. A MAD system that enhances mobility for one category of users might lead to mobility restriction for another one. As a result, a deployable MAD system has to be able to assess the mobility state of the user and to adapt its strategies accordingly, i.e. user-adaptation is important.

A MAD should provide physical interaction and optimal support to each user regardless of his mobility status. Thus, a context-aware robot control architecture should be implemented. Such a control strategy should use feedback from multiple modalities and the use of only one cue for the development of a generic control scheme is not effective and will not meet the special needs of people with variable motor inabilities. An intelligent MAD should also serve the purposes of medical monitoring, contributing to rehabilitation progress and fall prevention. Therefore, an on-line system for detecting gait parameters, that are used for medical diagnosis and are also associated with fall risk, will be a crucial part that should be incorporated in a user-adaptive context-aware control strategy. In such a control framework the real-time gait status assessment will trigger assistive actions and behaviors (velocity adjustment, approach of the patient due to changes in gait patterns) from the robotic assistant that tracks the user.

This paper presents a first experimental study of our in-house developed framework that provides a user gait status characterization for a robotic assistant platform, by validating its ablity to recognize the impact of different generic control designs on the patient's gait status. We experimentally validate the affect of custom-made control designs on the patient's walking performance, relative to his medical categorization (POMA score), through the estimation of appropriate gait parameters. The measured data used in this work are provided by a standard laser rangefinder sensor mounted on the robotic rollator platform, Fig. 1. Our system provides an on-board non-intrusive analysis of the patients' mobility state. While the patient uses the robotic assistant, the laser sensor provides the data for a tracking system that estimates the position and velocity of the legs by using two PFs with Probabilistic Data Association (**PDA-PF**), a method that achieves robust tracking of the user while performing complex maneuvers in cluttered environments, [21]. The estimated kinematic parameters of the user are the input of an HMM-based system that performs a pathological gait cycle recognition, [20]. Given the gait cycle time segmentation we can extract spatiotemporal gait parameters, which will be used for the gait status assessment. In this work, we enrich the list of the extracted gait parameters as compared to [20], in order to explore the use of those parameters in the control design of the MAD.

We present a statistical analysis to demonstrate the capability of our framework to provide on-line gait status information, by comparing the effect of generic custom-made control strategies on the estimated gait parameters regarding patients with variable POMA scores. We aim to validate that the gait parameters will be an appropriate and important feedback for a context-aware MAD, which will enhance the human-robot physical interaction and will assist each patient according to his mobility status. The first experimental results demonstrate that generic off the shelf control designs do not affect in the same way patients with different POMA scores; one control strategy may benefit some patients while it may decrease walking performance for others. Initial results show a correlation of the user gait status with his medical categorization, thus we aim to use this information for the design of a control strategy that will lead to a user-adaptive robotic personal assistant, by taking on-line feedback from our framework for a real-time adjustmet of the controller's parameters according to the user's needs.

II. GAIT PARAMETERS EXTRACTION SYSTEM BASED ON HIDDEN MARKOV MODEL

The sequential estimation of the gait parameters are necessary for the gait status assessment of the user. Those parameters are extracted by employing the raw laser data, provided by the laser sensor mounted on the robotic rollator, Fig. 2. The laser data are the observations of a PDA-PF leg tracking system, that sequentially estimates the relative position and velocity of the patient's legs w.r.t. the robotic rollator. The posterior estimates of the legs' states are fed into an HMM (Fig. 2), which recognizes the gait cycles and segments them into the corresponding gait phases. We, then, extract the gait parameters corresponding to each gait cycle, [19], [20], which are used for the exploration of the control effect on the users gait status.

