Experimental Validation of Human Pathological Gait Analysis for an Assisted Living Intelligent Robotic Walker

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***Abstract*— A robust and effective gait analysis functionality is an essential characteristic for an assistance mobility robot dealing with elderly persons. The aforementioned functionality is crucial for dealing with mobility disabilities which are widespread in these parts of the population. In this work we present experimental validation of our in house developed system. We are using real data, collected from an ensemble of different elderly persons with a number of pathologies, and we present a validation study by using a GaitRite System. Our system, following the standard literature conventions, characterizes the human motion with a set of parameters which subsequently can be used to assess and distinguish between possible motion disabilities, using a laser range finder as its main sensor. The initial results, presented in this work, demonstrate the applicability of our framework in real test cases. Regarding such frameworks, a crucial technical question is the necessary complexity of the overall tracking system. To answer this question, we compare two approaches with different complexity levels. The first is a static rule based system acting on filtered laser data, while the second system utilizes a Hidden Markov Model for gait cycle estimation, and extraction of the gait parameters. The results demonstrate that the added complexity of the HMM system is necessary for improving the accuracy and efficacy of the system.**

I. INTRODUCTION

A. Motivation

Elder care constitutes a major issue for modern societies, as the elderly population constantly increases. Mobility problems are common in seniors. As people age they have to cope with instability and lower walking speed, [1]. It is known that certain pathologies are responsible for changes in stride length and alterations in phases of walking, [2]. Most people with mobility issues, patients or elders, have to use walkers in their everyday activities and they need the constant supervision of a carer. Therefore, the use of non-invasive methods for medical monitoring is very 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.

The motivation in this work is to use intelligent mobile robotic mechanisms (e.g. a rollator, Fig. 1), which can monitor and understand specific forms of human walking activity in their workspace, [3], in order to deduce their needs regarding mobility and ambulation, and to provide context-based support, and intuitive assistance in domestic environments.

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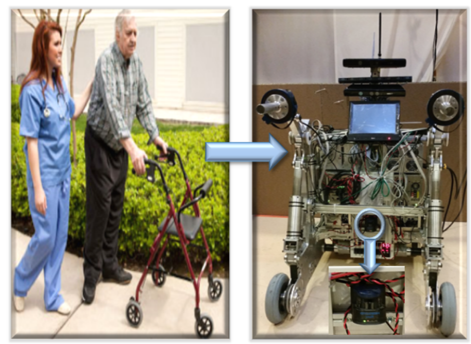

Fig. 1: Right: Typical passive assistive device for elderly. Left: A robotic platform based on the rollator prototype equipped with a Hokuyo Laser Sensor aiming to record the experimental gait data of the user (below knee level).

In this paper we address the challenge of developing a reliable pathological walking assessment system. The proposed system utilizes a laser sensor that detects and tracks the user (which does not interfere with human motion). We subsequently test two different approaches, of different complexity, for extracting the necessary gait parameters. The first approach is based on using a static rule book on the spatiotemporal information of the legs motions to compute the gait parameters. The second approach is based on Hidden Markov Model (HMM) for recognizing the different gait phases. This information is then used to extract the gait parameters.

B. Related Work

The automatic classification and modeling of specific physical activities of human beings is very useful for many technical and biomechanical applications. 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

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mobility activities, as well as to detect abnormalities and to assess rehabilitation procedures, [4]–[7]. Many researchers cope with gait analysis using machine learning algorithms, aiming to detect pathological cases that require medical treatment, using sparse representation for the detection of pathological gait patterns that indicate Parkinson's symptoms, [8], or fuzzy logic, [9].

For the extraction of gait motions, different types of sensors have been used, from gyroscopes and accelometers to cameras, [10]–[12], and inertial sensors on shoes, [13]. Other approaches refer to human detection and tracking, or recognition of human activity utilizing laser sensors, and in some cases complementary with cameras, or force sensors (e.g. [14]). Towards this direction, modeling human locomotion by estimating the legs' kinematic parameters with respect to the mobility aid is essential. The detection and tracking of humans is a common problem. Most research work focuses on detecting and tracking human legs from static sensors, as in pedestrian tracking (e.g. [15]), or from laser scanners mounted on mobile robotic platforms for person following, [16], [17]. In [18], [19], four laser rangefinders, placed at the corners of a room, are used to track the user's lower limbs using a novel method for extracting leg trajectories. Approaches for tracking users of robotic walkers can be found in [20], [21], while [22] refers to a walker that detects and tracks Parkinson's patients. Several works use the GAITRite System for validating their gait analysis results, as in [23]. GAITRite System is commonly used for gait impairments detection and analysis, [24], [25].

