

Estimating Double Support in Pathological Gaits using an HMM-based Analyzer for an Intelligent Robotic Walker

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

Abstract—For a robotic walker designed to assist mobility constrained people, it is important to take into account the different spectrum of pathological walking patterns, which result into completely different needs to be covered for each specific user. For a deployable intelligent assistant robot it is necessary to have a precise gait analysis system, providing real-time monitoring of the user and extracting specific gait parameters, which are associated with the rehabilitation progress and the risk of fall. In this paper, we present a completely non-invasive framework for the on-line analysis of pathological human gait and the recognition of specific gait phases and events. The performance of this gait analysis system is assessed, in particular, as related to the estimation of double support phases, which are typically difficult to extract reliably, especially when applying non-wearable and non-intrusive technologies. Furthermore, the duration of double support phases constitutes an important gait parameter and a critical indicator in pathological gait patterns. The performance of this framework is assessed using real data collected from an ensemble of elderly persons with different pathologies. The estimated gait parameters are experimentally validated using ground truth data provided by a Motion Capture system. The results obtained and presented in this paper demonstrate that the proposed human data analysis (modeling, learning and inference) framework has the potential to support efficient detection and classification of specific walking pathologies, as needed to empower a cognitive robotic mobility-assistance device with user-adaptive and context-aware functionalities.

I. INTRODUCTION

Mobility problems are common in seniors. As people age they have to cope with instability and lower walking speed. It is known that certain pathologies relate to changes in stride length and alterations in phases of walking, [1], while it seems that basic gait parameters of normal subjects are affected with aging, [2]. Medical studies for past-stroke patients establish the significance of evaluating the gait parameters for rehabilitation purposes, [3]. The need for non-invasive methods of medical monitoring is crucial. 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. For a robotic walker that aims to support patients of different mobility status and also assist their rehabilitation progress, it is important to be able to assess the mobility state of the user and to adapt its strategies accordingly.

This research work has been partially supported by two EU-funded Projects: MOBOT (FP7-ICT-2011.2.1, grant agreement no. 600796) and I-SUPPORT (H2020-PHC-19-2014, grant agreement no. 643666).

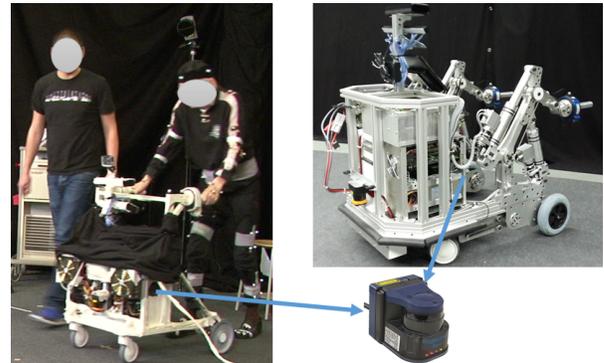


Fig. 1: On the left: a patient walking with support of the passive walker, while wearing a set of motion markers. On the right: a robotic platform, constructed with financial support of EU project MOBOT. Both devices are equipped with a Hokuyo Laser Sensor aiming to record the experimental gait data of the user (below knee level).

Our motivation is to use intelligent robotic walkers (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, [4]. A robotic walker should provide a physical interaction and optimal support to each user regardless of his mobility status. Thus, a context-aware robot control architecture should be implemented. Towards this end, the development of an online non-intrusive system that would recognize the pathological walking state along with the specific characteristics of each user's gait, is an important feature for such a control architecture. In our previous work, we have analysed the potential of a system based on a Hidden Markov Model (HMM) to recognize the normal human gait phases, [5], as well as the pathological human gait phases, [6], utilizing data from a laser sensor mounted on a robotic walker, Fig. 1. We have also used this system for extracting gait parameters that are commonly used for medical monitoring, [7]. In this work, we extend this system by employing a combination of HMMs for the detection also of the double limb support time period, which is an important gait parameter associated with fall risk, [8].