For the PDA-PF leg tracking, we have designed a system that uses two PFs for estimating the position and velocity of each leg separately and associate them probabilistically at each time instant, [21], using as input raw laser data converted from polar to Cartesian coordinates, Fig. 2. The users' legs' states posteriors, at time instant t, are denoted as: $\mathbf{x}_t^f = \begin{bmatrix} x & y & \upsilon_x & \upsilon_y \end{bmatrix}^T$, where the first two components are the positions and the last two the velocities of the legs along the axes and $f = \{L, R\}$ is the label for the left and right leg. Each time instant t, a set of N new particles for each state is sampled from an importance density function: $\mathbf{x}_t^{f,i} \sim p(\mathbf{x}_t^f | \mathbf{x}_{t-1}^f)$, where i denotes the i^{th} particle. This probability density function represents the transition probability of the state from time (t-1) to time t and constitutes the motion model, that propagates the particles' state of each leg at each time instant t, given the previously estimated state $\mathbf{x}_{t-1}^f$. We model the velocity of each leg by a Gaussian Mixture Model **(GMM)** of two mixtures and we draw N velocity samples for each leg. Those samples are then used for updating the particles position through time.

A weight is assigned to each particle, which is equal to the observation likelihood. Each particle regards as observations only the laser points that fall inside an observation window. Thus, every particle refers to a different cluster of laser points. We considered that each particle is a probable leg center and we expect the observations-laser points to be in a circular circumference around it. The observation likelihood is computed based on three factors: *a)* the distribution of the Euclidean distances of the laser points, which have been detected inside the observation window w.r.t. the particle's position, which serves as a probable leg center; *b)* the number of laser points inside each observation window that are on the circular circumference of the particle; *c)* an association probability that accounts the Euclidean distance between the positions of the two legs, [21]. To overcome the problems of weight degeneracy and sample impoverishment, we apply a Metropolis-Hastings based resampling method.

We find the maximum likelihood particle for each leg based on their weights and then collect the "best" particles, i.e those having a weight greater or equal than 80% of the maximum weight. The posterior state estimate results from the weighted mean of the "best" particles, providing smoother estimates.

The posterior estimates of the legs' states along with the distance between the legs are the observables of the HMM gait cycle recognition system. We consider seven hidden states according to the seven gait phases of human gait, [22], as shown in Fig. 2. The observation data are modeled using a GMM. This model can provide temporal segmentation of the time sequence of the legs' states, by estimating an optimal gait phases sequence, which is found using the Viterbi algorithm, [19].

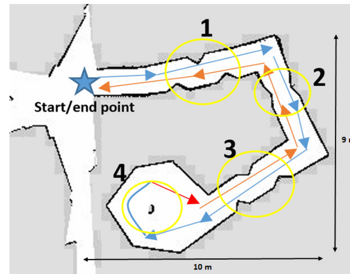
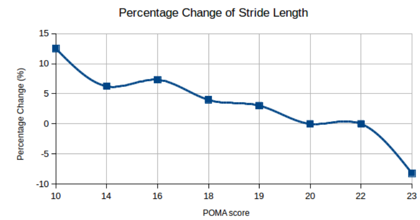
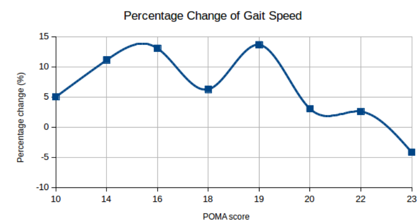


Fig. 3: Map of the experimentation scene. There were 3 areas with obstacles along the corridors (noted as numbers 1-3), and a turning point (noted as number 4).



(a) Percentage change of Stride Length w.r.t. POMA score.



(b) Percentage change of Gait Speed w.r.t POMA score.

Fig. 4: Stride Length's and Gait Speed's percentage changes from Scenario 1 to Scenario 2 for all subjects w.r.t. their POMA score.

The recognized segmentation of gait phases is used to compute the gait parameters from the range data, Fig. 2. We are computing the gait parameters: 1) ***stride length***, i.e. the distance traveled by both feet in a gait cycle, 2) ***stride time***: the duration of each recognized gait cycle, 3) ***stance time***: the stance phase duration in one cycle, i.e. the time between the gait phases **IC** and **PW** (Fig. 2), 4) ***gait speed***: results as the velocity through the stride, i.e. it was computed as the ratio of the stride length to the stride time and 5) ***cadence***: the ratio of steps per minute, computed as the total number of steps divided by the total walking time. These gait parameters are used for the statistical analysis of the affect of generic control designs on the gait status of patients with variant POMA scores.

