Mobile Gait Analysis using Personalised Hidden Markov Models for Hereditary Spastic Paraplegia Patients

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***Abstract*— Gait analysis provides a quantitative method to assess disease progression or intervention effect on gait disorders. While mobile gait analysis enables continuous monitoring in free living conditions, state of the art gait analysis for diseases such as hereditary spastic paraplegia (HSP) is currently limited to motion capture systems which are large and expensive. The challenge with HSP is its heterogeneous nature and rarity, leading to a wide range of ages, severity and gait patterns as well as small patient numbers. We propose a sensor-based mobile solution based on a personalised hierarchical hidden Markov Model (hHMM) to extract spatio-temporal gait parameters. This personalised hHMM achieves a mean absolute error of 0.04 s $\pm$ 0.03 s for stride time estimation with respect to a GAITRite® reference system. We use the successful extraction of initial ground contact to explore the limits of the double integration method for such heterogeneous diseases. While our personalised model compensates for the heterogeneity of the disease, it would require a new model per patient. We observed that the general model was sufficient for some of the less severely affected patients.**

I. Introduction

Although hereditary spastic paraplegia (HSP) is a rare disease, it greatly affects the quality of life of those affected [1]. Progression, age of onset and gait alternations vary within the HSP population [2]. Research into methods to better understand the disease and to alleviate the symptoms are ongoing. A qualitative clinical scale, the Spastic Paraplegia Rating Scale (SPRS), is commonly used to assess disease severity [3], [4]. However, there is also a case for assessment using quantitative measures such as gait anaylsis [5], [6].

Most studies use 3-D motion capture systems for gait analysis which are large, expensive, limited to the laboratory environment and often require experts to maintain and run them. A mobile gait analysis system would not only allow a quantitative, but also a continuous, measure of gait quality within more natural environments [7]. There are several solutions successfully used for mobile gait analysis; the dominant two are shoe mounted IMU based solutions and insole based solutions [7], [8].

In the context of HSP, 3D gait analysis has been used to assess the characteristics of small cohorts of patient groups, such as in children and within relatives [9], [10]. It has also been employed to assess intervention effects such as that of certain drugs or physical therapy [11], [12]. The use of gait parameters to distinguish between similar gait disorders can be helpful in understanding the mechanisms involved as well as for their diagnostic value. These were assessed in distinguishing between HSP and cerebral palsy [13], [14], cerebellar ataxia, Parkinson's disease [5] and healthy controls [4]. Clustering approaches were used, yielding sets of important gait parameters; however, Wolf, Rinaldi and Serrao et al. [4], [5], [13] concluded that the definition of specific subgroups within each disease were required due to their heterogeneous natures.

There are a variety of algorithms to choose from for the segmentation of strides [15], however, hidden Markov models seem the most promising [16]–[18]. Our previous work on mobile gait analysis solutions for HSP patients achieved an accuracy of 0.14 s $\pm$ 0.05 s for stride time estimation, compared to a manually labelled reference based on video data [16].

This paper aims to build on this result and proposes two modifications to the training of a hierarchical hidden Markov model (hHMM). We also validate the results against a gold standard system, GAITRite®. The proposed training of the hHMM uses both initial and terminal ground contact times. Secondly, the effect of a general model, trained on a population, is compared to that of a personalised one. The estimated initial contact times are then used to estimate a zero velocity point and the double integration method used by [19], [20] is employed to estimate stride length. We propose a training method, algorithm and set up to allow mobile gait analysis for HSP patients.

II. Dataset

We collected gait data from 10 subjects fulfilling the clinical diagnostic criteria for HSP. The characteristics of the patients are shown in Table I. The SPRS clinical scale was used to evaluate the severity of the disease [3]. The first section of this scale concerns gait related characteristics and, therefore, the sum of the values from Section A of the scale is also given (SPRS-SectA). 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-Nürnberg, Germany.

