Comparing the Impact of Robotic Rollator Control Schemes on Elderly Gait using on-line LRF-based Gait Analysis

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***Abstract*— For a user-friendly Mobility Assistive Device (MAD) aiming to assist mobility constrained people, it is important to take into account the different gait disabilities. Thus, an intelligent MAD should recognize and adapt to the particular needs of each user. In this work we present a thorough experimental analysis, using an on-line gait tracking and analysis system, to examine the impact of different control designs on the gait performance of elderly subjects who use an intelligent robotic rollator. The augmented human gait state estimates are provided by a system, that exploits laser data from a single Laser RangeFinder (LRF) sensor, mounted on the robotic MAD and capturing the users' legs motion. This augmented gait state estimation is the tool for online gait analysis, in order to detect gait cycles and extract certain gait parameters which are crucial for the mobility status characterization of the user. We compare statistically the gait performance of subjects with different mobility status, when using a MAD with a simple controller and a more sophisticated one, which take input only from the force/toque sensors on the handles of the MAD. The statistical analysis shows that the shared-control design in the second setting does not improve the gait parameters for most of the subjects, while there are cases of walking performance deterioration. This means that a generic control design does not meet every patient's needs, and therefore, a user-adaptive control design with feedback from the online gait analysis system is important for an intelligent robotic MAD, that can understand the specific needs of each user.**

I. INTRODUCTION

Mobility problems are prevalent in elderly population. Aging along with certain pathologies are responsible for gait 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. Specific effort is made to decode changes in stride length and in walking phases for the elderly, [3], [4]. Medical studies for past-stroke patients establish the significance of evaluating the gait parameters for rehabilitation purposes, [6]. Fall prevention of elders is equally important and researches associate gait speed with the functional independence and mobility impairment of the elderly, [7]. In a robotic society, elder people shall not be excluded by the benefits of technological innovation that could ameliorate their living standards.

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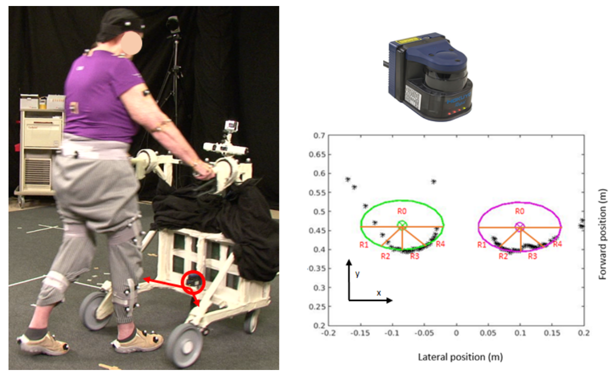

Fig. 1: **Left:** Elderly patient walking supported by a robotic MAD, which is equipped with a Hokuyo LRF sensor aiming to record the experimental gait data of the user (below knee level). **Right:** Representation of the detected legs at the sagittal plane used for the augmented gait state estimation, [5].

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, [8], [9]. 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. The development of MADs for elderly that provide physical, sensorial and cognitive assistance is a common research topic in recent years [10]. 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 and walking, to detect abnormalities, to estimate gait stability [11] and to assess rehabilitation procedures [12], [13].

Recent control architectures for mobile robots include adaptive admittance control schemes, [14]. In [15], 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 [16]. 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. A formation control was presented in [17] for safely navigating blind people, using