III. EXPERIMENTAL ANALYSIS & RESULTS

A. *Experimental setup and data description*

The experimental data used in this work were collected in Agaplesion Bethanien Hospital - Geriatric Center, under ethical approval by the ethics committee of the Medical Department of the University of Heidelberg. All subjects had signed written consent for participating in the experiments.

TABLE I: Demographics

Subject	1	2	3	4	5	6	7	8
Age	88	83	83	81	87	71	77	84
Sex	F	F	F	F	F	F	F	M
POMA	10	14	16	18	19	20	22	23
Falls	yes	yes	yes	yes	yes	yes	no	yes

Demographics for the subjects that participated in the experiments.

TABLE II: Extracted Gait Parameters

Subject	Parameter	Unit	Scenario 1	Scenario 2	p-value*
1	stride length	m	0.32 ± 0.06	0.36 ± 0.05	< **0.0001**
	stride time	s	1.61 ± 0.21	1.48 ± 0.30	< **0.0001**
	stance time	s	1.27 ± 0.22	1.10 ± 0.20	< **0.0001**
	gait speed	m/s	0.20 ± 0.03	0.21 ± 0.04	**0.0086**
	cadence	steps/min	75.73	81.58	
2	stride length	m	0.32 ± 0.04	0.34 ± 0.04	**0.0497**
	stride time	s	1.75 ± 0.16	1.63 ± 0.19	< **0.0001**
	stance time	s	1.39 ± 0.16	1.29 ± 0.18	< **0.0001**
	gait speed	m/s	0.18 ± 0.03	0.20 ± 0.02	< **0.0001**
	cadence	steps/min	69.70	74.28	
3	stride length	m	0.41 ± 0.05	0.44 ± 0.04	**0.0015**
	stride time	s	1.85 ± 0.29	1.73 ± 0.22	**0.0123**
	stance time	s	1.59 ± 0.25	1.49 ± 0.21	**0.0131**
	gait speed	m/s	0.23 ± 0.04	0.26 ± 0.04	< **0.0001**
	cadence	steps/min	65.87	69.93	
4	stride length	m	0.25 ± 0.03	0.26 ± 0.02	**0.0178**
	stride time	s	1.59 ± 0.16	1.52 ± 0.13	**0.0146**
	stance time	s	1.11 ± 0.20	1.03 ± 0.12	**0.0138**
	gait speed	m/s	0.16 ± 0.03	0.17 ± 0.02	0.5866
	cadence	steps/min	76.82	80.17	
5	stride length	m	0.33 ± 0.05	0.34 ± 0.05	**0.0471**
	stride time	s	1.53 ± 0.26	1.31 ± 0.12	< **0.0001**
	stance time	s	1.24 ± 0.25	1.03 ± 0.18	< **0.0001**
	gait speed	m/s	0.22 ± 0.04	0.25 ± 0.04	**0.0018**
	cadence	steps/min	79.63	92.27	
6	stride length	m	0.48 ± 0.08	0.48 ± 0.08	0.6331
	stride time	s	1.46 ± 0.09	1.41 ± 0.16	0.056
	stance time	s	1.16 ± 0.09	1.10 ± 0.15	**0.0383**
	gait speed	m/s	0.33 ± 0.06	0.34 ± 0.07	0.4119
	cadence	steps/min	83.76	86.64	
7	stride length	m	0.49 ± 0.09	0.49 ± 0.10	0.8093
	stride time	s	1.29 ± 0.17	1.25 ± 0.14	0.1411
	stance time	s	1.05 ± 0.16	0.96 ± 0.14	**0.0128**
	gait speed	m/s	0.39 ± 0.08	0.40 ± 0.08	0.3554
	cadence	steps/min	94.52	99	
8	stride length	m	0.61 ± 0.11	0.56 ± 0.12	0.0742
	stride time	s	1.29 ± 0.16	1.25 ± 0.14	0.1369
	stance time	s	1.05 ± 0.16	1.01 ± 0.14	0.1406
	gait speed	m/s	0.48 ± 0.12	0.46 ± 0.13	0.5373
	cadence	steps/min	95.05	98.46	

Gait parameters means and standard deviations for the two scenarios along with the p-values (* $p < 0.05$)

In this work, we provide results for 8 elderly subjects, 7 women and 1 man, with average age 81.5 ± 5.5.