Two Shimmer 3 (Shimmer Sensing, Dublin, Ireland) inertial measurement units (IMU) were attached to the lateral side of each shoe (Fig. 1). Each recorded acceleration ($\pm$ 6 g) and rate of change of angle ($\pm$ 500 dps) at 102.4 Hz. Each subject performed two 4 x 10 m walks at a self-selected pace.

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TABLE I

CHARACTERISTICS OF SUBJECTS

Age	58 years ± 7 years
Gender	6 female, 4 male
Weight	83 kg ± 24 kg
Height	1.72 m ± 0.11 m
SPRS score	19 ± 8
SPRS-SectA score	12 ± 5

The subjects were allowed to use their preferred walking aid. The GAITRite® pressure sensor carpet (GAITRite® Classic, CIR Systems, PA, USA), 792 cm, was used as a reference system with a scan rate of 240 Hz. It was positioned such that the subjects walked the entire length of the carpet within each 10 m section of the 4 x 10 m walk. This also ensured that the patient took some strides before and after the active area of the carpet per pass. For validation purposes, only the data collected from the sensors during the time in which the GAITRite® system was also active were used for this evaluation. Thus, we collected 8 passes per patient, with a total of 1158 strides used for evaluation.

The entire set up was also recorded by two cameras, one connected to the GAITRite® system and one independent camera capturing the entire room. The GAITRite® system provides a synchronisation signal which we used to synchronise the data from the sensors to the carpet, on a per stride basis.

The reference data was extracted from the GAITRite® 4.7. Software with, where possible, automatically detected walking aids. Manual labelling was performed, when needed, according to the GAITRite® recommendations. These cases were for patients with foot drag, or where the path of the walking aid coincided with the foot path on the carpet.

In total four passes of the GAITRite® system were excluded due to technical failure of either sensor or carpet. Only full strides, initial contact to initial contact, were considered for evaluation. The extracted labels were initial and terminal contact per foot allowing the calculation of temporal gait parameters. Stride length was also extracted.

III. METHODS

A. Segmentation Algorithm

The hierarchical hidden Markov model was used for stride segmentation due to its success in similar applications and its intrinsic use of the hierarchical nature of gait [15], [16]. The basic model parameters and architecture are similar to that in [16], the main differences are in the training scheme. The model parameters and features which achieved the best results from [16] were used, namely, a window size for feature extraction of 0.7 s where the features were extracted from the sagittal plane gyroscope axis (GZ) and the frontal plane accelerometer axis (AX). The mean, variance, first three coefficients of the second order polynomial fit and the raw data itself were used as features, after normalisation. The features were normalised per pass, per subject and per foot.

The features were modelled by Gaussian mixture models (GMM), initialised with a diagonal covariance matrix, where

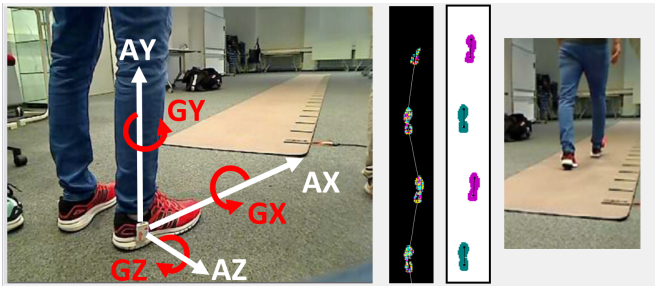

Fig. 1. Experimental set up showing Shimmer sensor with axes directions for 3D accelerometer (AX,AY,AZ) and gyroscope (GZ,GY,GZ), left, as well as GAITRite® carpet with example pressure map, right.

the number of required centres was four. 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. Due to a similar use of hHMM in time series analysis in speech, an implementation of hHMM from a speech toolbox was used, the Java Speech Toolkit (JSTK) [21].