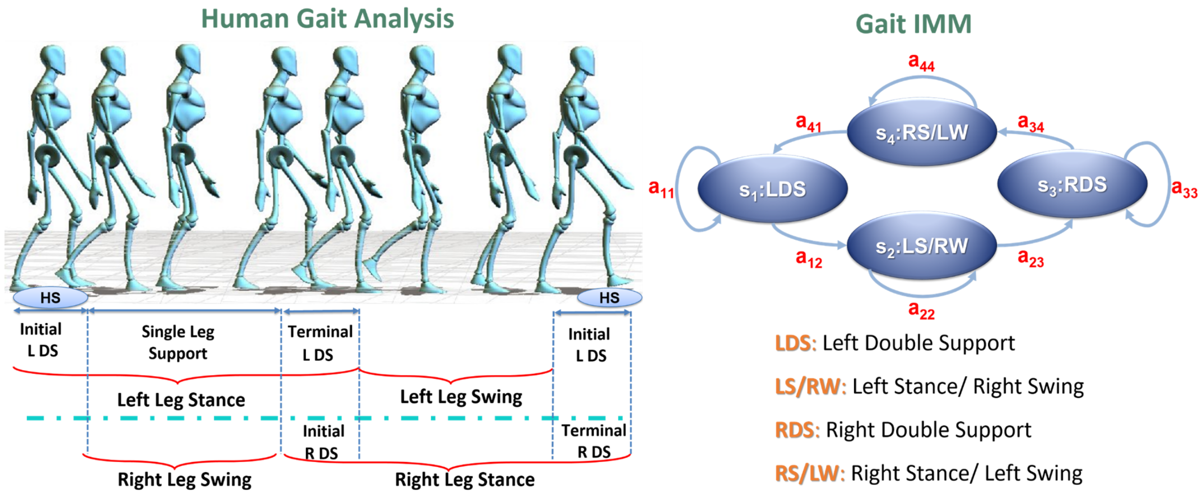

Fig. 2: **Left:** Sketch of a complete human gait cycle along with its temporal events. **Right:** The Markov model representing the Gait Interacting Multiple Model (IMM) used for the Augmented Gait state estimation framework..

as input the torso point-cloud. An adaptive shared control for a robotic MAD is presented in [18], using as input user-data from force/torque sensors on the handles and the LRF that detects obstacles. In [19], a front-following problem was considered with a kinematic controller adapting to users according to their pathological mobility class was presented.

For extracting gait motions, different types of sensors have been used, from gyroscopes and accelerometers to cameras, e.g. [20], [21]. The development of a low-cost pathological walking assessment tool was presented in [22], 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 employing data from wearable sensors, like gyroscopes mounted on human's feet, [23]. HMM-based gait analysis was used for modeling normal human gait, [24], as well as for pathological human gait recognition, [25] and for extracting gait parameters from range data in [26].

In our previous work [27], we have provided early findings regarding the impact of different generic control designs on the patient's gait status by experimentally validating the affect of custom-made control designs on the patient's walking performance, relative to their medical categorization (POMA score [2]). By estimating certain gait parameters, we have shown that subjects with low and moderate mobility function were affected negatively, while subjects with higher mobility function did not seem to present significant change in their gait, and therefore we have justified the necessity of incorporating a gait assessment system on the MAD's control strategy.

Our aim is to use intelligent MADs (Fig.1), which can monitor and understand the patient's walking state and 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, for an intelligent MAD user-adaptation is important, by assessing the mobility state of the user and adapting its control strategies accordingly.

In this paper we extend our work from [27] by presenting a thorough experimental analysis on the impact of two different control designs on the gait performance of thirty-two patients, who participated in experimental studies. We exploit our implementation for real-time augmented gait state estimation [5] from LRF data to track the user's legs and perform on-line gait analysis. Each time a gaitcycle is completed, we compute certain gait parameters, which are commonly used for diagnosis of the mobility pathological states of patients. Through this information, we experimentally evaluate the affect of custom-made control designs on the patient's walking performance, relative to their medical categorization (POMA score), through the estimation of the appropriate gait parameters. We aim to show that adaptation according to each user's gait parameters is 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 their mobility status.

II. HUMAN GAIT CYCLE DETECTION & ANALYSIS

A human gait cycle is based on the periodic movement of each foot from one position of support to the next, [28]. There are two main phases in the gait cycle, [29]: The stance phase, when the foot is on the ground, and the swing phase when that same foot is no longer in contact with the ground and is swinging through, in preparation for the next foot strike, Fig. 2. The stance period can be subdivided into three internal time intervals: the initial Double Support (DS), the single leg support and the terminal DS, Fig. 2. The initial DS begins with the Heel Strike (HS) and it is the time when both feet are on the ground. The single leg support is the period when only one leg is at stance while the opposite leg is swinging. The terminal DS begins with the HS of the contra lateral foot and continues until the original stance leg begins to swing.