Automatic gait recognition and analysis is very useful for many technical and biomechanical applications. Research approaches can be discriminated regarding whether they use wearable or non-wearable devices for capturing human

motion, [9]. In the wearable devices category, which is the most common approach [10], we find gait analysis methods using foot pressure distributions (Smart Shoes), [11], joint angles and accelerations (gyroscopes, accelerometers, inertial sensors, [12]–[14]), etc. Non-wearable systems for gait analysis commonly use cameras, [15], or foot-pressure mats, [16]. A number of research groups worldwide, are actively pursuing research, currently investigating problems related to the development of smart walking support devices, aiming to assist motor-impaired persons and elderly in standing, walking and other mobility activities, as well as to detect abnormalities and to assess rehabilitation procedures, [17], [18]. The development of a low-cost pathological walking assessment tool was presented in [19], using a robotic platform equipped with a Kinect sensor that detects targets placed on the subject’s heels and estimates the stride length. Several works use the GAITRite System for validating their gait analysis results, [20].

Gait analysis can be achieved by using Hidden Markov Models (HMMs), which can model the dynamic properties of walking. The versatility of HMMs makes them useful in extracting human patterns. HMMs are currently used for gait modelling employing data from wearable sensors, like gyroscopes mounted on human’s feet, [21].

This paper presents current results of our ongoing research for the development of a reliable online pathological gait analysis and assessment system for an intelligent robotic walker. As opposed to most of the literature available on the topic, the proposed method presented in this paper is completely noninvasive based on the use of a typical non-wearable device. Instead of using complex models and motion tracking approaches that require expensive or bulky sensors, like motion capture systems that are difficult to use because of their cost, setup and calibration, the measured data used in this work are provided by a laser rangefinder sensor mounted on a robotic rollator platform. The aim is that the users will not be subject to wearing any special clothing or specific shoes and they will walk, making habitual use of their typical assistive device such as a rollator walker frame.

In this work, we use two contralateral HMMs working for both left and right legs, providing independent gait analysis results that can be used in combination to extract more reliable stride-level gait parameters impossible to obtain with typical single-HMM segmentation schemes, employed in previous work, [7]. The new HMM-based approach can detect internal events and segment temporal phases, which enables the estimation of critical gait parameters such as stride time and stance time with reference to each leg, but also the double support time intervals, which are of special significance in characterising gait stability and walking impairment level and as indicators of specific gait pathologies. In this paper, we focus on validating the extraction of the temporal gait parameters from the HMMs-based framework using ground truth data from a VICON Motion Capture system and provide initial results regarding the validation of the temporal parameters of gait.

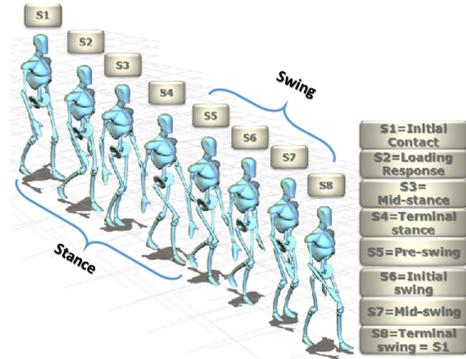


Fig. 2: Internal phases of human normal gait cycle along with the distinction of the stance/swing periods.

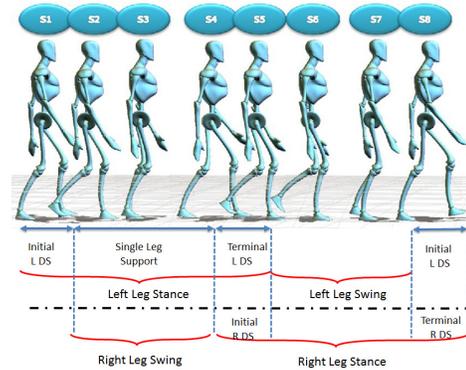


Fig. 3: Alternative representation of human gait cycle regarding Single Leg or Double Leg Support (DS).