The subjects presented mobility impairments, according to clinical evaluation of the medical experts, with an average POMA score of 17.75 ± 4.30 and high risk of falling, with 87.5% of the subjects having had fallen once or twice in the last year. Table I provides analytical demographic information about the participants. The subjects have been arranged according to their POMA score. Patients with POMA score $<= 18$ present high risk of falling, while a POMA score between 18 and 23 indicates a moderate risk of fall, [23]. The participants were wearing their normal clothes (no need for specific clothing or wearable sensors) and they were currently using conventional passive walkers in their everyday life. We have used a Hokuyo rapid laser sensor (UBG-04LX-F01 with mean sampling period of about 28msec), mounted on the robotic platform of Fig. 1 for detecting the patients' legs. In Fig. 3 the experimentation scene that was prepared in Bethanien Hospital is shown. It contained three corridors with certain obstacles placed at points 1 to 3 and a roundabout at point 4. The blue star indicates the experiment's starting/ending point, while the blue and red arrows represent the possible walking path. The subjects had to walk in this test area with support of the robotic rollator of Fig. 1, trying to avoid the obstacles and return back to the initial position. This complex experimental scenario was performed twice using each time a different control setting for the MAD: **Scenario 1**: the controller provided walking assistance with a constant virtual inertia and damping but without an obstacle avoidance module, [13]. **Scenario 2**: the controller incorporated walking assistance with an obstacle avoidance functionality based on a decision-making algorithm for the developed shared-control architecture analyzed in [13]. The controller of Scenario 1 is a simple control design that is commonly implemented in a human - mobile robot formation, while the control strategy of Scenario 2 is a more sophisticated one, developped in the context of EU project MOBOT for the MAD of Fig. 1.

B. Validation Strategy

The aim of the experimental study is to examine whether there were changes in the walking performance of the patients, Table I, associated with the control design. To this end, we exploit the gait parameters extracted by our framework of Fig. 2 for the two scenarios. We have used 500 particles per PF to track the users' legs in both scenarios. The HMM training procedure comprises data from the tracking system for 12 patients that performed simple walking scenarios in initial data collection experiments.

We aim to show that generic control strategies do not always enhance the walking performance of patients with different POMA scores and to evaluate the affect of those different control schemes through the gait parameters. Thus, we statistically analyzed the extracted gait parameters from the walking Scenarios 1 and 2; firstly, we performed a one-way analysis of variances (**ANOVA**) and searched for statistical significance on the mean values of the gait parameters between the two scenarios for each subject. Continuing this analysis, we provide graphical results for the comparison of the within-subjects gait parameters evolution between scenarios, in order to inspect the walking behavior of subjects with different mobility impairment status w.r.t. each controller. Finally, we present graphs of the percentage change of gait parameters from Scenario 1 to Scenario 2, to evaluate the improvement or not of the walking performance of the subjects according to their POMA scores.

C. Experimental Results

Table II presents the mean and standard deviations of the extracted gait parameters for Scenarios 1 and 2 along with the p-value that resulted by ANOVA. Inspecting Table II, we can generally say that during Scenario 2 the patients walked significantly faster in most cases, with increased cadence, decreased stride time and longer stride lengths. We will contradict the results of a subject that presented high mobility frailty with a POMA score 14 (subject #2), and of a subject with moderate mobility problems having a POMA score of 22 (subject #7). Subject #2 significantly improved her walking performance as she increased the stride length with an important decrease of stride time, that resulted in better gait speed. Also, subject #2 spent significantly less time in stance phase, and therefore spent more time in swing phase. On the other hand, subject #7 had no significant difference in stride length and gait speed, while performing Scenario 1 and 2. But, we should mention that although stride time did not differ significantly between the two Scenarios, the stance time was significantly decreased, meaning that the swing time was increased for subject #7. It is, however, obvious that the control strategy of Scenario 2 did not significantly improve the walking performance of the patients with higher POMA scores. To further justify, we will elaborate on qualitative examples.