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, [26], but also for discriminating human activities like walking/running, [27]. Data collected by IMUs mounted on human's chests are also modelled by HMMs for performing pedestrian activity and gait-phase classification simultaneously, [28].

This paper presents an experimental validation study for flexible and readily extensible pathological gait analysis and assessment system. As opposed to most of the literature available on the topic, the gait analysis and assessment approaches presented in this paper are 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, and recording devices that interrupt human motion, the measured data used in this work are provided by a standard 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 freely in physical environments. Thus, our method is suitable for domestic environments and can detect gait abnormalities whenever the elder uses the robotic walker, without having to walk on an electronic mat such as GAITRite. In this work, we aim to validate the extraction of gait parameters based on two methodologies; a HMM-based framework for gait modelling and a less complex methodology based on static rule base. We validate the results of both approaches using the ground truth data from a GAITRite System. The objective of this work is to design a reliable pathological walking assessment system as a subsystem within a larger cognitive behaviour-based context-aware robot control framework (that embodies several walking morphologies, including turning and maneuvering motions). This framework has the potential to be used for the classification of various walking pathologies and related impairments. On the same time, the design of our system is open, allowing inclusion of new patients with mobility difficulties.

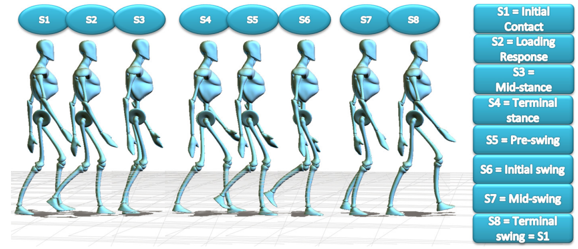

Fig. 2: Internal gait phases of human normal gait cycle.

II. HUMAN GAIT CYCLE ANALYSIS

Traditionally the gait cycle has been divided into eight events or periods, [29], as shown in Fig. 2, which are: 1. ***IC*** - Initial Contact, 2. ***LR*** - Loading Response, 3. ***MS*** - Midstance, 4. ***TS*** - Terminal Stance, 5. ***PW*** - Preswing, 6. ***IW*** - Initial Swing, 7. ***MW*** - Midswing, 8. ***TW*** - Terminal Swing. In this paper we have used the seven gait phases of walking in order to analyze the gait cycle, since the TW phase is characterized by heel strike that is an equivalent trigger to the IC phase, and therefore those phases are treated as identical.

Gait Analysis literature uses specific gait parameters for the quantification of each gait cycle, commonly used for medical diagnosis, [30], [31]. In this work, we are using two temporal parameters: a. ***stride***[1] ***time***: the duration of each gait cycle, b. ***swing time***: the swing phase duration in a gait cycle, and, c. one spatial parameter: ***stride length***, i.e. the distance travelled by the same foot from IC of a stride to a consecutive new IC.

III. GAIT PARAMETERS EXTRACTION BASED ON SPATIAL-TEMPORAL INFORMATION

The subject's legs are tracked using the laser data and subsequently, the tracked leg positions are filtered. The rule based gait parameter extraction function uses the filtered leg trajectories.

[1] Stride is the equivalent of gait cycle, i.e. two sequential steps define one stride, [29].

A. Tracking

The tracking procedure is divided into two steps. First, using the relative similarities between two subsequent laser data frames, a rough estimate of the motion of the tracked objects is computed. Then, the sensed laser data are clustered using the motion estimation of the objects to compute the new position of the tracked objects, i.e. the legs.

1) Segmentation: For each scanning frame the laser points are segmented into groups, [32]. Groups with small cardinality are discarded (i.e. most likely noisy measurements or outliers). These groups are not necessarily the subjects legs. For example when one leg is occluded the segmentation will produce one large object. A necessary condition for initialization of the algorithm is to find two groups, in the initial frame and mark them as the legs to be tracked.