From detecting those temporal events, specific gait parameters can be computed, which are commonly used for medical diagnosis, [30], [31]. In this work, we are using the following gait parameters for the subject's walking state assessment: 1) ***stride length***, i.e. the distance traveled by both feet in a gait cycle, 2) ***stride time***: the duration of each gait cycle, 3) ***stance time***: the stance phase duration in one cycle, 4) ***swing time***: the swing phase duration in one cycle, 5) ***gait speed***: the mean walking velocity of all gait cycles and 6) ***cadence***: the ratio of steps per minute.

A. IMM-PDA-PF: Augmented Human State Estimation

For the augmented human state estimation, we have proposed in [5] a novel framework for efficient and robust leg tracking along with estimating the human gait state, i.e. the respective gait phase at each time instant. This approach uses two Particle Filters (PFs) and Probabilistic Data Association (PDA) with an Interacting Multiple Model (IMM) scheme for a realtime selection of the appropriate motion model according to the human gait analysis and the use of the Viterbi algorithm for an augmented human gait state estimation. The gait state estimates also interact with the IMM as a prior information that drives the Markov sampling process, while the PDA ensures that the legs of the same person are coupled.

The IMM is inspired by human gait analysis [29], as we described in Sec. II. The gait cycle can be seen as an interacting model, Fig. 2.; when the one leg is in stance phase the other one is swinging. Thus, the gait IMM is the first-order Markov model of the human gait states, Fig. 2, i.e. the discrete states s_i, $i = 1,..,4$ and the possible transitions a_{ij} from s_i to s_j for $i, j = 1,..,4$, where LDS: "Left Double Support", LS/RW: "Left Stance/ Right Swing", RDS: "Right Double Support" and RS/LW: "Right Stance/ Left Swing". Each state s_i refers to both legs and imposes a different motion model. Namely, each state s_i is characterized by a set of velocity Gaussian Mixture Models, that alter the motion model of the PFs. The legs are tracked, and a maximum likelihood estimation of a human-centered state vector to belong to an IMM related state is computed. The gait state estimate drives the Markov sampling from the IMM for the next time frame. A thorough analysis of the IMM-PDA-PF methodology is described in [5].

B. Pathological Gait Parametrization

We employ the results of the IMM-PDA-PF methodology regarding the human gait phase estimation, to segment in real-time gait cycles and extract specific gait parameters used for medical diagnosis [31]. Having the recognized gait cycles and their internal phases (each gait state is related to a certain time instant, assisting in the temporal segmentation of the gait cycles), defined in Fig. 2, along with the legs' kinematic states from the IMM-PDA-PF, we can compute the appropriate gait parameters described in Sec. II. These gait parameters are used for the statistical analysis of the impact of the rollator's control designs on the gait status of patients with variant POMA scores.

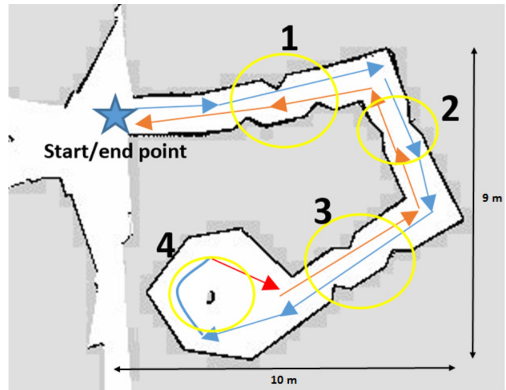

Fig. 3: Map of the experimentation scene. There were 3 areas with obstacles along the corridors (noted as numbers 1-3), and a turning point (noted as number 4).

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.

In this work, we provide a full-scale statistical analysis for 32 elderly subjects, 30 women and 2 men, with average age 84 ± 5.5 (Table I). The subjects presented mobility impairments, according to clinical evaluation of the medical experts, with an average POMA score of 20 ± 5.30. Patients with POMA score $<= 18$ present high risk of falling, while a POMA score between 18 and 23 indicates a moderate risk of fall, [32]. POMA score greater than 23 means low fall risk. The subjects have been arranged according to their POMA score in Table I. We also provide the Mini-Mental State Examination (MMSE) score, which indicates the level of cognitive impairment [33]. The severity of cognitive impairment results from the following score ranges; no cognitive impairment: 24-30; mild cognitive impairment: 19-23; moderate cognitive impairment: 10-18; and severe cognitive impairment < 9. According to Table I, the participants presented no to mild cognitive impairment with MMSE score 24 ± 3.90.

