An Optimal Procedure for Stride Length Estimation Using Foot-Mounted Magneto-Inertial Measurement Units

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***Abstract*— Stride length is often used to quantitatively evaluate human locomotion performance. Stride by stride estimation can be conveniently obtained from the signals recorded using miniaturized inertial sensors attached to the feet and appropriate algorithms for data fusion and integration. To reduce the detrimental drift effect, different algorithmic solutions can be implemented. However, the overall method accuracy is supposed to depend on the optimal selection of the parameters which are required to be set. This study aimed at evaluating the influence of the main parameters involved in well-established methods for stride length estimation. An optimization process was conducted to improve methods' performance and preferable values for the considered parameters according to different walking speed ranges are suggested. A parametric solution is also proposed to target the methods on specific subjects' gait characteristics. The stride length estimates were obtained from straight walking trials of five healthy volunteers and were compared with those obtained from a stereo-photogrammetric system. After parameters tuning, percentage errors for stride length were 1.9%, 2.5% and 2.6% for comfortable, slow, and fast walking conditions, respectively.**

Keywords—gait analysis, inertial sensor, optimal parameters, stride length.

I. Introduction

Locomotion patterns and gait spatio-temporal parameters provide valuable information to investigate mobility, describe the severity of gait impairments, monitor the progression of neurodegenerative diseases and target rehabilitation programs [1-5]. An objective and reliable gait characterization during daily-life activities can be obtained by using wearable sensors. Gait spatio-temporal parameters can be conveniently estimated in free-living conditions using magneto-inertial measurement units (MIMUs) [6]. These sensors allow to acquire 3D accelerations, angular velocities, local magnetic field signals and 3D orientation of the body segment to which they are attached [7]. Various MIMU locations have been tested and it has been observed that the foot allows for the most accurate estimation of spatial parameters [8].

A key outcome of gait performance is the stride length (SL), as it allows to derive other variables such as gait speed and dynamic base of support [9-12]. Several solutions for the SL estimation can be found in the literature and the most accurate are generally based on the double integration of the acceleration between two consecutive ground contacts of the same foot, after the gravity removal [9] [13]. Only few methods [14-15] have been implemented to reduce the integration drift due to noise and gyroscope bias, typical of MIMU recordings. However, the optimization of the parameters involved is often overlooked. Since each subject is characterized by a personal way of walking, it would be appropriate to customize the algorithms for the estimation of the gait parameters. The aim of this work was to optimize the performance of the implemented methods for the SL estimation and to analyze the influence of the parameters involved. SLs obtained from data acquired during straight walking of five healthy subjects were analyzed. Results were validated with respect to the concurrent stereo-photogrammetric (SP) data, used as gold standard.

II. Material and Methods

A. Experimental Setup

The experimental setup (Fig. 1) consisted of two MIMUs (mod. MITCH, 221e S.r.l., Italy) [16] fixed on the instep of each shoe. Data from a 3D accelerometer (range ±16 g), a 3D gyroscope (range ±2000 dps), and a 3D magnetometer (range ±50 Gauss) were sampled at 100 Hz and stored onboard the MIMU. The communication between the laptop and the MIMUs was based on the Bluetooth low energy technology.

Fig. 1. Experimental setup: a retro-reflective marker is attached on the MIMU which is fixed to shoelaces of each foot.

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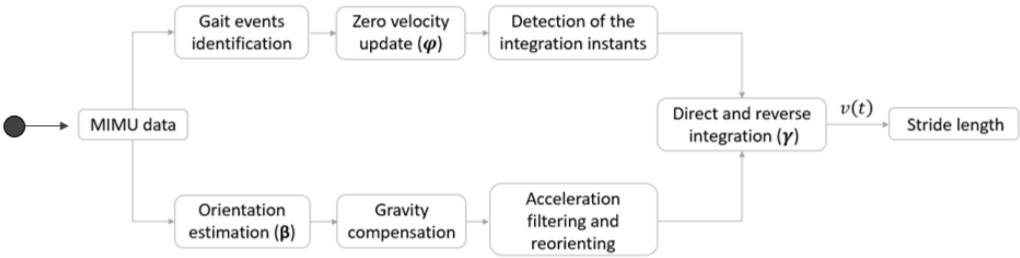

Fig. 2. Methods implemented for the stride length estimation and relevant parameters to optimize. v(t) is the velocity.