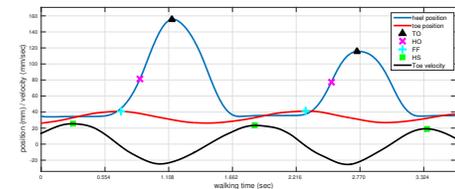


Fig. 4: Example of the detected gait phases HS, FF, HO and TO from the heel and toe markers.

II. HUMAN GAIT CYCLE ANALYSIS

There are two main periods in gait cycle, [22]: The stance, when the foot is on the ground, and the swing when that same foot is no longer in contact with the ground and is swinging through, in preparation for the next foot strike. The gait cycle can be successively divided into eight events, Fig. 2. This segmentation is sufficiently general to be applied to most types of human gait, including five during stance phase and three during swing, which are (as a percentage of the total duration of the gait cycle): 1. **Initial contact** (0%) - **[IC]** - **Heel strike (HS)** initiates the gait cycle. 2. **Loading response** (0-10%) - **[LR]** - **Foot-flat (FF)** is the time when the plantar surface of the foot touches the ground. 3. **Midstance** (10-30%) - **[MS]** - Midstance occurs when the swinging (contralateral) foot passes the stance foot. 4. **Terminal stance** (30-50%) - **[TS]** - **Heel-off (HO)** occurs as the heel loses contact with the ground and pushoff is initiated. 5. **Preswing** (50-60%) - **[PW]** - **Toe-off (TO)**

terminates the stance phase as the foot leaves the ground. 6. **Initial Swing** (60-70%) - [IW] - Acceleration begins as soon as the foot leaves the ground. 7. **Midswing** (70-85%) - [MW] - Midswing occurs when the foot passes directly beneath the body, coincidental with midstance for the other foot. 8. **Terminal swing** (85-100%) - [TW] - The foot stabilizes in preparation for the next HS. In this paper, we have used the seven gait phases of walking in order to analyze the gait cycle, since the TW phase is an equivalent trigger to the IC phase, and therefore are treated as identical.

According to [22], we can alternatively subdivide the stance period into three internal time intervals: the initial Double Support (DS), the single leg support and the terminal DS, Fig. 3. The initial DS begins with the initial contact 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 contralateral foot and continues until the original stance leg begins to swing.

Specific gait parameters can be computed, which are commonly used for medical diagnosis, [9], [23]. In this work, besides from detecting the sequence of gait events according to Fig. 2, we are also experimentally validating the following temporal gait parameters: 1) **stride time**: the duration of each gait cycle, 2) **stance time**: the stance phase duration in one cycle and 3) **double support**: the time period when both feet are in contact with the ground, as shown in Fig. 3.

III. HMMs-BASED PATHOLOGICAL GAIT PHASES RECOGNITION SYSTEM

The recognition of gait patterns that can be associated to specific medical conditions along with the sequential estimation of gait parameters are necessary for continuously assessing the gait status of the user as required to enable user-adaptive and context-aware control of a cognitive mobility-assistance robotic device. Those parameters are extracted by processing the raw laser data, provided by a laser rangefinder sensor mounted on the walker (see Fig. 1), using a Probabilistic Data Association Particle Filtering (PDA-PF) system to track user legs. The PDA-PF sequentially estimates the relative position and velocity of the patients legs w.r.t. the robotic rollator. The posterior estimates of the legs' states are fed into two HMMs that recognize the left and right gait cycles respectively. The distinction of the gait cycles can be seen in Fig. 3. The HMMs recognize the respective left/right gait cycles and segment them into the corresponding gait phases of Fig. 2. Subsequently, we use the HMM time segmentation of the respective gait cycles in order to compute the temporal gait parameters.