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 28 msec), 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

TABLE I: ANOVA of the extracted Gait Parameters

Subject	Demographics	Parameter	Scenario 1	Scenario 2	p-value*
1	age: 89	stride length (m)	0.35	0.44	< **0.0001**
	sex: F	stride time (s)	2.61	2.46	< **0.0001**
	POMA: 7	stance time (s)	1.91	1.60	**0.0063**
	MMSE: 18	swing time (s)	0.70	0.86	**0.0058**
	falls: yes	gait speed (m/s)	0.16	0.21	< **0.0001**
		cadence (steps/min)	80.44	83.45	
2	age: 88	stride length (m)	0.33	0.28	< **0.0001**
	sex: F	stride time (s)	1.65	1.85	< **0.0001**
	POMA: 10	stance time (s)	1.13	1.36	< **0.0001**
	MMSE: 27	swing time (s)	0.52	0.49	< **0.0001**
	falls: yes	gait speed (m/s)	0.20	0.185	**0.016**
		cadence (steps/min)	72.61	64.88	
3	age: 83	stride length (m)	0.64	0.62	0.22
	sex: F	stride time (s)	2.24	2.13	0.93
	POMA: 11	stance time (s)	1.46	1.42	0.66
	MMSE: 20	swing time (s)	0.77	0.71	0.32
	falls: yes	gait speed (m/s)	0.31	0.31	0.53
		cadence (steps/min)	53.66	56.44	
4	age: 94	stride length (m)	0.50	0.51	0.37
	sex: F	stride time (s)	1.44	1.52	0.23
	POMA: 14	stance time (s)	0.91	0.97	0.46
	MMSE: 29	swing time (s)	0.53	0.55	0.48
	falls: yes	gait speed (m/s)	0.35	0.35	0.96
		cadence (steps/min)	83.2	78.89	
5	age: 83	stride length (m)	0.32	0.32	0.62
	sex: F	stride time (s)	1.80	1.70	< **0.0001**
	POMA: 14	stance time (s)	1.30	1.21	**0.003**
	MMSE: 25	swing time (s)	0.50	0.49	0.45
	falls: yes	gait speed (m/s)	0.18	0.19	**0.007**
		cadence (steps/min)	66.65	70.41	
6	age: 83	stride length (m)	0.32	0.32	**0.03**
	sex: F	stride time (s)	1.94	1.76	**0.002**
	POMA: 16	stance time (s)	1.21	1.15	0.18
	MMSE: 30	swing time (s)	0.73	0.61	< **0.0001**
	falls: yes	gait speed (m/s)	0.23	0.25	**0.0001**
		cadence (steps/min)	61.87	68.23	
7	age: 85	stride length (m)	0.54	0.54	0.83
	sex: F	stride time (s)	2.28	2.02	< **0.0001**
	POMA: 18	stance time (s)	1.43	1.28	< **0.0001**
	MMSE: 24	swing time (s)	0.85	0.74	< **0.0001**
	falls: no	gait speed (m/s)	0.24	0.27	**0.0001**
		cadence (steps/min)	52.55	59.48	
8	age: 81	stride length (m)	0.26	0.25	0.35
	sex: F	stride time (s)	1.89	1.96	0.59
	POMA: 18	stance time (s)	1.23	1.29	0.87
	MMSE: 19	swing time (s)	0.66	0.67	0.74
	falls: yes	gait speed (m/s)	0.15	0.14	0.09
		cadence (steps/min)	63.66	61.24	
9	age: 90	stride length (m)	0.37	0.38	0.32
	sex: F	stride time (s)	1.53	1.46	**0.015**
	POMA: 19	stance time (s)	0.99	0.97	0.11
	MMSE: 20	swing time (s)	0.54	0.49	0.06
	falls: yes	gait speed (m/s)	0.25	0.26	**0.028**
		cadence (steps/min)	78.34	81.99	
10	age: 83	stride length (m)	0.48	0.48	0.66
	sex: F	stride time (s)	1.31	1.27	0.07
	POMA: 19	stance time (s)	0.81	0.79	0.14
	MMSE: 20	swing time (s)	0.50	0.49	0.67
	falls: yes	gait speed (m/s)	0.37	0.18	**0.028**
		cadence (steps/min)	99.45	94.21	