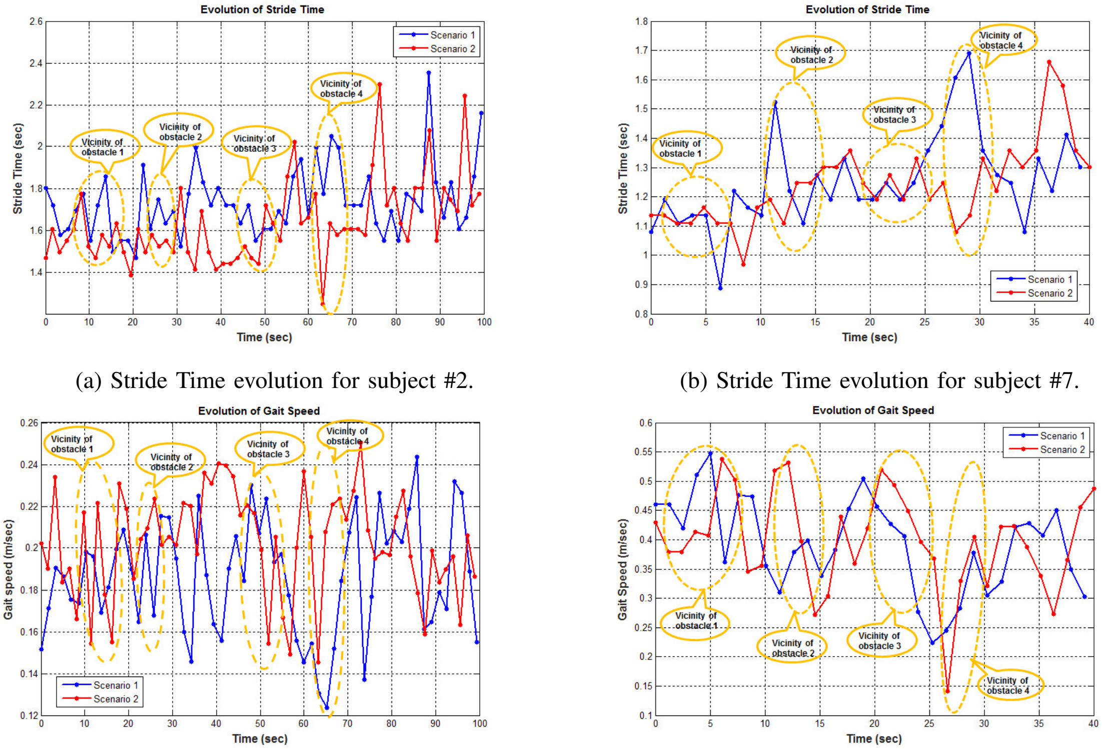
In Fig. 5, we present the gait parameters Stride Time and Gait Speed evolutions for the same subjects for the respective Scenarios 1 & 2. We have isolated the time sequences that contain the first pass of the experimental path of Fig. 3. Considering the different cadence of each patient, we can instantly see from Fig. 5, that patient #2 with the low POMA score (and the respective low cadence, Table II), needs more time to complete the first pass than subject #7 (with the higher POMA score and cadence). Inspecting Fig. 5a, we can see that the Stride Time is significantly lower in Scenario 1 than in Scenario 2, as shown also in Table II. In the vicinity of the obstacles during Scenario 2, we can notice that the controller affects the walking behavior, since the patient manages to perform strides of lower duration. Respectively, in Fig 5c, it is obvious that the gait speed of the patient with the lower POMA score is significantly higher during Scenario 2 than Scenario 1, achieving lower speeds while approaching the obstacles and speeding up after passing them through.

