Validation of an IMU Gait Analysis Algorithm for Gait Monitoring in Daily Life Situations

Lin Zhou[1], Can Tunca[2], Eric Fischer[1], Clemens Markus Brahms[3], Cem Ersoy[2], Urs Granacher[3] and Bert Arnrich[1]

Abstract— **Gait is an essential function for humans, and gait patterns in daily life provide meaningful information about a person's cognitive and physical health conditions. Inertial measurement units (IMUs) have emerged as a promising tool for low-cost, unobtrusive gait analysis. However, large varieties of IMU gait analysis algorithms and the lack of consensus for their validation make it difficult for researchers to assess the reliability of the algorithms for specific use cases. In daily life, individuals adapt their gait patterns in response to changes in the environment, making it necessary for IMU gait analysis algorithms to provide accurate measurements despite these gait variations. In this paper, we reviewed common types of IMU gait analysis algorithms and appropriate analysis methods to evaluate the accuracy of gait parameters extracted from IMU measurements. We then evaluated stride lengths and stride times calculated from a comprehensive double integration based IMU gait analysis algorithm using an optoelectric walkway as gold standard. In total, 729 strides from five healthy subjects and three different walking patterns were analyzed. Correlation analyses and Bland-Altman plots showed that this method is accurate and robust against large variations in walking patterns (stride length: correlation coefficient (r) was 0.99, root mean square error (RMSE) was 3% and average limits of agreement (LoA) was 6%; stride time: r was 0.95, RMSE was 4% and average LoA was 7%), making it suitable for gait evaluation in daily life situations. Due to the small sample size, our preliminary findings should be verified in future studies.**

I. INTRODUCTION

Gait is an important indicator of a person's cognitive and physical health, and gait speed has been found to correlate with a person's health status, functional decline, and even mortality [1][2]. Clinical gait analyses are routinely conducted by medical professionals during the treatment or rehabilitation process of neurological disease patients or stroke patients [3]. Gait can be quantified using spatio-temporal parameters such as stride length, stride time, clearance, and gait speed. In a laboratory setting, multi-camera systems or instrumented walkways can assess gait parameters with high accuracy, however, the costs and efforts of setting up such systems are very high [4].

A. Gait Analysis with Inertial Measurement Units (IMUs)

The ultimate goal of rehabilitation is to regain mobility in daily life, which means that the assessment of the rehabilitation process should also be continuously carried out after the patients are discharged from the rehabilitation clinic. In order to provide personalized and pervasive healthcare, low-cost and unobtrusive methods for gait analysis is needed. Inertial measurement units (IMUs) is often used for this purpose. In fact, estimating gait parameters using IMUs has been intensively investigated over the past years, and the approaches can be summarized in three broad categories: 1) Model based approaches, where the legs are modelled as double pendulums. By combining gyroscope data and an individual's leg length, gait parameters such as stride length, swing- and stance time can be estimated [5][6]. 2) Machine learning approaches, where a set of features extracted from the sensor data is used for directly estimating gait parameters [7][8]. 3) Double integration approaches, which is based on the physical principles of acceleration and angular velocity, and applies sensor fusion methods to calculate spatio-temporal gait parameters [9][10].

B. Validating Gait Analysis Algorithms with Gold Standards

Despite their advantage of low-cost and convenience compared to traditional gold standards in gait analysis, IMU gait analysis methods have to cope with the integration drift problem that may lead to large errors of positional estimates in the integration results. Therefore, it is crucial for researchers to understand ways of evaluating the agreement of the IMU algorithms with gold standards.

The various gold standards used for evaluating IMU gait analysis algorithms can be divided into three major categories. 1) Putting artificial restrains to walking, such as limiting the subject to walk with fixed stride length, or estimating only total distance covered by the subject. These methods are simple but less robust. 2) Instrumented walkways, which offer more detailed and reliable measurements on gait parameters. Examples from this group of methods include: treadmill with pressure sensors (h/p/cosmos) [11], pressure sensitive walkway (GAITRite®) [12], and walkway with optical sensors

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[1]L. Zhou, E. Fischer, B. Arnrich are with Digital Health Center, Hasso Plattner Institute, University of Potsdam, 14482 Potsdam, Germany lin.zhou@hpi.de

[2]C. Tunca and C. Ersoy are with NETLAB, Department of Computer Engineering, Bogazici University, 34342 Istanbul, Turkey

[3]C. M. Brahms and U. Granacher are with Division of Training and Movement Sciences, University of Potsdam, 14469, Potsdam, Germany

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(OptoGait) [13]. 3) Multi-camera systems, such as Vicon [4] or Qualisys [14] systems, which also provide detailed movement parameters and are commonly used for gait assessment.