11	age: 91	stride length (m)	0.20	0.29	**0.0003**
	sex: F	stride time (s)	2.35	1.44	**0.005**
	POMA: 19	stance time (s)	1.91	1.04	**0.005**
	MMSE: 28	swing time (s)	0.44	0.40	0.75
	falls: yes	gait speed (m/s)	0.12	0.22	< **0.0001**
		cadence (steps/min)	51.08	83.42	
12	age: 83	stride length (m)	0.54	0.56	0.12
	sex: F	stride time (s)	1.56	1.36	< **0.0001**
	POMA: 19	stance time (s)	0.96	0.86	< **0.0001**
	MMSE: 29	swing time (s)	0.61	0.50	< **0.0001**
	falls: yes	gait speed (m/s)	0.35	0.42	< **0.0001**
		cadence (steps/min)	77.13	88.26	
13	age: 87	stride length (m)	0.23	0.33	< **0.0001**
	sex: F	stride time (s)	2.09	1.32	< **0.0001**
	POMA: 19	stance time (s)	1.44	0.80	**0.0007**
	MMSE: 24	swing time (s)	0.65	0.51	**0.008**
	falls: yes	gait speed (m/s)	0.13	0.25	< **0.0001**
		cadence (steps/min)	57.17	91.24	
14	age: 74	stride length (m)	0.51	0.54	0.09
	sex: F	stride time (s)	1.73	2.01	**0.0001**
	POMA: 20	stance time (s)	1.04	1.19	**0.0001**
	MMSE: 22	swing time (s)	0.68	0.82	**0.007**
	falls: yes	gait speed (m/s)	0.30	0.28	0.06
		cadence (steps/min)	69.49	59.78	
15	age: 91	stride length (m)	0.50	0.48	0.32
	sex: F	stride time (s)	1.18	1.14	**0.003**
	POMA: 20	stance time (s)	0.85	0.78	**0.0001**
	MMSE: 27	swing time (s)	0.33	0.36	0.51
	falls: yes	gait speed (m/s)	0.44	0.47	0.36
		cadence (steps/min)	101.9	105.66	
16	age: 71	stride length (m)	0.48	0.47	0.32
	sex: F	stride time (s)	1.53	1.53	0.99
	POMA: 20	stance time (s)	1.02	1.02	0.99
	MMSE: 30	swing time (s)	0.51	0.51	0.95
	falls: yes	gait speed (m/s)	0.33	0.33	0.88
		cadence (steps/min)	78.29	78.28	
17	age: 90	stride length (m)	0.44	0.44	0.92
	sex: F	stride time (s)	1.49	1.43	**0.006**
	POMA: 21	stance time (s)	0.93	0.88	**0.006**
	MMSE: 23	swing time (s)	0.56	0.55	0.053
	falls: no	gait speed (m/s)	0.30	0.32	0.25
		cadence (steps/min)	80.44	83.45	
18	age: 84	stride length (m)	0.58	0.63	0.13
	sex: F	stride time (s)	1.53	1.67	**0.03**
	POMA: 21	stance time (s)	1.04	1.13	0.09
	MMSE: 17	swing time (s)	0.49	0.54	0.06
	falls: yes	gait speed (m/s)	0.41	0.41	0.99
		cadence (steps/min)	78.43	71.89	
19	age: 92	stride length (m)	0.44	0.45	0.40
	sex: F	stride time (s)	1.29	1.21	**0.002**
	POMA: 22	stance time (s)	0.84	0.78	**0.044**
	MMSE: 22	swing time (s)	0.46	0.43	0.14
	falls: no	gait speed (m/s)	0.34	0.37	0.06
		cadence (steps/min)	92.45	99.34	
20	age: 77	stride length (m)	0.49	0.50	0.66
	sex: F	stride time (s)	1.30	1.33	0.47
	POMA: 22	stance time (s)	0.86	0.89	0.44
	MMSE: 27	swing time (s)	0.44	0.43	0.99
	falls: no	gait speed (m/s)	0.38	0.38	0.99
		cadence (steps/min)	92.52	90.55	
21	age: 84	stride length (m)	0.60	0.56	**0.04**
	sex: M	stride time (s)	1.34	1.24	0.06
	POMA: 23	stance time (s)	0.91	0.81	**0.03**
	MMSE: 28	swing time (s)	0.42	0.43	0.77
	falls: yes	gait speed (m/s)	0.47	0.46	0.78