A continuous, left-right HMM was used where one model represented a stride. Within each stride were two phases: swing and stance. The boundaries of these phases were supervised using the labels extracted from the GAITRite® data. The number of states per phase within the model was four. These states were trained in an unsupervised manner.

B. Training and Evaluation

1) General Model: One version of the hHMM was trained on the complete population of HSP patients and required no further training for a new patient. To test the accuracy of this, a leave one subject out cross validation was used. This means that 9 subjects were used for training the model, and the final subject for testing. This was repeated for all subjects. The estimated gait parameters were averaged per person.

2) Personalised Model: Due to the wide variety of gait patterns possible in HSP patients, the other version of the hHMM was personalised, with a patient specific model. Due to unevenly affected gait, the model was also foot specific. Therefore, a model was created per subject, per foot. It was tested using a cross validation approach where one 10 m pass was used for testing, per subject, and the remainder to train. This cross validation was performed such that no pass used for training the model appeared in the test set.

3) Gait Parameter Calculation and Evaluation: The hHMM estimated the initial and terminal contact times, enabling the calculation of temporal gait parameters. From the initial contact time, the zero velocity phase was estimated as described in [19]. Subsequently, the double integration approach was used to estimate the stride length from mid stance to mid stance using the SensorDataToolbox (Machine Learning and Data Analytics Lab, FAU).

Each stride detected by the GAITRite® system was matched to the corresponding stride predicted by the hHMM by finding the strides with the maximum overlap. In cases where strides where more strides were predicted than were

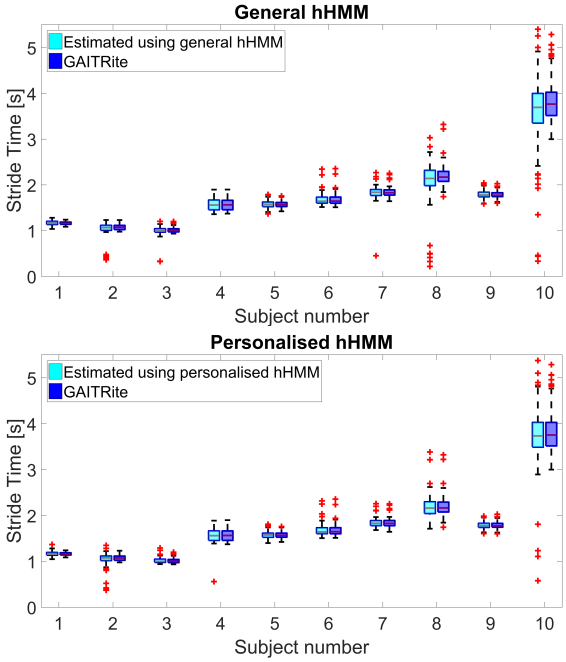

Fig. 2. Paired box plots of hHMM estimated versus GAITRite® stride times, using the general hHMM model, top, and the personalised model, bottom. Subject numbers in ascending order of SPRS-SectA score.

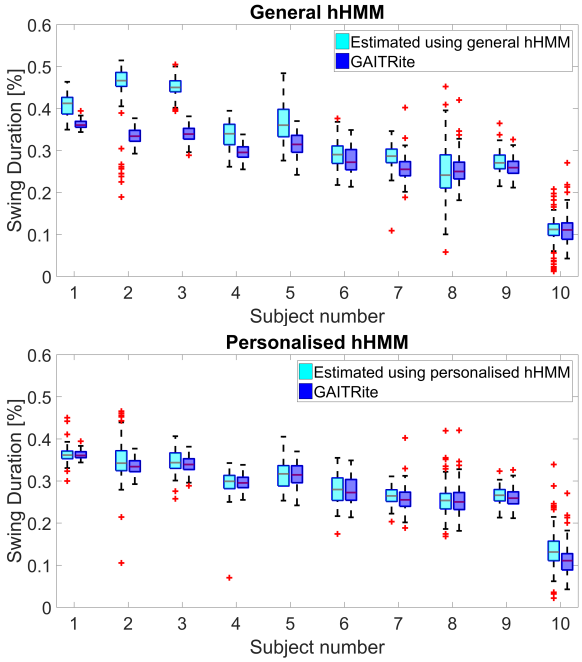

Fig. 3. Paired box plots of hHMM estimated versus GAITRite® swing durations, using the general hHMM model, top, and the personalised model, bottom. Subject numbers in ascending order of SPRS-SectA score.

found in the reference data, the one with maximum overlap was used. The frequency of this occurrence was calculated.