In terms of the metrics used for evaluating the accuracy of the gait parameters, stride-by-stride evaluation provides more information compared to average values. Typically, gait analysis methods are evaluated on the basis of their agreement with a gold standard on the same measurements. According to a systematic review by Zaki et al. [15], the most commonly used measures of agreement are 1) Bland-Altman plot, which is a scatter plot of the difference between two measures against the average of those two measures, and limits of agreement (LoA) at 1.96 standard deviation that reflect the agreement between the assessed methods. In the case of gait analysis, one can simply plot the measurements from the gold standard method (e.g. stride lengths from OptoGait) as the x axis - since the gold standard methods are known to be reliable. Because the LoA is determined by the standard deviation, this method is robust against outliers. 2) Correlation analysis, which can be nicely visualized using a scatter plot with measurements obtained from the two methods as x- and y axis. The regression line shows the linear relationship between the two measurements. In the case of gait analysis, ideally, all the stride lengths from IMU should be the same as the ones from the gold standard system, resulting in a regression line of $y = x + 0$ and correlation coefficient of 1. Other commonly used metrics to compare the evaluated gait parameters estimated by an algorithm and measured by the reference system include: comparing means, significance tests, intra-class correlation coefficient (ICC), mean error and standard deviations [15].

C. Aim of the Study

The aim of the study is to validate the accuracy of the gait analysis algorithm proposed by Tunca et al. [10], and evaluate its potential to be used in daily life. This algorithm provides an extensive set of gait parameters, and the authors reported high accuracy for both spatial- and temporal gait parameters compared to similar studies [16]. However, one limitation of the study is that the gait parameters were validated with a Kinect camera and a slow-motion camera, both of which lack proof of their own accuracy.

Therefore, in this study, we validated spatio-temporal gait parameters calculated from the algorithm by comparing them to a gold standard. By analyzing different stride lengths (short, normal, long) that were made intentionally by the same subject, we investigated the ability of the algorithm to account for large intraindividual variations in the gait pattern, which might occur in daily life situations.

II. METHODS

A. Experimental Setup

Physiolog®5 IMUs (Gait Up, Switzerland) were used for data collection, with sampling rate at 128 Hz. The Gait Up company also provides a comprehensive gait analysis solution (PhysiGait Lab), which has been validated and used in large number of studies [17][18]. Since we did not intend to reevaluate the Gait Up algorithm, only the raw data from the IMUs, but not the PhysiGait Lab analysis results, were used in the current study.

An OptoGait system (Microgait, Italy) was used as a reference for assessment of the spatio-temporal gait parameters [19][20]. The system consists of two 10-meter photoelectric cell bars, one for signal transmission and the other one for signal reception. Once the recording is initiated, the system detects the time and location of signal interruption - caused by subject's feet movement while walking between the bars - and outputs spatio-temporal gait parameters, such as stride length, stance- and swing times, and walking speed. The optical sensors have a sampling rate of 1000 Hz and spatial resolution of 1.041 cm [13].

Five young, healthy subjects were recruited for the experiments. In each experimental session, two IMUs were fixed on the top of the left- and right shoes of the subject. Upon receiving detailed instructions about the procedure, subjects walked between the OptoGait bars six times for a total distance of 60 m and stopped outside of the OptoGait area. Each subject was asked to perform three walking sessions in total: 1) short strides, without the feet overlapping in the anteroposterior direction during double-support phase, as this might cause problems for the OptoGait foot detection mechanism, 2) normal strides, 3) long strides, but still with double-support (not running). Apart from the above mentioned restrictions, subjects were allowed to walk with their own preferred patterns. This protocol helps to create more variations of gait patterns, thus simulating possible strides in daily life. Whenever applicable, the study design was in line with the guidelines for clinical applications of spatio-temporal gait analysis [21]. The study was approved by the ethics committee of the University of Potsdam and all experiments were conducted according to the latest revision of the declaration of Helsinki. Fig. 1 shows the experimental setup.