PDA-PF Leg Tracking: 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, using as input raw laser data converted from polar to Cartesian coordinates. The users' legs' states posteriors, at time instant t , are denoted as: $\mathbf{x}_f^t = [x \quad y \quad v_x \quad v_y]^T$, 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. The details of the PDA-PF implementation can be found in [24].

HMM Gait Cycle Recognition: We assume that each gait cycle potentially consists of seven internal events, as shown in Fig. 2, since the TW phase is characterized by HS that is an equivalent trigger to the IC phase, and therefore those phases are treated as identical. These seven phases can define the hidden states of the HMM, which detects the gait cycles and the double support, Fig. 3. The states of the HMM at time $t = 1, 2, \dots, T$, where T is the total time, are the values of the (hidden) variable $s_t = i \in \mathbf{S}$, for $i = 1, \dots, 7$, where $1 \equiv IC/TW$, $2 \equiv LR$, $3 \equiv MS$, $4 \equiv TS$, $5 \equiv PW$, $6 \equiv IW$, and $7 \equiv MW$. As observables we utilize the posterior estimates of the legs' states provided by the PDA-PF tracking system, i.e. the observations at time t , are represented by the vector $O_t = [\mathbf{x}_L^T \quad \mathbf{x}_R^T \quad Dlegs]^T$, where \mathbf{x}_f is defined above and $Dlegs$ is the distance between the legs. The observation data for the HMM are modelled using a GMM, [6].

The sequence of the gait phases recognised by the two HMMs, in parallel for both legs, can be used to compute the temporal gait parameters: the **stride time**: the time from one IC till the next detected IC, the **stance time**: computed as the time between the gait phases IC and PW, the **double support**: the time intervals during which the left and right stance phases overlap constitute the DS periods (Fig. 3). In this work, we assume a Right-HMM reference for the gait parameters estimation. However, all parameters can be extracted for both left and right leg gait cycles.

IV. GAIT PHASES DETECTION FROM MOTION CAPTURE DATA

For validation purposes we have used a VICON Motion Capture system (Fig. 1). We have developed an automatic gait phases detection system for motion capture data based on the algorithms presented in [25], [26]. In Fig. 5 a snapshot of the experimentation scene with a subject walking supported by the robotic rollator while wearing a set of visual markers is shown. On the left a CAD representation of the walker-human configuration is presented, while on the right a representation of the markers from the MOKKA visualization system is provided. Marked with green are the Heel and Toe markers, with red the Tibia markers, while with blue are depicted the Rollator markers. For the automatic gait phases detection we are using 1 Heel marker and 3 Toe markers for each foot. The following approach is an off-line rule-based method. Although we have 3D information we will be only considering the impact of those markers on the vertical direction, i.e. along the z-axis as shown in Fig. 5, and more specifically we are interested in computing the vertical heel and toe trajectory and also the toe vertical velocity. Linear interpolation is applied on the raw data, for retrieving as much information as possible from each marker (information loss occurs due to occlusions, or reflection problems, etc.). We, then, uniformly resample the data streams in order to accommodate the frame rate of the VICON system to that of the laser scanner device that captures the leg's motion as



Fig. 5: A snapshot from the experimentation scene. A patient with his normal clothes wears a set of visual markers while walking with support of the passive rollator. The position of the laser is marked on the rollator and the respective field of view.

shown in Fig. 1. Subsequently, we low pass filter the data using a Butterworth filter with a cutoff frequency of 7Hz, [26], but also apply a moving average filter with a ten frame span. After the filtering, we get the heel trajectory, while for the toe trajectory we combine the three toe markers data by calculating their median for each time instant, thus giving the final vertical toe trajectory. Also, for the needs of our algorithmic approach we have also calculated the respective toe velocity, which is computed as the first derivative of the toe positions using finite difference equations.

Having computed the heel and toe vertical trajectories as well as the toe velocity in the vertical direction, we can now detect certain gait phases that are important for the detection of the gait cycles, the stance/swing phases and the double support periods. More specifically, we can extract the following gait phases: HS, FF, HO and TO, which are described in Section II. In Fig. 4 the heel (blue line), toe (red line) trajectories and the toe velocity (black line) are depicted, along with the detected gait phases, which are important for the analysis of our approach.