IV. Results and Discussion

The stride time per subject was calculated and compared to the reference GAITRite® values, for both the personalised and general model, as illustrated in Figure 2. Subject numbers are ordered in ascending SPRS-SectA values. The estimated stride times correspond well with the GAITRite® values, although the actual range of values vary per subject. The personalised model has less outliers; this is most noticeable for Subjects 8 and 10. To quantify these errors, the mean and standard deviation of the error per stride, per subject, are shown in Table II, for both the personalised and general models. Each subject's total SPRS score and gait related SPRS score (SPRS-SectA) is also given. In general, the results are subject specific in that for some subjects the personalised and general model work equally well, where for others, mostly corresponding to those with a higher SPRS score, the personalised model would be a better choice.

The mean errors for stride time for both models are good compared to that reported in [16], where the mean absolute error was 0.14 s $\pm$ 0.08 s. These two studies are comparable due to the use of a very similar cohort and sensor set up. The difference between the [16] model and the general model presented here is the use of both initial and terminal contact time to train stance and swing phase models per stride.

The subjects where too many strides were predicted, in the case of the general model, were subjects 2, 3, 7, 8 and 10 where there were, respectively, 9.8 %, 2.0 %, 1.0 %, 3.6 % and 15.8 % too many strides detected. The personalised model predicted too many strides for subjects 2, 4 and 10 by, respectively, 5.6 %, 1.0 % and 2.1 %. There were no missed strides. This shows that the personalised model produced fewer false positives. The effect of these false positives is seen in the corresponding standard deviations in Table II for these subjects.

Due to the hHMM detecting both swing and stance phase, swing duration was also calculated. The swing duration per subject is shown in Figure 3. Here, one can clearly see the effect of the personalised model. The swing duration error, given in Table II, show in detail the worse results for the general model.

The results for stride length estimation are given in Table II. While the mean stride length error is reasonable at 0.13 m for the general model, the standard deviation is high with respect to an average stride length of 0.96 m $\pm$ 0.24 m. For subjects 1, 3 and 9, the estimated stride lengths are acceptable, showing that this solution could be useful on for particular types of subjects. This error in the stride length could be due to the variety of ground contact techniques within HSP patients. The heel, where the sensor is located, may not remain at zero velocity during the midstance phase which would violate the zero velocity assumption [20].

V. Summary and Outlook

In general the personalised model is superior for temporal gait parameters, due to a lower mean error and fewer false positive stride detections. While stride length estimation using double integration works for some subjects, it is not a general solution for a population where the zero velocity assumption may be violated due to ground contact technique and sensor position. This could be mitigated by choosing a sensor position which ensures a zero velocity phase, such