B. Data Analysis

IMU data was analyzed using a gait analysis algorithm based on the study by Tunca, et al. [10]. In short, the method takes raw acceleration and gyroscope data as input, identifies stance phases using zero-velocity update, and employs an error-state Kalman filter to estimate the 3D positions over time of the feet for each stride. Foot orientation was determined by a particle filter, thus the turning steps made by the subject outside the OptoGait area

Fig. 1: Experimental Setup. Left: the 10-meter OptoGait walkway. Right: the IMUs were fixed on top of the shoes.

could be recognized and excluded from our analysis. A set of spatio-temporal gait parameters such as stride length, stride time, clearance and stance /swing ratio could be obtained for each stride. By aggregating individual stride data, it also is possible to obtain information about average values, variations, and left-right asymmetries.

In this study, we compared the stride lengths as well as the stride times calculated from the gait analysis algorithm with those measured by the OptoGait system using correlation analysis and Bland-Altman plots. The validation of swing times, instead of stride times, was reported in the original study of the gait analysis algorithm [10]. However, for the OptoGait system, the optical centre of the sensors are elevated to 3 mm above the lower edge of the bars (i.e. ground level), this causes the system to detect ground contact slightly earlier than the actual time (when the foot hits the ground), and foot-off later than the actual time, thus resulting in a shorter swing phase and longer stance phase. Therefore, the gait cycle time (sum of stance- and swing phase) will be a more reliable parameter for validation. The strides calculated from the gait analysis algorithm and those detected by the OptoGait system were matched using the timestamps of ground contact recorded from the IMUs and the OptoGait system. The first and last strides made at the ends of the OptoGait walkway were discarded, since some of these strides were only partially inside the OptoGait walkway, and the gait parameters (e.g. stride length, stride time) were incomplete.

III. RESULTS

In total, 729 strides were used in this study to validate the stride lengths and stride times estimated from the IMU algorithm. Table I summarizes correlation as well as agreement between the two measurements.

Fig. 2 shows the validation for stride lengths. Linear regression indicated high correlation between the stride lengths from IMU algorithm and from the OptoGait measurement. The correlation coefficient was 0.99, and the regression line was $y = x - 0.05$, with root mean square error (RMSE) of 0.05 m (3%). The average limits of agreement (LoA) from Blant-Altman plot was 0.09 m (6%). The results highly agree with the original study of the algorithm, where the authors reported r^2 of 0.98, the regression line at $y = 0.97x + 0.02$, with RMSE of 0.05 m, and the LoA was 0.09 m [10]. Since the algorithm relies on a fixed sampling rate, the bias of 0.05 m in our analysis could be the result of a small error in the real sampling rate of the IMUs. Once the exact error is identified and corrected, the stride length calculations could be improved. It is worth noting that the original study only included strides with lengths less than 1.5 m, but not the large strides (mostly 1.5 m to 2 m) analyzed in this study. In our analysis, the larger errors of the long strides reduced the accuracy of the overall stride length estimations. The fact that the overall accuracy of stride length estimations from our analysis matched those of similar studies, despite larger variations in stride characteristics, indicates the robustness of the algorithm for real-life scenarios.

Fig. 3 shows the validation for stride times. The correlation analysis and the Blant-Altman plot also showed high accuracy of the selected temporal parameter, with a correlation coefficient of 0.95, the regression line of $y = x + 0.01$, RMSE of 0.04 s (4%), and the LoA of 0.08 s (7%). The stride time is larger than swing time, resulting in larger error values for the same measurement accuracy. Therefore, the results here for stride time were also consistent with those for swing time reported in the original study, where the r^2 was 0.95, the regression line was $y = x + 0$, RMSE was 0.02 s, and the LoA was 0.04 s. Similar to the results for stride lengths above, the errors from the stride times were larger for big strides, and the overall accuracy for the gait analysis algorithm was comparable to similar studies, indicating that the algorithm is robust for daily life gait measurements.

Overall, the results from our study are also comparable to similar IMU gait analysis algorithms. Since studies measured different populations and gait paramters, and various metrics could be used for evaluation of the gait parameters, one-to-one comparisons between studies are not always possible. As examples of comparable results for young healthy subjects, Yeo et al. reported average LoA of 0.08 m for stride length and 0.08 s for stride time [16], and Hori et al. reported correlation coefficient of 0.98 for stride length and 0.99 for stride time [22].