2) Object Association: The initial estimate of the updated position of the tracked objects is computed as a linear combination of different vectors. For the first vector, the laser data of frame $n+1$ are clustered around the position of the objects on frame n. The first vector connects the centroid of the clusters on frame n to the centroids of the aforementioned new clusters. For the second vector, each tracked object on frame n is associated, using an appropriately computed association function (a $2D$ Gaussian similarity metric, with larger variance in the walking direction) with the objects produced by the segmentation of the laser data of frame $n+1$. Finally, a third vector is introduced, as repulsion between the tracked objects. This models the actual behavior of the legs and is used to avoid degenarations due to occlusions.

Using this computed centroid position, nearest neighbor assignment of the laser points belonging to the next frame is executed. The points assigned to this centroid represent the observed position of the object in the next frame.

3) Motion Estimation: For each object, the result of the tracking step is two sets of points in successive frames. The motion parameters causing this movement are retrieved via non-rigid point matching method, [33].

The new (estimated) position of the object results from applying the non-rigid transformation to all of its laser points in frame n. In this way, we track the position of each laser point through all the frames.

B. Filtering

The filtering procedure smooths and fuses the noisy point trajectories for a single leg, to provide a single estimate about its centroid position, and it is performed on a time window, rather than sample-wise. The trajectories of all laser points belonging to a tracked object are filtered using Savitzky-Golay FIR filter, [34]. Then, the smoothed trajectories are fused via weighted average and median operators, to compute the trajectory of the objects center. Finally, a Savitzky-Golay is applied to the center's trajectory.

C. Gait Parameters Extraction

The computation of the gait parameters is based on the extracted smooth estimates of the user's leg position. We use the relative distance of the two legs $\Delta x = x^R - x^L$, where x^R and x^L are the position of right and left leg in x-axis, which spans along the patient's walking direction, as depicted in Fig. 5. A heel strike, in the Δx waveform, is close to a peak, which is difficult to pinpoint exactly. Instead, for segmenting the gait, we use the "zero-crossing" moments, when the moving leg is passing in front of the still leg (**MS** or **MW**, Section II).

Graphically, the gait parameters are shown in Fig. 5. The *stride length* is computed by the distance between a peak and a valley. The *stride duration* is computed by the time between two zero-crossings with same slope sign. The *swing time* is computed by the time interval when $\Delta x(t) \in [\Delta x_{valley} + ds\_thr,\ \Delta x_{peak} - ds\_thr]$, with $t \in (t_{\Delta x_{peak}}, t_{\Delta x_{valley}})$, where ds_thr is a threshold to define the double support time. This threshold can be tuned using a healthy user corpus, where the double support time is $20-25\%$ of the gait cycle, [29].

IV. GAIT PARAMETERS EXTRACTION BASED ON HIDDEN MARKOV MODEL

Hidden Markov Models are well suited for gait recognition because of their statistical properties and their ability to reflect the temporal state-transition nature of gait. In our previous work, we analyze extensively the properties of our HMM system and its applications for modelling normal human gait, [35], as well as for pathological gait recognition, [36]. The scope of this paper is to present validation data for our system. Therefore, we will only briefly discuss the specific details.

A. Detection and Tracking

The observations for the HMM gait cycle recognition are provided at each time frame by a detection and tracking system of the user's legs, exploiting the raw data collected by the laser range scanner mounted on the robotic rollator (the measurements are relative to the robotic platform motion), Fig.1. This system uses K-means clustering and Kalman Filtering (**KF**) for the estimation of the central positions and velocities of the left and right leg of the user along the axes, [36].

The raw laser data are preprocessed using a background extraction and a simple method for grouping laser points based on experimental thresholds. We aim to end up with two groups, which are labelled as left/right leg by the K-means clustering algorithm. Circle Fitting is then used for computing the legs' centers. Those centers are the observation vector that enters a constant acceleration KF. The KF tracks the central positions of the limbs by stochastically estimating their position and velocity. The predicted positions are fed back to the preprocessing stage as a prior information of the expected positions of the legs for the next time frame. If one leg is occluded by the other (common problem while turning) or there is interference of the carers legs close to the patient's legs, we have a false detection case. In false detection we do not account any observations. To overcome such situations, we only apply the prediction step of the KF.