The TO phases correspond to the peaks of the heel trajectory, i.e. the black triangles in Fig. 4. Before each TO event we search within a predefined time window for the HO event. The HO occurs when the heel trajectory exceeds a threshold. This threshold is adjustable according to each patient and was computed as the mean of the valleys of the heel trajectories plus a 40mm bias (the bias was set according to [25]). The HO events are represented by the magenta “x” in Fig. 4. On the other hand, a HS occurs when the toe velocity reaches a local maximum, inside a time-window after each TO event. In Fig. 4, the HS is denoted by the green squares. Finally, FF is detected between a HS and a consecutive HO, at the moment when the toe velocity is approaching zero with a negative slope and the toe vertical position is at the same level as the heel position with a small offset. The FF event is depicted with a cyan cross in Fig. 4.

This approach has been implemented on the markers data of both feet.

A stride is detected between two consecutive HS, while the stance phase starts with a HS and ends before TO and the swing phase starts with a TO and ends at the next HS. The DS period has been calculated as the time interval between the HS of one leg till the HO of the opposite leg, and vice versa.

V. EXPERIMENTAL ANALYSIS & RESULTS

A. Experimental setup and data description

The experimental data used in this work were collected in Agaplesion Bethanien Hospital - Geriatric Center with the participation of real patients, 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. The participants presented moderate to mild mobility impairment, according to clinical evaluation. The patients were wearing their normal clothes. A set of motion markers from a VICON Motion Capture system was placed on certain areas of the subjects’ body, Fig. 5. For the detection of the patients’ legs, we have used a Hokuyo rapid laser sensor (UBG-04LX-F01 with mean sampling period of about 28msec/scan, scanning range of 20 to 5600mm, angle range -120° to 120° and angular resolution 0.36°), mounted on the passive rollator of Fig. 1, which was designed for data collection experiments. The laser sensor is placed at a height of about 40 cm from the ground in order to capture the motion of the subject’s tibia.

In this work, we present results for four patients aged over 65 years old. The subjects participated in a walking scenario, where they walked with physical support of the rollator on a straight direction of about 3 m, performed a 180° turn and returned to initial position, Fig. 1. All patients performed the experimental scenarios under appropriate carer’s supervision. The subjects were instructed to walk as normally as possible. This results in a different walking speed for each subject. We have used 300 particles per PF to track the users’ legs. The HMMs training procedure comprises data from the tracking system for a training set of 12 patients with different pathologies that performed simple walking scenarios in initial data collection experiments.

B. Validation Strategy

Our validation strategy comprises qualitative and quantitative comparisons of the pathological gait recognition system that can detect the double support periods using HMMs w.r.t. ground truth (GT) data, which were extracted from motion markers. We aim to validate the time segmentation provided by the HMMs-based system by comparing to the recognised temporal gait parameters stride time, stance time and double support time w.r.t. those extracted by the ground truth data. We have isolated the data corresponding to the same strides per subject. We provide statistical results of the mean values and standard deviations, along with the Mean Absolute Error (MAE) and Mean Absolute Deviation (MAD) of the errors for four patients from a dedicated testing

