Segmentation of Gait Sequences using Inertial Sensor Data in Hereditary Spastic Paraplegia

Christine F. Martindale[1†] *Student Member, IEEE, EMBS*, Martin Strauss[1],
Heiko Gaßner[2], Julia List[2], Meinard Müller[3] *Senior Member, IEEE*, Jochen Klucken[2],
Zacharias Kohl[2] and Bjoern M. Eskofier[1] *Senior Member, IEEE, EMBS*

***Abstract*— Gait analysis is an important tool for diagnosis, monitoring and treatment of neurological diseases. Among these are hereditary spastic paraplegias (HSPs) whose main characteristic is heterogeneous gait disturbance. So far HSP gait has been analysed in a limited number of studies, and within a laboratory set up only. Although the rarity of orphan diseases often limits larger scale studies, the investigation of these diseases is still important, not only to the affect population, but also for other diseases which share gait characteristics.**

In this paper we use foot-mounted inertial measurement units (IMU) as a mobile solution to measure the gait of 21 HSP patients while performing a 4 by 10 m walk at self-selected pace. Two algorithms common to other gait analysis solutions, the hidden Markov model (HMM) and dynamic time warping (DTW), were applied to these signals in order to investigate their effectiveness when faced with the heterogeneous nature and range of foot strike techniques of HSP gait, sometimes even lacking a heel strike. Using a nested cross validation for parameter choice and validation, the HMM was found to be superior for segmentation purposes with a mean segmentation error of 0.10 ± 0.05 s.

Stride segmentation of such a diverse dataset is the first step towards creating a clinically relevant system which could assist physicians working with HSP patients by providing objective, automated gait parameters. To the best of the authors' knowledge, this is the first paper to investigate solutions for mobile gait analysis of patients affected by HSPs. Ultimately, automated, mobile gait analysis of HSP patients would allow ongoing and long term monitoring, providing useful insights into this orphan disease.

I. INTRODUCTION

Hereditary spastic paraplegias (HSPs) are a group of genetic disorders whose predominant feature is gait disturbance [1], [2]. They represent a group of orphan diseases with a prevalence of 2 to 10 per 100 000 people [2], whose severity negatively affects quality of life [3]. Validated measures for orphan diseases are often missing or lacking sufficient clinical trials [2]. In the case of HSP, a thirteen point rating scale has been developed by Schüle et al., the Spastic Paraplegia Rating Scale (SPRS) [4], and employed for the analysis of the clinical severity of HSP in a cohort of 608 patients [2], although it has not been validated in other, independent studies.

[1] Digital Sports Group, Pattern Recognition Lab, Department of Computer Science, Friedrich-Alexander-University Erlangen-Nürnberg (FAU), Erlangen, Germany

[2] Department of Molecular Neurology, University Hospital Erlangen, Germany

[3] International Audio Laboratories Erlangen, Erlangen, Germany

[†] Corresponding author: C. Martindale (christine.martindale@fau.de)

Patients suffering from HSP differ in age, with the age-of-symptom onset ranging from early childhood to senescence [1], as well as in variability of gait alternations and progression of disease, even within a family [5]. There is currently no cure, only symptom reduction options such as spasticity reducing drugs, physiotherapy, gait phase dependent nerve stimulation and assistive orthopedic devices [1], [6]. Robotic training and hydrotherapy have also been used to increase the quality of life of the patients [7]–[9].

For the analysis of the effectiveness of these symptom reducing solutions, as well as to provide more objective measures of disease severity and progression, 3D gait analysis has been investigated on cohorts ranging from 9 to 50 patients [5], [10]–[12]. Klebe et al. calculated gait parameters from roughly 20 consecutive gait cycles of 22 patients while walking on a treadmill and found significantly reduced gait velocity, stride length, step length and knee-angle as compared to an age-gender matched control group [5]. They followed this up with a longitudinal study investigating the effect of the drug methylphenidate on HSP gait, finding that while gait velocity improved in the short term there seemed to be no long term effect [13]. In contrast, Serrao et al. investigated possible subgroups of HSP patients based on spatiotemporal parameters, range of angular motion and muscle co-activation values [10]. The proposed subgroups also nominally corresponded to the SPRS of the patients. The differences between HSP gait and cerebral palsy gait [14] or spastic diplegia gait [11] have also been investigated using 3D gait analysis, although using only small cohorts of 10 or less HSP patients.