B. HMM Gait Cycle Recognition

The seven gait phases can define the hidden states of the HMM, Fig. 2. As observables, we utilize several quantities that represent the motion of the subjects' legs, (relative position w.r.t. the laser, velocities, etc.), which are estimated using sequential signals from a laser sensor. The state and observations at time t are denoted as s_t and O_t, respectively. The seven states at time $t = 1,2,...,T$, where T is the total time, are expressed by the value of the (hidden) variable $s_t = i$, for $i = 1,\ldots,7$, where $1 \equiv IC/TW$, $2 \equiv LR$, $3 \equiv MS$, $4 \equiv TS$, $5 \equiv PW$, $6 \equiv IW$, and $7 \equiv MW$. The observations at time t, are represented by the vector $O_t = [o_t^1 \ldots o_t^k]^T$, for $k = 1,\ldots,9$, where $o_t^1 \equiv x^R$, $o_t^2 \equiv y^R$, $o_t^3 \equiv x^L$, $o_t^4 \equiv y^L$, $o_t^5 \equiv \upsilon_x^R$, $o_t^6 \equiv \upsilon_y^R$, $o_t^7 \equiv \upsilon_x^L$, $o_t^8 \equiv \upsilon_y^L$, and $o_t^9 \equiv Dlegs$. The quantities (x^R, y^R, x^L, y^L) are the positions and $(\upsilon_x^R, \upsilon_y^R, \upsilon_x^L, \upsilon_y^L)$ are the velocities of the right and left leg along the axes, and $Dlegs$ is the distance between the legs. The observation data are modeled using a mixture of Gaussian distributions.

C. Gait Parameters Extraction

The recognized sequence of gait phases is indicative of the subject's underlying pathology, since it differs from the normal gait phase sequences. Using this segmentation we can compute the gait parameters from the range data.

Each recognised gait cycle is used for the gait parameter extraction. The *stride time* equals the duration of the recognised gait cycle. Given the time segmentation by the HMM, we have isolated the stance and swing phase of the gait cycle, and then we have computed the *swing time* between the gait phases **IW** and **MW**. The summation of the absolute distances travelled by each leg during the gait cycle provides the *stride length*.

V. EXPERIMENTAL ANALYSIS & VALIDATION

A. Experimental setup and data description

The experimental data used in this work were collected in Agaplesion Bethanien Hospital - Geriatric Center. Patients with moderate to mild impairment, according to clinical evaluation of the medical associates, took part in this experiment. The patients were wearing their normal clothes (no need of specific clothing). We have used a Hokuyo rapid laser sensor (UBG-04LX-F01 with mean sampling period of about 28msec and accuracy of 10mm), mounted on the robotic platform of Fig. 1 for the detection of the patients' legs. A GAITRite System was used to collect ground truth data. GAITRite is an electronic mat, of length 4.6 meters, equipped with pressure sensors placed at 1.27 cm each, used for gait analysis. GAITRite provides measurements of the spatial and temporal gait parameters and is commonly used for medical diagnosis, [24].

We have used data from five patients with moderate mobility impairment (aged over 65 years old). Each subject walked straight with physical support of the robotic rollator over the walkway defined by the GAITRite mat. The HMM was trained by using the recorded data from twelve different

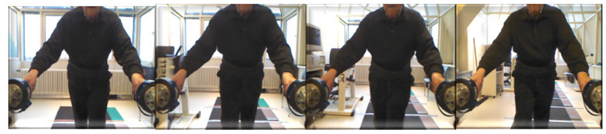

Fig. 3: Snapshots of a subject walking on the GAITRite walkway assisted by the robotic platform, during one stride.

Fig. 4: The captured footprints of the subject by the GAITRite System.

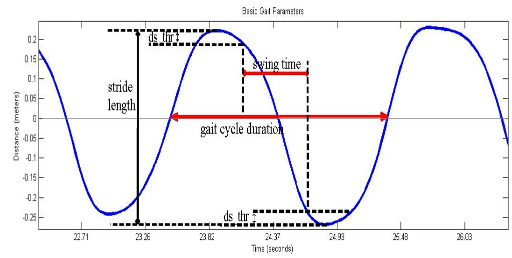

Fig. 5: Gait parameters w.r.t. Δx waveform along the walking direction, as computed by the rule based approach.

patients (without any GAITRite recording), [36]. 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, and in different gait parameters.