IV. CONCLUSIONS

In this study, we validated a double-integration based algorithm proposed by Tunca et al. [10] and showed that the spatio-temporal gait parameters estimated by the algorithm have high accuracy compared to a gold standard dedicated to measuring spatio-temporal gait parameters. In contrast to the great majority of gait analysis studies where subjects were asked to just walk normally, the current study

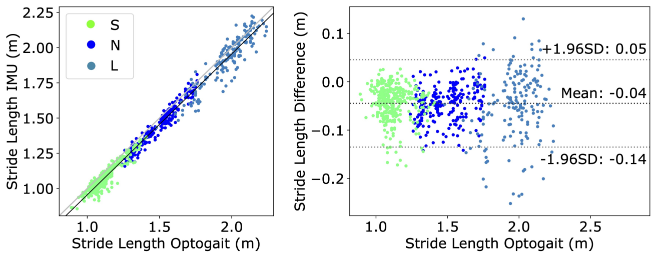

Fig. 2: Validation of stride lengths by comparing values from IMU and OptoGait. Left: Correlation plot, Right: Bland-Altman plot. S: short strides, N: normal strides, L: long strides

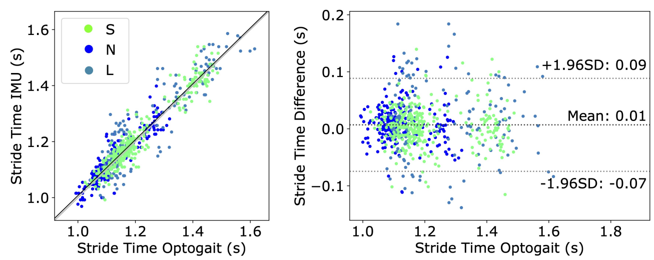

Fig. 3: Validation of stride times by comparing values from IMU and OptoGait. Left: Correlation plot, Right: Bland-Altman plot. S: short strides, N: normal strides, L: long strides

explored possible variations of walking patterns by asking the same healthy subjects to walk with short-, normal-, and long strides. It is worth emphasizing that the long strides showed larger deviations from the OptoGait measurements for both stride length and stride time compared to other strides. Nevertheless, our analysis demonstrated that the current algorithm is capable of estimating spatio-temporal gait parameters with high accuracy comparable to similar studies which only evaluated short- and normal strides. Therefore, the evaluated IMU gait analysis algorithm is robust against intraindividual gait variations and is suitable for gait monitoring in daily life situations. Due to the rather smal sample size of this study, we interpret our findings as preliminary and suggest that they should be verified in future studies.

TABLE I: Comparison of spatio-temporal gait parameters calculated from the IMU gait analysis algorithm and measured with the OptoGait system.

Gait Parameters	Stride Length (m)	Stride Time (s)
Num. of Strides	729	729
r	0.99	0.95
Slope	1.00	1.00
Intercept	-0.05	0.01
RMSE	0.05 (3%)	0.04 (4%)
LoA	0.09 (6%)	0.08 (7%)

r: correlation coefficient, RMSE: root mean square error, LoA: average limits of agreement.

References

[1] Richard D. Sanders and Paulette Marie Gillig. Gait and its assessment in psychiatry. *Psychiatry (Edgemont)*, 7(7):38–43, 2010.

[2] Stephanie Studenski, Subashan Perera, Kushang Patel, Caterina Rosano, Kimberly Faulkner, Marco Inzitari, Jennifer Brach, Julie Chandler, Peggy Cawthon, Elizabeth Barrett Connor, Michael Nevitt, Marjolein Visser, Stephen Kritchevsky, Stefania Badinelli, Tamara Harris, Anne B. Newman, Jane Cauley, Luigi Ferrucci, and Jack Guralnik. Gait speed and survival in older adults. *JAMA - Journal of the American Medical Association*, 305(1):50–58, 2011.

[3] Jacquelin Perry. *Gait Analysis: Normal and Pathological Function*. SLACK Incorporated, 1992.

[4] Vicon 3d motion capture system. https://www.vicon.com/. Accessed: 2020-05-06.

[5] K. Aminian, B. Najafi, C. Büla, P. F. Leyvraz, and Ph Robert. Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes. *Journal of Biomechanics*, 35(5):689–699, 2002.