Five healthy subjects (3 females, age: 29.2 ± 7.6 y.o., body mass: 59.2 ± 9.0 kg, height: 1.72 ± 0.09 m) were asked to walk twice along a 5m-straight path at three different self-selected speeds (comfortable, slow, and fast). The trajectories of two retro-reflective markers attached to both MIMUs were recorded by a 12-camera SP system (mod. Vero, Vicon, Oxford, UK), synchronized with the MIMUs. The Declaration of Helsinki was fulfilled during the experimental sessions.

B. Data Analysis

The algorithm for the SL estimation is divided into the following steps [13-15]:

1. Identification of gait events: the initial and final contacts with the ground are estimated with the methods proposed by Salarian et al. [17] and Trojaniello et al. [9], adapted to foot-positioning.

2. Identification of the integration intervals: the SL estimation is based on the double integration over time of the acceleration components and the consequent integration drift is reduced by applying the hypothesis of zero-velocity at each integrating instant [8]. In this study, the beginning (and end) of the stride cycle is searched in the mid-stance during the flat-foot phase. To identify the flat-foot phase, a zero-velocity update (ZUPT) detector based on the gyroscope signal is implemented [14]. Briefly, the detector determines whether the MIMU is stationary or moving by comparing a function T of angular velocity with a threshold φ. The zero-velocity hypothesis is applicable if the function T in (1) is lower than φ.

$$T = \frac{\sum_j \|\omega_j\|^2}{N} \leq \varphi \tag{1}$$

   where $\|\omega_j\|$ is the norm of the angular velocity at the j-th instant, N the window size and φ the threshold value. Skog et al. [14] reported that N does not significantly affect the detector performance, but φ does. The ZUPT threshold φ is the first parameter analyzed in this study.

3. Orientation estimation and gravity subtraction: to subtract the gravity from raw accelerations, the 3D foot orientation must be available. An implemented complementary filter based on the sensor fusion algorithm proposed by Madgwick [18] was used to this purpose. This filter enables the tuning of a single parameter (β), which establishes how the accelerometer and the magnetometer data are weighted with respect to the gyroscope ones. The studies from Caruso et al. highlight the importance of properly tuning the parameter(s) of each sensor fusion filter to obtain reliable orientation estimates [19-21]. For this reason, β is the second parameter to optimize.

4. Re-orientation along the direction of progression: since the SL is defined as the displacement in the anteroposterior direction during a gait cycle, the coordinate system at every stride is rotated from the sensor system to the anatomical (anteroposterior-mediolateral-vertical) system. For each stride, the angle that maximizes the mean anteroposterior linear velocity is selected to identify the direction of progression and the filtered acceleration is projected on it [15].

5. Direct and reverse integration: once the stride direction and the integration interval are determined, a double integration of gravity-free linear accelerations can be performed. To reduce the integration drift due to noise and residual gravity, the velocity is estimated with the direct and reverse integration method (DRI) [15]. The DRI consists of weighting the direct integration and the reverse in time integration with respect to a weighting function *w(t)*. In this study *w(t)* is normalized between 0 and 1 and has a sigmoid shape:

$$w(t) = \operatorname{atan}\left(\frac{2t-L}{2\gamma L}\right) \tag{2}$$

   where L is the length of the integration interval and γ establishes the curve steepness. The latter is the third parameter to optimize.

6. Displacement estimation: the SL is obtained by integrating the velocity between two consecutive mid-stance instants.

Fig. 2 summarizes the methods and highlights the parameters involved in the optimization process.

C. Optimization Process

The parameters that mostly affect the SL estimation are the ZUPT threshold (φ), the orientation parameter (β) and the DRI parameter (γ). The SL estimates differences with respect to SP data of the five enrolled subjects were averaged to investigate the influence of the three parameters on the SL estimation according to different gait velocities. Considering healthy subjects, results from right and left foot were combined because they did not lead to different performances or asymmetries.

With different subjects and walking speeds, the *T* function in (1) has different patterns and value ranges. The small feet movements during stance, the signal noise and the possible gyroscope bias may cause non-null *T* values during stance [8]. The main drawback associated to the use of a fixed low ZUPT threshold is to miss some flat-foot phases and thus merge two strides together and/or to miss some strides. Conversely, a high ZUPT threshold could lead to identify some false positive flat-foot phases. A fine-tuning of this parameter has been performed to investigate the influence of the SL estimation on it. A first investigation within the interval from 0 $(rad/s)^2$ to 1 $(rad/s)^2$ is performed to establish whether a single fixed value can be suitable for all gait speeds. The aim of this first step was to select a φ value that allows to correctly detect ZUPT intervals in all the analyzed trials.