In Fig. 3, snapshots of a subject are presented, while performing the experimental scenario, captured by the Kinect camera that was also mounted on the robotic rollator (Fig. 1). Also, in Fig. 4 the sequence of the detected footprints by the GAITRite System for the same subject are depicted.

B. Validation Strategy

As discussed, this work has two main objectives. Firstly, to validate the HMM-based methodology and the rule based approach on the extraction of gait parameters using ground truth data. Secondly, to assess whether the added complexity of the HMM approach is necessary, by comparing the results of the two schemes. We have isolated the laser data corresponding to the same strides per subject, i.e. the same three strides per patient. These data were processed according to the two approaches, in order to extract the gait parameters, as described in subsections III-C and IV-C. The gait parameters, as extracted by the GAITRite System are utilized as ground truth data to validate the results.

The validation of the results comprises both quantitative and qualitative comparisons. Table I contains the statistics of the gait parameters, as computed by the two methods used. Also, we present the maximum absolute percentage error between the ground truth data and the estimated gait parameters, Table II.

TABLE I: Extracted Gait Parameters

Subject	Parameter	Unit	HMM-based	Rule-based	GAITRite
	stride length	m	0.737 ± 0.036	0.725 ± 0.037	0.746 ± 0.012
1	stride time	s	1.062 ± 0.016	1.074 ± 0.032	1.096 ± 0.007
	swing time	s	0.414 ± 0.041	0.437 ± 0.014	0.417 ± 0.019
	stride length	m	0.720 ± 0.010	0.649 ± 0.023	0.698 ± 0.006
2	stride time	s	1.170 ± 0.056	1.305 ± 0.074	1.183 ± 0.019
	swing time	s	0.447 ± 0.014	0.427 ± 0.006	0.479 ± 0.014
	stride length	m	0.887 ± 0.029	0.886 ± 0.016	0.864 ± 0.055
3	stride time	s	1.040 ± 0.016	1.046 ± 0.043	1.062 ± 0.033
	swing time	s	0.387 ± 0.041	0.436 ± 0.014	0.388 ± 0.013
	stride length	m	0.596 ± 0.023	0.572 ± 0.007	0.573 ± 0.029
4	stride time	s	1.168 ± 0.034	1.201 ± 0.042	1.197 ± 0.026
	swing time	s	0.412 ± 0.026	0.415 ± 0.008	0.472 ± 0.036
	stride length	m	0.746 ± 0.046	0.764 ± 0.044	0.810 ± 0.082
5	stride time	s	1.017 ± 0.041	1.046 ± 0.016	1.029 ± 0.052
	swing time	s	0.378 ± 0.027	0.419 ± 0.006	0.387 ± 0.038

Gait parameters means and standard deviations computed by the HMM-based methodology and the rule based approach, along with the ground truth measured parameters of the GAITRite System for the five subjects.

TABLE II: Maximum Absolute Percentage Error

Parameter	Unit	HMM-based	Rule-based
stride length	%	7.98 ± 5.22	10.13 ± 6.75
stride time	%	5.12 ± 1.70	7.48 ± 6.50
swing time	%	10.93 ± 6.28	16.93 ± 5.72

Maximum absolute percentage error's means and standard deviations of the HMM-based methodology and the rule based approach with respect to the ground truth data per parameter for all subjects.

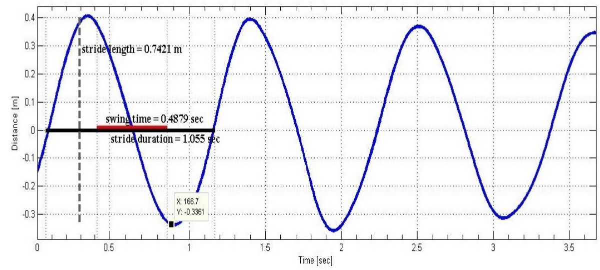

Fig. 6: Experimental Results: Subject's #1 gait parameters during the first stride, as estimated by the rule based approach.