On the other hand, inspecting in Fig. 5c the Stride Time evolution of patient #7 with the high POMA score, we can notice that in Scenario 2 the controller stalls the patient in the vicinity of the obstacles, making her need more time to approach the obstacles than in Scenario 1. In Fig. 5d, where patient's #7 Gait Speed evolution is presented, we can more easily observe the delay in approaching the obstacles, although the Gait Speed evolution in Scenario 2 seems to follow quite the same pattern as in Scenario 1, leading to no significant differences between the two scenarios as it is also mentioned in Table II. The examination of those results leads to some important conclusions. Firstly, there is a strong evidence that the controller design affects the gait performance of the patients, as presented in Table II and Fig. 5, but not all patients are affected in the same way, justifying our claim that a robotic personal assistance should be user-adaptive. Secondly, there seems to be an important correlation between the POMA score and the gait parameters extracted by our framework. This remark will have to be further examined since it could lead to an on-line automated mobility impairment characterization of the user that would be incorporated in a context-aware robot control architecture. We, also, present the percentage change of the parameters Stride Length and Gait Speed from Scenario 1 to Scenario 2 w.r.t. the POMA scores of the participants in Fig. 4. The percentage change of the Stride Lengths, shown in Fig. 4a, is descending w.r.t. the increase in POMA score. This means that the use of a different control design in Scenario 2 seems to have affected positively the walking perfomance of patients with low POMA scores (positive percentage change for POMA scores 10-19), had no influence on subjects with POMA scores 20-22; more importantly, it had deteriorated the gait status of the subject with POMA score 23 (negative percentage change). In Fig. 4b, we examine the percentage change in Gait Speed. This plot also has a descending trend especially for patients with moderate mobility impairment. We observe variable yet positive changes in the gait speed of subjects with POMA 10-19, a very small positive effect on the walking speed of subjects with POMA 20-22 and a negative percentage change for the patient with the higher POMA score, which is an important outcome since Gait Speed is associated with falling risks, [6]. Therefore, a general remark is that the controller of Scenario 2 seems to improve the walking performance of patients with lower POMA, while it either does not affect significantly or even deteriorates the gait status of subjects with higher POMA scores. It can be safely deduced from these figures, that the application of a general control design does not benefit in the same way all patients. This shows the need of a user-adaptive control strategy that would take on-line feedback from the patient's gait status estimation.

IV. CONCLUSIONS AND FUTURE WORK

We aim to develop a completely non-invasive pathological walking analysis and assessment system, as a subsystem of a context-aware robot control for an intelligent robotic walker. We utilize data from a laser scanner mounted on a robotic assistant platform to track the user's legs using PDA-PF method and an HMM-based pathological gait cycle recognition system, constituting a non-invasive approach using a non-wearable device. We compute gait parameters, which are commonly used for medical diagnosis. We test our on-board framework with patients of variable mobility impairment according to medical assessment (low to moderate POMA scores), who performed walking scenarios in cluttered environments that required difficult maneuvers, and we evaluate the effect of different controllers on patients' walking performance by using the gait parametrers. We provide strong evidence that the control design affects, in a different way, the users' walking status according to their POMA scores. Thus, we believe that it is crucial to design an adaptive control architecture with an on-line feedback from the extracted gait parameters, to provide optimal support to each patient by real-time tuning the controller according to the patient's gait status assessment.

Our ongoing research includes a thorough analysis of how generic control strategies of the MAD affect the walking performance of a larger number of patients with variable POMA scores. We will work along with medical experts to examine the correlation of the POMA score and the gait status to provide a full characterization of the user. Our



(a) Stride Time evolution for subject #2.

(b) Stride Time evolution for subject #7.

(c) Gait Speed evolution for subject #2.

(d) Gait Speed evolution for subject #7.

Fig. 5: Evolution of the parameters Stride Time and Gait Speed w.r.t. time: a,c) Stride Time and Gait Speed evolution of subject #2 with low POMA score. b,d) Stride Time and Gait Speed evolution of subject #7 with moderate POMA score.

immediate goal is to design a more sophisticated control architecture that will take on-line feedback from the extracted gait parameters, to adjust the platform's motion according to the user's gait status.

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