TABLE II

ERROR OF GENERAL AND PERSONALISED HHMM PER SUBJECT. CORRESPONDING SPRS AND SPRS SECTA VALUES ARE ALSO REPORTED

Subject Number	Mean Error Stride Time Personalised [s]	Mean Error Stride Time General [s]	Mean Error Stride Length Personalised [m]	Mean Error Stride Length General [m]	Mean Error Swing Duration Personalised [%]	Mean Error Swing Duration General [%]	SPRS	SPRS SectA
Subject 1	0.00 ± 0.04	0.01 ± 0.05	-0.05 ± 0.05	-0.05 ± 0.05	0.0 ± 2.2	4.4 ± 2.9	7	5
Subject 2	-0.04 ± 0.17	-0.08 ± 0.21	-0.11 ± 0.30	-0.19 ± 0.41	1.0 ± 5.4	10.9 ± 7.8	8	5
Subject 3	0.00 ± 0.02	-0.02 ± 0.09	-0.03 ± 0.09	-0.08 ± 0.18	0.8 ± 2.1	11.3 ± 2.2	11	6
Subject 4	-0.01 ± 0.09	-0.00 ± 0.02	-0.06 ± 0.15	-0.06 ± 0.11	0.0 ± 2.7	4.2 ± 2.3	19	11
Subject 5	0.00 ± 0.03	0.00 ± 0.03	0.17 ± 0.30	0.18 ± 0.30	0.0 ± 1.6	5.1 ± 3.7	26	13
Subject 6	0.00 ± 0.04	0.00 ± 0.03	0.14 ± 0.21	0.11 ± 0.26	0.7 ± 2.2	1.5 ± 1.7	21	14
Subject 7	0.00 ± 0.06	-0.02 ± 0.14	0.25 ± 0.30	0.24 ± 0.33	0.7 ± 2.1	2.7 ± 3.1	24	15
Subject 8	0.00 ± 0.07	-0.11 ± 0.44	0.09 ± 0.18	0.08 ± 0.38	-0.0 ± 1.9	0.9 ± 10.1	21	16
Subject 9	0.00 ± 0.03	0.00 ± 0.04	0.04 ± 0.06	0.04 ± 0.06	0.6 ± 1.3	1.1 ± 2.2	22	16
Subject 10	-0.06 ± 0.48	-0.20 ± 0.63	1.16 ± 1.05	1.04 ± 0.96	2.4 ± 4.1	-0.3 ± 4.5	31	18
Mean	**-0.01 ± 0.02**	**-0.04 ± 0.07**	**0.16 ± 0.37**	**0.13 ± 0.34**	**0.6 ± 0.9**	**4.2 ± 4.0**	**19**	**12**
Mean Absolute	**0.04 ± 0.03**	**0.07 ± 0.08**	**0.25 ± 0.34**	**0.26 ± 0.31**	**1.9 ± 0.9**	**5.5 ± 3.7**	**19**	**12**

as near the ball of the foot. The clear advantage of a personalised approach for such a rare disease is that one does not need a large population of subjects to train the model.

As an outlook, we plan to use semi-supervised learning approaches and a clearly specified task, such as an exact number of strides to be taken, to initialise the personalised model. Furthermore, subgroups could be found according to the SPRS-SectA scores and stride and a model trained per subgroup.

This paper provides a mobile gait analysis solution which achieves a stride time error of 0.04 s and swing duration error of 1.9 % for HSP patients, using the personalised model. These gait parameters also vary with the gait related section of the SPRS scale, showing that such a mobile gait analysis system could be a useful, quantitative clinical tool. Furthermore, we have shown the limitations of double integration based approaches to stride length estimation for such a population.

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REFERENCES

[1] S. Klimpe, R. Schüle, J. Kassubek *et al.*, "Disease severity affects quality of life of hereditary spastic paraplegia patients," *Eur. J. Neurol.*, vol. 19, no. 1, pp. 168–171, 2012.

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

[3] R. Schule, T. Holland-Letz, S. Klimpe *et al.*, "The Spastic Paraplegia Rating Scale (SPRS): A reliable and valid measure of disease severity," *Neurology*, vol. 67, no. 3, pp. 430–434, 2006.

[4] M. Rinaldi, A. Ranavolo, S. Conforto *et al.*, "Increased lower limb muscle coactivation reduces gait performance and increases metabolic cost in patients with hereditary spastic paraparesis." *Clinical biomechanics (Bristol, Avon)*, vol. 48, pp. 63–72, oct 2017.