TABLE I: Temporal Gait Parameters Estimation

Patient	Parameter	Mean \pm std		MAE	MAD
		HMM	Ground truth		
1	stride time (s)	1.33 \pm 0.10	1.32 \pm 0.09	0.02	0.02
	stance time (s)	0.76 \pm 0.07	0.73 \pm 0.07	0.06	0.05
	DS time (s)	0.10 \pm 0.06	0.12 \pm 0.06	0.03	0.00
2	stride time (s)	1.29 \pm 0.11	1.30 \pm 0.09	0.04	0.02
	stance time (s)	0.74 \pm 0.06	0.71 \pm 0.08	0.05	0.04
	DS time (s)	0.13 \pm 0.07	0.13 \pm 0.06	0.06	0.04
3	stride time (s)	1.27 \pm 0.09	1.32 \pm 0.09	0.06	0.06
	stance time (s)	0.72 \pm 0.09	0.78 \pm 0.11	0.13	0.06
	DS time (s)	0.04 \pm 0.02	0.10 \pm 0.05	0.06	0.05
4	stride time (s)	1.57 \pm 0.13	1.58 \pm 0.12	0.06	0.02
	stance time (s)	0.97 \pm 0.09	1.05 \pm 0.11	0.12	0.14
	DS time (s)	0.20 \pm 0.07	0.18 \pm 0.09	0.03	0.04

Comparison of the mean values and standard deviations of the estimated temporal gait parameters from the HMM-based method and the ground truth extraction, along with their MAE and MAD.

set. These randomly selected four subjects presented various pathological status associated with their walking activity, without knowing whether such medical conditions appear in the training set.

C. Experimental Results & Discussion

The accumulated results per patient are introduced in Table I. In this table, we present the mean and standard deviation of the temporal parameters that were extracted by the HMMs methodology and the GT data from markers. Those are followed by the MAE and MAD errors per patient. Inspecting the results of Table I, we notice that the HMMs-based method has a very good performance in recognizing the gait cycles and the DS periods. For all patients the MAE and the respective MAD values for the stride time are less than 60 msec. Only stance time estimations exhibit slightly bigger errors, having better results for Patients 1 & 2 (less than 60 msec MAE and MAD), for Patient 3 a MAE of 130 msec but small variability of errors with MAD of 60 msec, and finally, for patient 4 bigger errors and higher variability, with a MAE of 120 msec sec and MAD 140 msec.

We provide graphical results of the evolution of the temporal parameters for seven strides per patient. In Fig. 6 the evolution of the HMMs-based estimated stride time and stance time per patient w.r.t. those extracted by the GT data during the whole experiments is depicted. On those graphs, the y-axis is the time in seconds and the x-axis refers to the current number of stride while walking. The stride time segmentation is very accurate presenting small variabilities from GT for all patients, as this was also evident in the results of Table I. The stance time is also well estimated; we can see that even for Patients 3 & 4, which exhibited errors higher than 60 msec according to Table I, in the majority of the strides the estimations follow the same pattern with a small error. Meaning that the HMMs-based methodology has the ability to recognise the dispersion of the data and retain the information about the gait variability, which is also a crucial feature of gait analysis.

On the other hand, in Fig. 7 the evolution of DS time periods, as those were estimated by the HMMs-based method contrasted to the evolution of the DS period computed from

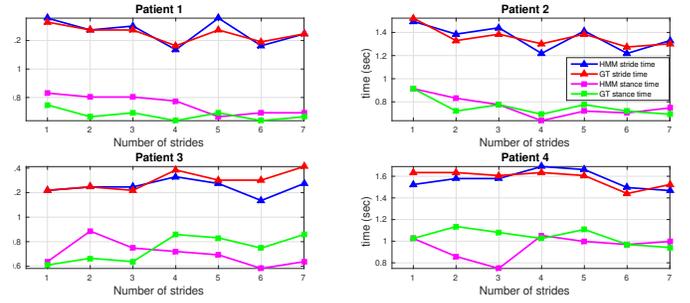


Fig. 6: Evolution of the estimated stride time and stance time over the stride number obtained by the proposed the HMM-based approach (blue and magenta respectively), as compared to the respective stride and stance times provided by the ground truth (GT) data (red and green lines respectively) for each one of the four patients of the current study.