An alternative to 3D gait analysis is mobile gait analysis based on IMU systems, such as those successfully applied to the study of other neurological diseases such as Parkinsons [15]. This paper aims to explore the possibility of using an IMU based, mobile method for gait analysis of HSP patients. One of the main challenges when applying these techniques to HSP gait is the sheer variety of gait disturbances as well as the range of foot strike techniques: striking the floor with the mid-lateral plantar surface, the balls of the feet or only the toes (toe walking), as opposed to the more usual heel strike in most Parkinson's patients or healthy persons [1], [15], [16]. The current methods for automatic gait analysis using foot mounted IMU sensors rely on heel strike and midstance detection in order to calculate spatiotemporal parameters [1], [17]. The necessary

Preprint submitted to 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Received February 17, 2017.

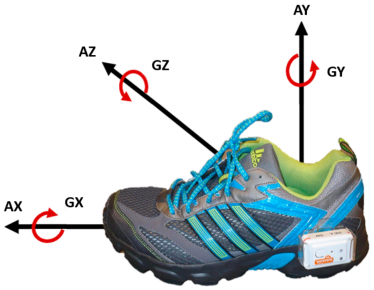

Fig. 1. Shimmer sensor placement on lateral side of left shoe, showing axes directions for 3D accelerometer (AX,AY,AZ) and gyroscope (GX, GY, GZ).

assumption of zero velocity at midstance may be violated by these HSP specific gait forms.

Due to the variety of gait patterns, segmentation of the gait data into individual strides is a non-trivial task which will be tackled by this paper with the aim to calculate spatiotemporal gait parameters. Ultimately, an automatic, mobile gait analysis tool would assist in the diagnosis, analysis and symptom management without being restricted to an expensive, laboratory-based 3D gait analysis system. This can be achieved by tackling the segmentation task and zero velocity assumption, the latter will not be addressed in this paper.

II. DATASET

The study population consisted of 21 subjects fulfilling the clinical diagnostic criteria for HSP [4], 8 males and 13 females with an average age of 47.2 ± 13.3 years. All subjects gave written informed consent, prior to the data collection. (This study was approved by the local ethics committee Nr. 4208, 21.4.2010, IRB, Medical Faculty, Friedrich-Alexander-University Erlangen-Nuremberg, Germany). The severity of the disease was evaluated using the SPRS [4], with this cohort having an average score of 17.8 ± 6.9. Each subject performed a 4 by 10 m walk at a self-selected speed while being recorded with a camera (30 fps). Two Shimmer 2R (Shimmer Sensing, Dublin, Ireland) inertial measurement units (IMU), recording acceleration (± 6 g) and rate of change of angle ($\pm$ 500 dps) at 102.4 Hz, were attached to the lateral side of the shoe (Fig. 1).

The strides were labelled using simultaneous analysis of video and sensor data with a stride being labelled from initial ground contact (GC_i) to the subsequent ground contact of the same foot (GC_{i+1}). The stride definitions from [15], [17], [18] were used as a guide (Fig. 2). The video and sensor data were synchronised using reference movements, such as lifting one foot three times, or rest periods. The labelling was performed by one person familiar with the gait data. The data was classified into three classes: rest, stride and transition, where rest refers to the subject standing still and transition to anything that is neither a stride from GC_i to GC_{i+1} nor rest (Fig. 2).