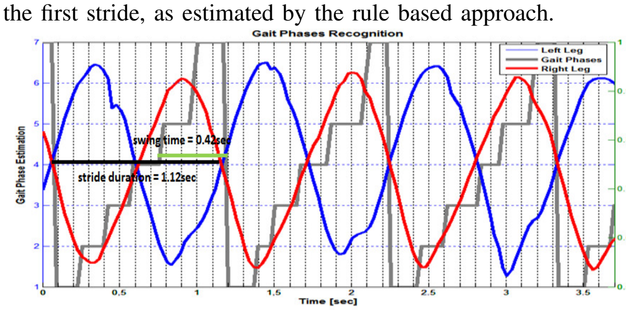

Fig. 7: Experimental Results: Subject's #1 gait phase recognition and gait parameters during the first stride as estimated by the HMM-based approach, according to grey line (axis on the left). The blue and red lines are the displacement of the left and right leg in the sagittal plane, respectively (axis on the right).

C. Validation Results and Discussion

For the demonstration of the experimental results we present the example of Subject #1. In Fig. 6, the subject's gait parameters, as estimated by the rule based approach, are depicted. In the same figure, the segmentation of each stride along with the computed gait parameters for the first stride are presented. For the same subject the exact gait phase recognition based on the HMM-based approach, is depicted in Fig. 7. The blue and red lines are presenting the displacement of the left and right leg in the sagittal plane, respectively, during about the three strides (axis on the right). The grey line depicts the gait phase segmentation that was extracted from the HMM (axis on the left).

The means and standard deviations of gait parameters for the validation set (five subjects) are presented in Table I. Each of the three gait parameters is computed by the HMM-based methodology (fourth column) and the rule based approach (fifth column), along with the ground truth measured parameters of the GAITRite System (sixth column). Firstly, both the proposed methodologies manage, in general, to extract the gait parameters. Most of the times the deviation between the results of the proposed approaches and the ground truth data is not significant, even though the fact that the GAITRite system measures the heel to heel distances, while the laser range scanner measures the lower limbs. Furthermore, the laser scanner measurements depend on the subject's height, and also the movement of the lower limb, while the motion of its hypothetical center, is not aligned with the heel center movement, making the extraction of the gait parameters even more difficult.

Moreover, the results clearly show that the added complexity of the HMM approach is necessary for improved accuracy, as shown in Table II. This table presents the means and standard deviations of the maximum absolute percentage error for both the HMM-based methodology and the rule based approach with respect to the ground truth data per parameter, where it is obvious that the HMM-based approach outperforms the rule based one. This is a result of the HMM-based methodology capability to successfully recognize the exact gait cycle and the specific gait phases. The rule-based approach is effective as long as the walking subject is close to normal. On the other hand, the HMM-based approach extract comprehensive information about the specific action of each leg, and therefore can be very useful for medical diagnosis. Finally, the results clearly demonstrate that there is significant space for increasing the accuracy of our system.

VI. CONCLUSIONS AND FUTURE WORK

The main aim of our research program is the development of a completely non-invasive pathological walking analysis and assessment system, as a subsystem of a context-aware robot control for an intelligent robotic walker. Towards this end, we present a validation study for a human pathological gait analysis and assessment system using methodologies of different complexity. Specifically, we test a rule based approach and a Hidden Markov Model (HMM) to recognize the gait phases of the legs and extract specific gait parameters that are used for medical diagnosis. Our system is based on sensor data provided by a typical laser rangefinder sensor, thus constituting a completely non-invasive approach using a non-wearable device.

The two methodologies are validated using ground truth data provided by a GAITRite System, and both can successfully extract the gait parameters in most cases. The experimental results clearly show that the HMM gait recognition system is more reliable than the rule based approach, as it can better estimate the gait parameters. There is significant room for further accuracy increase. Furthermore, the HMM-based approach, because of its statistical learning properties, is quite flexible and readily extensible to different gait models, thus presenting a strong potential to support a behaviour-based cognitive robot control framework.

The data presented here are an initial 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. 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 main research goal is to use the HMM-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 are working to incorporate a more sophisticated detection and tracking system based on particle filtering to cope with these situations. The aim is to create a system that can detect in real time specific gait pathologies and automatically classify the patient status or the rehabilitation progress, thus providing the necessary information for effective cognitive (context-aware) active mobility assistance robots.

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