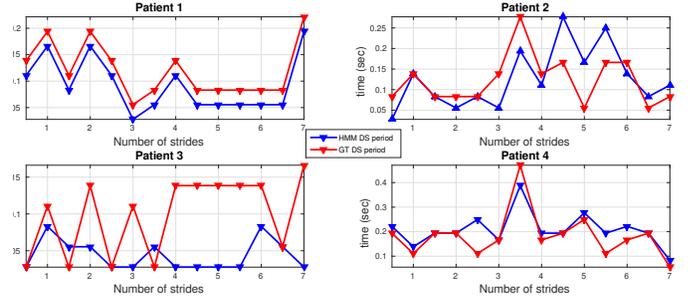


Fig. 7: Evolution over the stride number of the double-support (DS) duration estimates obtained by the proposed HMM approach compared to GT data.

the GT data, is presented. Also, in those graphs the y-axis refers to the time duration of the double support event in seconds, while the x-axis refers to the current number of stride. Two DS events contribute to each stride, assuming for presentation purposes that the initial DS is depicted at the half of each stride. At a first glance, we can inspect that for patients 1 and 4 the HMMs-based method achieves very good recognition of the DS periods, following the pattern and the variability of the DS periods for those patients. Regarding patient 2, we notice that the HMM-based estimation of the DS periods follows quite well the pattern of the GT evolution, however presenting higher variations from the GT. Only for patient 3, our method underestimates the duration of the DS events, as it can also be ascertained by the results of Table I. The most probable reason is that patient 3 presented a type of pathological walking that was not present in the training set of the HMM. In Fig. 7 we can notice that for patient 3 the GT double support periods present higher variability than for the rest of the patients. Thus, the HMM approach was not able to accurately estimate the DS durations and follow their evolution pattern for patient 3.

A general remark is that the proposed methodology of using a combination of HMMs for the recognition of the left and right gait cycles and their internal events, along with the computation of the double support period, seems to be performing well in our first experimental results. Taking into

account the large variations of pathologies, our system shows important evidence that it could be an efficient non-intrusive gait analysis and assessment tool using data from a non-wearable device. However, there is still room for increasing the accuracy of the system, which will be confronted in our future work, extending the training set with a broader range of datasets associated with different pathologies.

VI. 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 two PFs which are probabilistically associated, constituting a non-invasive approach using a non-wearable device. The legs' state estimates are the observations of a pathological gait cycle recognition system consisting of a combination of HMMs that detect the left and right gait cycles. The time segmentation of the gait cycles, provided by the HMMs, is exploited for computing temporal gait parameters, which are commonly used for medical diagnosis and are important for predicting the risk of falling. We validate our on-board framework with patients of variable mobility impairment, who performed walking scenarios simulating normal daily living walking activities. We evaluate the ability of the HMMs-based system to accurately recognize pathological gait patterns and validate the given temporal segmentation, by comparing them with ground truth data, which were extracted by an automatic gait phases segmentation algorithm employing data provided by a motion capture (VICON) system.

The data presented here are a first part of a broad ongoing study with more subjects that will be reported upon conclusion of the study. We plan to test different HMM schemes for improved accuracy, such as parallel HMMs with associated estimations for the left and right gait cycles. As the accuracy of the system is heavily influenced by the training data, we plan to utilize ground truth training data to increase the system's accuracy. Our ongoing research includes the HMMs-based methodology to classify specific gait abnormalities according to pathologies, allowing a variety of abnormal gaits (corresponding to specific motor impairments) to be characterized by different models. Furthermore, within our future plans is to model more gait patterns based on HMM, regarding turning motions during indoor ambulation, as well as more complicated and maneuvering motions that appear in daily activities. We intend to create a system for detecting in real time specific gait pathologies and automatically classify the patient status or the rehabilitation progress, thus providing the necessary information for a user-adaptive context-aware robotic assistant walker.

REFERENCES

[1] J. M. Hausdorff, "Gait dynamics, fractals and falls: Finding meaning in the stride-to-stride fluctuations of human walking," *Human Movement Science* 2007.

[2] T. Oberg et. al., "Basic gait parameters : Reference data for normal subjects, 10-79 years of age," *Journal of Rehabilitation Research and Development*, 1993.