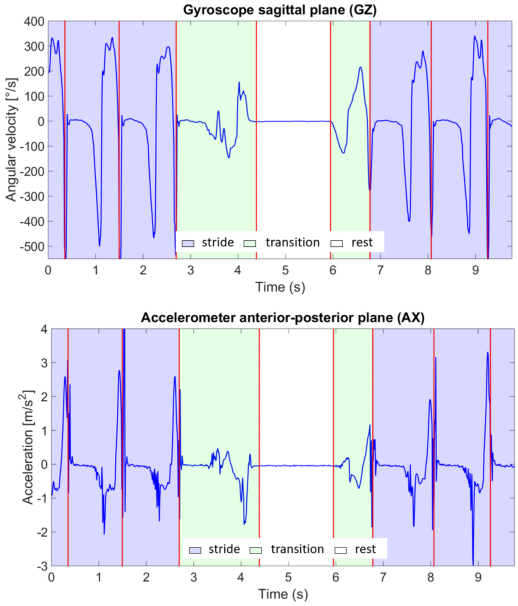

Fig. 2. Labelling example with all three classes: rest, stride and transition. The upper graph represents the the gyroscope sagittal plane and the lower, accelerometer anterior-posterior plane. The vertical lines indicate the labelling points for GC_i. The represented time point is a pause and turn during the 4 by 10 m walk.

III. METHODS

The sensor data was segmented using two different algorithms; multi-dimensional subsequence dynamic time warping (msDTW) and a hierarchical hidden Markov model (hHMM). DTW and HMM algorithms, or variants thereof, were chosen for this segmentation task due to their successful use in IMU-based gait analysis of other neurological diseases such as Parkinson's and Huntington's disease [15], [19].

A. Dynamic Time Warping

Multi-dimensional subsequence DTW [15] was used due to its ability to handle multidimensional features, as well as its ability to compare a template, in this case a stride, to a longer sequence, in this case the complete 40 m test sequence. The SensorDataToolbox implementation (Digital Sports Group, Pattern Recognition Lab, FAU Erlangen-Nuremberg) was used. All strides from the training group were used to generate a stride template by interpolating or filtering each stride to the average stride length. The Euclidean norm was used as a distance measure in the cost matrix. The threshold was found in the parameter optimisation step. The raw data was filtered using a 10 point moving average filter and normalised to $[-1\,,1]$ using the maximum sensor range.

B. Hidden Markov Model

A hierarchical HMM [20] was chosen due to its ability to model strides, rest and transitions by exploiting their repetitive nature. The number of states per HMM was chosen during the parameter optimisation step, with the exception of the rest HMM which was fixed to 3 states. The models were trained in a supervised manner using the stride borders (GC), while learning the internal phases was done in

Preprint submitted to 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Received February 17, 2017.

TABLE I

ROUGH GRID SEARCH FOR PARAMETER OPTIMISATION

hHMM Parameters	
Number of states per HMM	4, 8, 10
Sliding window length (s)	0.30, 0.50, 0.70
Number of GMM components	4, 8, 10
Axes combinations	AXGZ, GYGZ, AXAYAZGYGZ
msDTW Parameters	
Threshold (steps of 5)	40-80, 40-80, 150-180
Axes combination	AXGZ, GYGZ, AXAYAZGYGZ

TABLE II

EVALUATION METRICS OF DTW AND HMM

	hHMM	msDTW
Mean absolute GC error	0.10 ± 0.05 s	0.09 ± 0.04 s
Mean absolute stride time error	0.14 ± 0.08 s	0.33 ± 0.07 s
F1-score	92.09 ± 0.01 %	90.35 ± 0.02 %

an unsupervised manner. The observations (features) were modelled with Gaussian Mixture Models (GMM) initialised with a diagonal covariance matrix, where the number of required centres was found within the parameter optimisation step. The GMM densities were calculated using estimation maximisation (EM) within 10 iterations. Viterbi training was used and the stride boundaries were found using Viterbi decoding. The implementation used was the Java Speech Toolkit (JSTK) [21].

Features were calculated using a sliding window approach. The size of the sliding window was determined in the parameter optimisation step. The mean, variance, first three coefficients of the second order polynomial fit and the raw data itself were used as features, after normalisation. The choice of axes used for feature calculation was part of the parameter optimisation step. This simple feature set was chosen to minimise processing time while still describing the data.

C. Training and Parameter Optimisation

Nested cross validation was used for evaluation. A 3-fold outer cross validation was used for the model creation and test set. The model creation set was further split with an inner 5-fold cross validation for parameter choice. The best parameters per fold were chosen via a rough grid search, the parameter optimisation step Tab. I. The grid search values were chosen based partially on literature and partially empirically [15], [19], [22]. This cross validation was performed such that no subject used for training the model or parameter selection appeared in the test set.