[6] E. Allseits, V. Agrawal, J. Lučarević, R. Gailey, I. Gaunaurd, and C. Bennett. A practical step length algorithm using lower limb angular velocities. *Journal of Biomechanics*, 66:137–144, 2018.

[7] Julius Hannink, Thomas Kautz, Cristian F. Pasluosta, Jens Barth, Samuel Schulein, Karl Gunter Gabmann, Jochen Klucken, and Bjoern M. Eskofier. Mobile Stride Length Estimation with Deep Convolutional Neural Networks. *IEEE Journal of Biomedical and Health Informatics*, 22(2):354–362, 2018.

[8] Huanghe Zhang, Yi Guo, and Damiano Zanotto. Accurate Ambulatory Gait Analysis in Walking and Running Using Machine Learning Models. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 28(1):191–202, 2020.

[9] Alberto Ferrari, Pieter Ginis, Michael Hardegger, Filippo Casamassima, Laura Rocchi, and Lorenzo Chiari. A mobile Kalman-filter based solution for the real-time estimation of spatio-temporal gait parameters. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 24(7):764–773, 2016.

[10] Can Tunca, Nezihe Pehlivan, Nağme Ak, Bert Arnrich, Gülüstü Salur, and Cem Ersoy. Inertial sensor-based robust gait analysis in non-hospital settings for neurological disorders. *Sensors (Switzerland)*, 17(4):1–29, 2017.

[11] h/p/cosmos kernel description. https://www.hpcosmos.com/en. Accessed: 2020-05-06.

[12] GAITRite pressure sensitive walkway. https://www.gaitrite.com/. Accessed: 2020-05-06.

[13] OptoGait walkway with optic sensors. https://www.optogait.com/. Accessed: 2020-05-06.

[14] Qualisys 3d motion capture system. https://www.qualisys.com/. Accessed: 2020-05-06.

[15] Rafdzah Zaki, Awang Bulgiba, Roshidi Ismail, and Noor Azina Ismail. Statistical methods used to test for agreement of medical instruments measuring continuous variables in method comparison studies: A systematic review. *PLoS ONE*, 7(5):1–7, 2012.

[16] Sang Seok Yeo and Ga Young Park. Accuracy Verification of Spatio-Temporal and Kinematic Parameters for Gait Using Inertial Measurement Unit System. *Sensors (Switzerland)*, 20(1343), 2020.

[17] Benoit Mariani, Constanze Hoskovec, Stephane Rochat, Christophe Büla, Julien Penders, and Kamiar Aminian. 3D gait assessment in young and elderly subjects using foot-worn inertial sensors. *Journal of Biomechanics*, 43(15):2999–3006, 2010.

[18] Farzin Dadashi, Benoit Mariani, Stephane Rochat, Christophe J. Büla, Brigitte Santos-Eggimann, and Kamiar Aminian. Gait and foot clearance parameters obtained using shoe-worn inertial sensors in a large-population sample of older adults. *Sensors (Switzerland)*, 14(1):443–457, 2013.

[19] Karin Lienhard, David Schneider, and Nicola A. Maffiuletti. Validity of the Optogait photoelectric system for the assessment of spatiotemporal gait parameters. *Medical Engineering and Physics*, 35(4):500–504, 2013.

[20] Myung Mo Lee, Chang Ho Song, Kyoung Jin Lee, Sang Woo Jung, Doo Chul Shin, and Seung Ho Shin. Concurrent validity and test-retest reliability of the OptoGait photoelectric cell system for the assessment of spatio-temporal parameters of the gait of young adults. *Journal of Physical Therapy Science*, 26(1):81–85, 2014.

[21] Reto W Kressig, Olivier Beauchet, et al. Guidelines for clinical applications of spatio-temporal gait analysis in older adults. *Aging clinical and experimental research*, 18(2):174–176, 2006.

[22] Koyu Hori, Yufeng Mao, Yumi Ono, Hiroki Ora, Yuki Hirobe, Hiroyuki Sawada, Akira Inaba, Satoshi Orimo, and Yoshihiro Miyake. Inertial Measurement Unit-Based Estimation of Foot Trajectory for Clinical Gait Analysis. *Frontiers in Physiology*, 10:1–12, 2020.