		cadence (steps/min)	89.62	96.73	
22	age: 76	stride length (m)	0.49	0.49	0.95
	sex: F	stride time (s)	1.88	1.52	< **0.0001**
	POMA: 23	stance time (s)	1.21	1.08	**0.01**
	MMSE: 18	swing time (s)	0.66	0.44	< **0.0001**
	falls: yes	gait speed (m/s)	0.28	0.34	< **0.0001**
		cadence (steps/min)	63.98	78.88	
23	age: 80	stride length (m)	0.54	0.33	< **0.0001**
	sex: F	stride time (s)	1.88	1.52	< **0.0001**
	POMA: 24	stance time (s)	1.22	1.33	0.19
	MMSE: 29	swing time (s)	0.83	0.88	0.36
	falls: no	gait speed (m/s)	0.45	0.27	< **0.0001**
		cadence (steps/min)	98.59	80.29	
24	age: 79	stride length (m)	0.52	0.42	**0.0001**
	sex: M	stride time (s)	1.30	1.39	0.39
	POMA: 24	stance time (s)	0.83	1.11	**0.02**
	MMSE: 28	swing time (s)	0.47	0.29	< **0.0001**
	falls: no	gait speed (m/s)	0.41	0.34	**0.003**
		cadence (steps/min)	92.25	80.89	
25	age: 91	stride length (m)	0.39	0.42	0.06
	sex: F	stride time (s)	1.21	1.13	**0.05**
	POMA: 24	stance time (s)	0.84	0.77	**0.05**
	MMSE: 26	swing time (s)	0.37	0.36	0.65
	falls: no	gait speed (m/s)	0.33	0.38	< **0.0001**
		cadence (steps/min)	99.16	105.85	
26	age: 80	stride length (m)	0.64	0.65	0.85
	sex: F	stride time (s)	1.48	1.26	0.07
	POMA: 25	stance time (s)	0.99	0.89	0.31
	MMSE: 30	swing time (s)	0.49	0.37	0.08
	falls: no	gait speed (m/s)	0.49	0.52	0.27
		cadence (steps/min)	81.26	95.28	
27	age: 89	stride length (m)	0.53	0.55	0.23
	sex: F	stride time (s)	1.19	1.31	**0.0005**
	POMA: 25	stance time (s)	0.79	0.85	**0.03**
	MMSE: 26	swing time (s)	0.40	0.45	**0.01**
	falls: no	gait speed (m/s)	0.45	0.43	0.52
		cadence (steps/min)	100.93	91.90	
28	age: 82	stride length (m)	0.54	0.54	0.77
	sex: F	stride time (s)	1.24	1.20	0.41
	POMA: 26	stance time (s)	0.81	0.80	0.92
	MMSE: 23	swing time (s)	0.43	0.40	0.34
	falls: no	gait speed (m/s)	0.44	0.45	0.57
		cadence (steps/min)	97.09	100.04	
29	age: 78	stride length (m)	0.77	0.72	0.38
	sex: F	stride time (s)	2.00	2.10	0.76
	POMA: 27	stance time (s)	1.44	1.60	0.60
	MMSE: 30	swing time (s)	0.56	0.50	0.47
	falls: no	gait speed (m/s)	0.42	0.41	0.63
		cadence (steps/min)	59.92	57.11	
30	age: 86	stride length (m)	0.48	0.49	0.51
	sex: F	stride time (s)	1.28	1.32	0.77
	POMA: 27	stance time (s)	0.82	0.89	0.46
	MMSE: 27	swing time (s)	0.46	0.43	0.72
	falls: no	gait speed (m/s)	0.40	0.40	0.90
		cadence (steps/min)	93.61	90.89	
31	age: 87	stride length (m)	0.54	0.59	0.07
	sex: F	stride time (s)	1.44	1.52	0.26
	POMA: 28	stance time (s)	0.95	0.95	0.92
	MMSE: 28	swing time (s)	0.49	0.56	0.07
	falls: yes	gait speed (m/s)	0.40	0.39	0.85
		cadence (steps/min)	83.45	79.09	
32	age: 88	stride length (m)	0.44	0.45	0.54
	sex: F	stride time (s)	1.17	1.19	0.56
	POMA: 28	stance time (s)	0.79	0.80	0.83
	MMSE: 27	swing time (s)	0.38	0.40	0.47
	falls: no	gait speed (m/s)	0.38	0.39	0.62
		cadence (steps/min)	102.32	100.15	