For the evaluation of the segmentation accuracy of the two algorithms, three main evaluation metrics were chosen: the absolute average error in stride time, the absolute average error of each GC point and the F1-score for stride detection. The F1-score was also used for determining the best parameters. The evaluation metrics, of the outer fold, were averaged. Sections labelled as transition in the ground truth were ignored for these calculations.

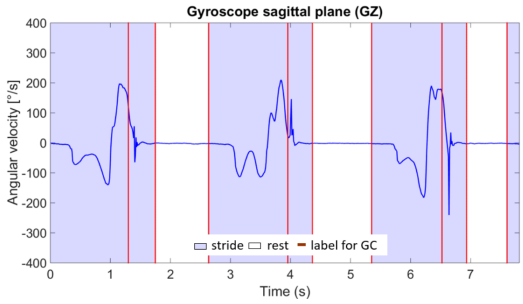

Fig. 3. Misclassification of rest within a walking sequence of one subject with severely impaired gait. The image illustrates the inserted rest sections created by the hHMM, however a similar result can be seen using DTW.

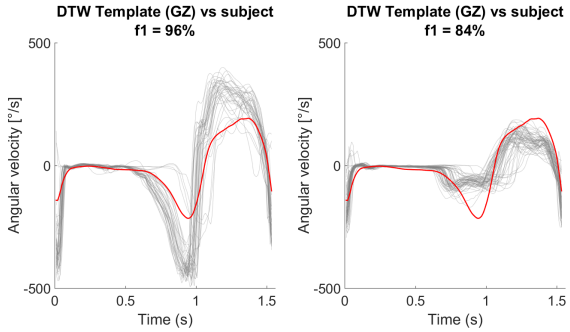

Fig. 4. All strides from a subject (thin, grey) compared to the template (thick, red), showing subject specific F1-score using DTW. The strides from the subject where DTW achieved a lower F1-score, right, do not match the template as well as those from the subject with the higher F1-score (left).

IV. RESULTS AND DISCUSSION

The results of the best models used in the outer cross validation are shown in Tab. II. Given the variety of gaits and size of this dataset, a classification of over 90 % is a reasonable outcome. It is important to note that some subjects lacked a heel strike. The HMM outperformed DTW, achieving an F1-score of 92.09 % for strides. With an average stride time of 1.56 s, the absolute error in stride time for both algorithms was roughly 10 % to 20 % of a stride. The error in the GC point is under 0.09 s.

A larger cohort should naturally improve these results, however this may be difficult to achieve given that HSP is an orphan disease. The most common problem for both algorithms was the relatively long midstance phase which was often misclassified as rest or standing as illustrated in Fig. 3. This explains why the stride time error was almost 10 % of an average stride for the HMM. The error in the calculation of the GC point is therefore a good indicator of the effectiveness of the algorithms, should the falsely detected rest phases be solved. These falsely detected rest phases might be improved by forcing the algorithms to detect only steps during walking phases which would require a separate rest detection phase in the pipeline.

The gait variability between subjects was not addressed here due to the general training of the models. The effect of this can be illustrated by comparing the template used for DTW to all the strides of individual subjects (Fig. 4). This effect might be mitigated by a personalised approach

Preprint submitted to 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society. Received February 17, 2017.

to training the models, which may also compensate for the smaller size of the dataset. Finding solutions for gait analysis which can handle small datasets is an important factor when dealing with rare or more person specific gait disturbances or treatments. It would also be informative to group the subjects by disease severity and analyse the effect of this on the error and classification accuracy of the algorithms. HMMs performed better in this case and have the added advantage of implicitly modelling the gait phases which could yield useful information about the gait phases.