[3] H. von Schroeder et. al., "Gait parameters following stroke: a practical assessment," *Journal of Rehabilitation Research and Development*, 1995.

[4] X. Papageorgiou et. al., "Advances in intelligent mobility assistance robot integrating multimodal sensory processing," *Lecture Notes in Computer Science, Universal Access in Human-Computer Interaction. Aging and Assistive Environments*, 2014.

[5] —, "Hidden markov modeling of human normal gait using laser range finder for a mobility assistance robot," in *ICRA 2014*.

[6] —, "Hidden markov modeling of human pathological gait using laser range finder for an assisted living intelligent robotic walker," in *IROS 2015*.

[7] X. Papageorgiou et. al., "Experimental validation of human pathological gait analysis for an assisted living intelligent robotic walker," in *Biorob 2016*.

[8] S. R. Lord et. al., "Sensori-motor function, gait patterns and falls in community-dwelling women." *Age and ageing*, 1996.

[9] A. Muro-de-la-Herran et. al., "Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications," *Sensors* 2014.

[10] S. Chen et. al., "Toward pervasive gait analysis with wearable sensors: A systematic review," *IEEE Journal of Biomedical and Health Informatics*, 2016.

[11] J. Bae and M. Tomizuka, "Gait phase analysis based on a hidden markov model," *Mechatronics*, 2011.

[12] C. Nickel et. al., "Using hidden markov models for accelerometer-based biometric gait recognition," in *CSPA 2011*.

[13] W. Kong et al., "Comparison of gait event detection from shanks and feet in single-task and multi-task walking of healthy older adults," in *2016 IEEE Int'l Conf. on Robotics and Biomimetics (ROBIO)*, 2016.

[14] H. C. Chang et. al., "A wearable inertial measurement system with complementary filter for gait analysis of patients with stroke or parkinson's disease," *IEEE Access*, 2016.

[15] E. Gianaria et. al., "Kinect-based gait analysis for automatic frailty syndrome assessment," in *2016 IEEE Int'l Conference on Image Processing (ICIP)*, 2016.

[16] S. R. Hundza et. al., "Accurate and reliable gait cycle detection in parkinson's disease," *IEEE Trans. on Neural Systems and Rehabilitation Engineering*, 2014.

[17] J. Lin et. al., "Automatic human motion segmentation and identification using feature guided hmm for physical rehabilitation exercises," in *IROS*, 2011.

[18] Y. Zhang et. al., "Pathological gait detection of parkinson's disease using sparse representation," in *DICTA*, 2013.

[19] V. Bonnet et. al., "Towards an affordable mobile analysis platform for pathological walking assessment," *Robotics and Autonomous Systems*, 2015.

[20] R. Hu et al., "3d pose tracking of walker users' lower limb with a structured-light camera on a moving platform," in *Computer Vision and Pattern Recognition Workshops (CVPRW), 2011 IEEE Computer Society Conf. on*, 2011.

[21] A. Mannini et. al., "Online decoding of hidden markov models for gait event detection using foot-mounted gyroscopes," *IEEE JBHI*, 2014.

[22] J. Perry, "Gait Analysis: Normal and Pathological Function", 1992.

[23] R. Kressig et. al., "Temporal and spatial features of gait in older adults transitioning to frailty," *Gait Posture* 2004.

[24] G. Chalvatzaki et. al., "Comparative experimental validation of human gait tracking algorithms for an intelligent robotic rollator," in *ICRA 2017 (to appear)*.

[25] I. Pappas, M. Popovic, T. Keller, V. Dietz, and M. Morari, "A reliable gait phase detection system," *IEEE Trans. on Neural Systems and Rehabilitation Engineering*, vol. 9, no. 2, pp. 113-125, 2001.

[26] C. M. O'Connor et al., "Automatic detection of gait events using kinematic data," *Gait Posture*, 2007.