[5] M. Serrao, G. Chini, M. Bergantino *et al.*, "Identification of specific gait patterns in patients with cerebellar ataxia, spastic paraplegia, and Parkinson's disease: A non-hierarchical cluster analysis," *Human Movement Science*, sep 2017.

[6] M. Serrao, M. Rinaldi, A. Ranavolo *et al.*, "Gait Patterns in Patients with Hereditary Spastic Paraparesis," *PLoS One*, vol. 11, no. 10, 2016.

[7] R. Caldas, M. Mundt, W. Potthast *et al.*, "A systematic review of gait analysis methods based on inertial sensors and adaptive algorithms." *Gait & posture*, vol. 57, pp. 204–210, sep 2017.

[8] H. Jagos, K. Pils, M. Haller *et al.*, "Mobile gait analysis via eSHOEs instrumented shoe insoles: a pilot study for validation against the gold standard GAITRite ®," *J. of Med. Eng. & Tech.*, vol. 41, no. 5, pp. 375–386, jul 2017.

[9] B. Adair, J. Rodda, J. L. McGinley *et al.*, "Kinematic gait deficits at the trunk and pelvis: characteristic features in children with hereditary spastic paraplegia," *Dev. Med. Child Neurol.*, vol. 58, no. 8, pp. 829–835, 2016.

[10] S. Armand, K. Turcot, A. Bonnefoy-Mazure *et al.*, "Gait evolution in a family with hereditary spastic paraplegia," *Eur. J. Paediatr. Neurol.*, vol. 19, no. 1, pp. 87–92, 2015.

[11] Y. Zhang, R. Roxburgh, L. Huang *et al.*, "The effect of hydrotherapy treatment on gait characteristics of hereditary spastic paraparesis patients," *Gait Posture*, vol. 39, no. 4, pp. 1074–1079, 2014.

[12] S. Klebe, H. Stolze, F. Kopper *et al.*, "Gait analysis of sporadic and hereditary spastic paraplegia," *J. Neurol.*, vol. 251, no. 5, pp. 571–578, 2004.

[13] S. I. Wolf, F. Braatz, D. Metaxiotis *et al.*, "Gait analysis may help to distinguish hereditary spastic paraplegia from cerebral palsy," *Gait & Posture*, vol. 33, no. 4, pp. 556–561, 2011.

[14] A. Bonnefoy-Mazure, K. Turcot, A. Kaelin *et al.*, "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] N. Haji Ghassemi, J. Hannink, C. Martindale *et al.*, "Segmentation of Gait Sequences in Sensor-Based Movement Analysis: A Comparison of Methods in Parkinson's Disease," *Sensors*, vol. 18, no. 1, p. 145, jan 2018.

[16] C. F. Martindale, M. Strauss, H. Gassner *et al.*, "Segmentation of gait sequences using inertial sensor data in hereditary spastic paraplegia," in *Proc. EMBC*. IEEE, jul 2017, pp. 1266–1269.

[17] F. Cuzzolin, M. Sapienza, P. Esser *et al.*, "Metric learning for Parkinsonian identification from IMU gait measurements," *Gait & Posture*, vol. 54, pp. 127–132, may 2017.

[18] J. Taborri, S. Rossi, E. Palermo *et al.*, "A Novel HMM Distributed Classifier for the Detection of Gait Phases by Means of a Wearable Inertial Sensor Network," *Sensors*, vol. 14, no. 9, pp. 16 212–16 234, 2014.

[19] A. Rampp, J. Barth, S. Schülein *et al.*, "Inertial Sensor Based Stride Parameter Calculation from Gait Sequences in Geriatric Patients." *IEEE Trans. Biomed. Eng.*, vol. 62, no. 4, pp. 1089–1097, 2015.

[20] A. Peruzzi, U. Della Croce, and A. Cereatti, "Estimation of stride length in level walking using an inertial measurement unit attached to the foot: A validation of the zero velocity assumption during stance," *Journal of Biomechanics*, vol. 44, no. 10, pp. 1991–1994, jul 2011.

[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.