V. SUMMARY AND OUTLOOK

Despite the wide variety of gait disturbances and the different types of first ground contact typical of HSP gait data, a segmentation error of 0.10 s or less was achieved demonstrating that it is possible to segment HSP gait data, collected from a mobile system, into strides. The hierarchical hidden Markov model seems superior to multidimensional subsequence dynamic time warping achieving a $92.09\,\%$ F1-score and stride time was calculated with an error of 0.14 s. Stride segmentation of such a diverse dataset is the first step towards creating a clinically relevant system which could assist physicians working with HSP patients by providing objective, automated gait parameters. Such parameters are useful for diagnosis, progression and treatment analysis.

The limitations of the current processing pipeline were highlighted; the most influential of which was the classification of rest periods within each stride. This effect may be mitigated by employing a model per subject or by separating the individual stride detection from the rest/motion class detection. Further improvements may be found with a more fine grained grid search or a more specific feature selection.

To the best of the authors' knowledge, this is the first paper to investigate solutions for mobile gait analysis of patients affected by HSPs. Ultimately, automated, mobile gait analysis of HSP patients would allow ongoing and long term monitoring, providing useful insights into this orphan disease. The rarity of orphan diseases often limits larger cohorts, and, despite their rarity, the study of them is important not only to the affected patients but also due to the developed algorithms' use in diseases with similar symptoms. In this case the methods developed for HSP may be relevant for other heterogeneous gait disorders.

ACKNOWLEDGMENT

This work was in part supported by the FAU Emerging Fields Initiative (EFIMoves). Bjoern Eskofier gratefully acknowledges the support of the German Research Foundation (DFG) within the framework of the Heisenberg professorship programme (grant number ES 434/8-1).

REFERENCES

[1] J. K. Fink, "Hereditary spastic paraplegia," *Curr. Neurol. Neurosci. Rep.*, vol. 6, no. 1, pp. 65–76, 2006.

[2] R. Schüle, S. Wiethoff, P. Martus, K. N. Karle, S. Otto, S. Klebe, S. Klimpe, C. Gallenmüller, D. Kurzwelly, D. Henkel, F. Rimmele, H. Stolze, Z. Kohl, J. Kassubek, T. Klockgether, S. Vielhaber, C. Kamm, T. Klopstock, P. Bauer, S. Züchner, I. Liepelt-Scarfone, and L. Schöls, "Hereditary spastic paraplegia: Clinicogenetic lessons from 608 patients," *Ann. Neurol.*, vol. 79, no. 4, pp. 646–658, 2016.

[3] S. Klimpe, R. Schüle, J. Kassubek, S. Otto, Z. Kohl, S. Klebe, T. Klopstock, S. Ratzka, K. Karle, and L. Schöls, "Disease severity affects quality of life of hereditary spastic paraplegia patients," *Eur. J. Neurol.*, vol. 19, no. 1, pp. 168–171, 2012.

[4] R. Schule, T. Holland-Letz, S. Klimpe, J. Kassubek, T. Klopstock, V. Mall, S. Otto, B. Winner, and L. Schols, "The Spastic Paraplegia Rating Scale (SPRS): A reliable and valid measure of disease severity," *Neurology*, vol. 67, no. 3, pp. 430–434, 2006.

[5] S. Klebe, H. Stolze, F. Kopper, D. Lorenz, R. Wenzelburger, J. Volkmann, H. Porschke, and G. Deuschl, "Gait analysis of sporadic and hereditary spastic paraplegia," *J. Neurol.*, vol. 251, no. 5, pp. 571–578, 2004.

[6] J. K. Fink, "Hereditary spastic paraplegia: clinico-pathologic features and emerging molecular mechanisms," *Acta Neuropathol.*, vol. 126, no. 3, pp. 307–328, 2013.

[7] F. Bertolucci, S. Di Martino, D. Orsucci, E. C. Ienco, G. Siciliano, B. Rossi, M. Mancuso, and C. Chisari, "Robotic gait training improves motor skills and quality of life in hereditary spastic paraplegia." *NeuroRehabilitation*, vol. 36, no. 1, pp. 93–9, 2015.

[8] H. G. Seo, B.-M. Oh, and K. Kim, "Robot-Assisted Gait Training in a Patient With Hereditary Spastic Paraplegia," *PM&R*, vol. 7, no. 2, pp. 210–213, 2015.