Gait parameters for the two scenarios along with the p-values for comparing statistical significance (* $p < 0.05$)

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, while 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, [18].
- **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 [18].

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, developed in the context of EU project MOBOT for the MAD of Fig. 1.

For the experimental evaluation, since we aim to show that generic control strategies do not always enhance the walking performance of patients with different needs, i.e. different POMA scores and MMSE scores, and to evaluate the impact of those different control schemes on the gait performance of the elderly. Thus, we statistically compare the gait parameters from the walking Scenarios 1 and 2. To do so, 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.

B. Experimental Results

Table I presents the mean values for the extracted gait parameters of the thirty two patients for Scenarios 1 and 2 along with the p-values that resulted by ANOVA. Inspecting the results of Table I, we can generally say that the integration of a shared-control scheme in Scenario 2 did not contribute to the improvement of the elderly gait performance. We can see that for subjects with low POMA scores (subjects #1 - #6), there were detected some significant changes. Total improvement can only be detected for subject #1, who walked faster with larger steps and decreased gait cycle duration; subjects #5 and #6 decreased the stance time duration, thus increasing their gait speed significantly. Very important is the case for subject #2, where there is a total deterioration of the gait performance for Scenario 2. Subjects #7 to #22 belong to the moderate fall risk class based on their POMA scores.

For subjects #8, #16 and #20 there were no significant changes in gait performance. Subjects #7, #9, #11, #12, #13, #15,#17, #19 and #22 presented significant improvement for at least one gait parameter, while for subjects #10, #14, #18 and #21 the controller of Scenario 2 decreased their gait performance. Patients with higher POMA scores, i.e. subjects #23 to #32, presented fewer changes in their gait parameters, where only subjects #25 and #27 improved some gait parameters significantly, patients #26 and #28 to #32 presented no significant changes, while subject #23, #24 and #27 presented a very important deterioration in their gait parameters. Overall, only 43.75% of the participants have presented improvement with the controller of Scenario 2, 25% of the subjects presented decreased gait performance and the rest of the patients presented no significant changes in their gait performance regardless of the implemented control scheme.

A general remark is that the controller of Scenario 2 seems to improve the walking performance for some patients with lower to moderate 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 the results presented in Table I, that the application of a general control design does not benefit in the same way all patients. Therefore, it is necessary for a user-adaptive control strategy for a robotic rollator to take into consideration the gait status of each particular user, by incorporating the on-line gait analysis system to the control design of the intelligent robotic rollator.

IV. CONCLUSIONS AND FUTURE WORK

In this paper we present detailed statistical results regarding the impact of two different control designs for a robotic rollator on the gait performance of elderly subjects. We leverage our previous work for augmented human state estimation from data of an LRF sensor mounted on the robotic rollator, to acquire on-line gait analysis for evaluating the walking performance of patients with different mobility status. We compute gait parameters, which are commonly used for medical diagnosis, and 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 those gait parameters.

Statistical results computed by ANOVA for all participants show a very important conclusion. General control designs do not affect the same way all patients; while for some patients a more sophisticated control design contributed to a better walking performance, for the majority of the participants this control setting had no effect or even deteriorated their performance. Thus, it is our strong belief that it is crucial to design a user-adaptive control architecture with feedback from the on-line gait tracking and analysis framework, in order to provide optimal support to each specific user by real-time tuning the controller according to the patient's gait status.

In our future work, we aim to provide a microscopic analysis of specific gait patterns along the experimental path, especially when approaching obstacles. We will compare the different executed robot paths in the different experimental scenatios. 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 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 mobility status.

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