[9] Y. Zhang, R. Roxburgh, L. Huang, J. Parsons, and T. C. Davies, "The effect of hydrotherapy treatment on gait characteristics of hereditary spastic paraparesis patients," *Gait Posture*, vol. 39, no. 4, pp. 1074–1079, 2014.

[10] M. Serrao, M. Rinaldi, A. Ranavolo, F. Lacquaniti, G. Martino, L. Leonardi, C. Conte, T. Varrecchia, F. Draicchio, G. Coppola, C. Casali, and F. Pierelli, "Gait Patterns in Patients with Hereditary Spastic Paraparesis," *PLoS One*, vol. 11, no. 10, p. e0164623, 2016.

[11] L. Piccinini, V. Cimolin, M. G. D'Angelo, A. C. Turconi, M. Crivellini, and M. Galli, "3D gait analysis in patients with hereditary spastic paraparesis and spastic diplegia: A kinematic, kinetic and EMG comparison," *Eur. J. Paediatr. Neurol.*, vol. 15, no. 2, pp. 138–145, 2011.

[12] S. I. Wolf, F. Braatz, D. Metaxiotis, P. Armbrust, T. Dreher, L. Döderlein, and R. Mikut, "Gait analysis may help to distinguish hereditary spastic paraplegia from cerebral palsy," *Gait Posture*, vol. 33, no. 4, pp. 556–561, 2011.

[13] S. Klebe, G. Deuschl, and H. Stolze, "Methylphenidate fails to improve gait and muscle tone in patients with sporadic and hereditary spastic paraplegia," *Mov. Disord.*, vol. 21, no. 9, pp. 1468–1471, 2006.

[14] A. Bonnefoy-Mazure, K. Turcot, A. Kaelin, G. De Coulon, and S. Armand, "Full body gait analysis may improve diagnostic discrimination between hereditary spastic paraplegia and spastic diplegia: A preliminary study," *Res. Dev. Disabil.*, vol. 34, no. 1, pp. 495–504, 2013.

[15] J. Barth, C. Oberndorfer, C. Pasluosta, S. Schülein, H. Gassner, S. Reinfelder, P. Kugler, D. Schuldhaus, J. Winkler, J. Klucken, and B. M. Eskofier, "Stride segmentation during free walk movements using multi-dimensional subsequence dynamic time warping on inertial sensor data." *Sensors*, vol. 15, no. 3, pp. 6419–40, 2015.

[16] C. McDermott, K. White, K. Bushby, and P. Shaw, "Hereditary spastic paraparesis: a review of new developments." *J. Neurol. Neurosurg. Psychiatry*, vol. 69, no. 2, pp. 150–60, 2000.

[17] A. Rampp, J. Barth, S. Schülein, K.-G. Gaßmann, J. Klucken, and B. M. Eskofier, "Inertial Sensor Based Stride Parameter Calculation from Gait Sequences in Geriatric Patients." *IEEE Trans. Biomed. Eng.*, vol. 62, no. 4, pp. 1089–1097, 2014.

[18] A. Sabatini, C. Martelloni, S. Scapellato, and F. Cavallo, "Assessment of Walking Features From Foot Inertial Sensing," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 3, pp. 486–494, 2005.

[19] A. Mannini, D. Trojaniello, A. Cereatti, and A. Sabatini, "A Machine Learning Framework for Gait Classification Using Inertial Sensors: Application to Elderly, Post-Stroke and Huntington's Disease Patients," *Sensors*, vol. 16, no. 2, p. 134, 2016.

[20] S. Fine, Y. Singer, and N. Tishby, "The Hierarchical Hidden Markov Model: Analysis and Applications," *Mach. Learn.*, vol. 32, no. 1, pp. 41–62, 1998.

[21] S. Steidl, K. Riedhammer, and T. Bocklet, "Java Visual Speech Components for Rapid Application Development of GUI Based Speech Processing Applications." in *INTERSPEECH 2011, 12th Annu. Conf. Int. Speech Commun. Assoc.*, 2011.

[22] J. Taborri, E. Palermo, S. Rossi, and P. Cappa, "Gait Partitioning Methods: A Systematic Review," *Sensors*, vol. 16, no. 1, p. 66, 2016.