Although, given the high variability of *T* function values among subjects and walking speeds, it may be preferable to avoid the use of a fixed threshold derived from heuristic observations. Therefore, a parametric ZUPT detector based on gyroscope energy is proposed. The basic idea is to look for the stance portions with the lowest mean *T* value to define quasi-ZUPT intervals. Since the foot-flat phase has very low probability to happen in the first or last 10% of the stance phase, these stance portions are discarded. Within the remaining part of each stance phase, the moving average of the *T* function is carried out and a sliding window searches for the interval corresponding to the lowest mean *T* function value. This interval becomes the quasi-ZUPT interval. The length of the sliding window is set to 30% of the entire stance phase and the integration interval is defined by the last instant of the detected quasi-ZUPT intervals.

The influence of the orientation parameter β on the SL estimation is investigated by varying its value from 0 rad/s to 1 rad/s with an increment of 0.01 rad/s (Fig. 3). Afterwards, a limited range from 0 rad/s to 0.2 rad/s with an increment of 0.01 rad/s is further investigated in depth (Fig. 4). To give more weight to the most reliable data in the orientation estimation we investigated the option to adopt two different values of β during motion: *i)* $\beta_{statics}$ when the foot is in flat-foot intervals and *ii)* $\beta_{dynamics}$ during the remaining of the gait cycle. The former is expected to be higher than the latter, since the angular velocity is almost zero during flat-foot phase and, thus, the information coming from the accelerometer and the magnetometer should be more weighted. It was also conducted an optimization process to evaluate the most suitable values for $\beta_{statics}$ and $\beta_{dynamics}$ in gait applications (Fig. 4). Lastly, a further restricted range of $\beta_{dynamics}$ between 0 rad/s and 0.01 rad/s is explored, while $\beta_{statics}$ is fixed to the value corresponding to the lowest errors.

The influence of DRI parameter γ is investigated studying the stride errors obtained according to γ values from 0 to 10 with an increment of 0.1 (Fig. 5). Fig. 6 shows how the steepness of sigmoid weighting function w(t) changes according to different γ values. The zero value is discarded to avoid discontinuities.

III. Results

A total 136 strides have been analyzed: 46, 57, and 33 strides for comfortable, slow, and fast walking speed, respectively. SL errors are calculated as the differences between those estimated with the implemented methods and those obtained from the SP data. The SL errors were grouped by walking speed and averaged over subjects.

Investigating the ZUPT threshold φ range from 0 $(rad/s)^2$ to 1 $(rad/s)^2$ and averaging the SL errors among all the trials with the same gait speed, the maximum mean percentage error was 13.8% with φ equal to 1 $(rad/s)^2$. Furthermore, it was observed that higher speeds required a higher minimum φ value necessary to correctly detect ZUPT intervals. A fixed threshold value of at least 0.5 $(rad/s)^2$ is necessary to enable the detection of all the strides at different paces. Table I shows the results obtained with a fixed ZUPT threshold value set to 0.5 $(rad/s)^2$. The SL errors obtained with the proposed parametric method are also illustrated in Table I.

Results reported in Fig. 3 show that approximately zero β values provide lower SL errors among all walking speeds. The mean percentage error range, varying β from 0 rad/s to 1 rad/s, was 1.8% – 14%. In Fig. 4 the SL errors according to different combinations of $\beta_{statics}$ and $\beta_{dynamics}$ are illustrated. Considering the same $\beta_{dynamics}$, slightly lower SL errors were obtained with $\beta_{statics}$ equal to 0.2 rad/s (e.g., up to 6 mm lower than adopting $\beta_{statics}$ equal to 0 rad/s). Maintaining a constant $\beta_{statics}$ (0.2 rad/s) and zooming in $\beta_{dynamics}$ (between 0 rad/s and 0.01 rad/s), the maximum difference in the mean percentage SL errors is 0.1% for all walking speed conditions.

As resulting from Fig. 5, γ is the least influent parameter.

TABLE I. STRIDE LENGTH ERRORS ACCORDING TO DIFFERENT WALKING SPEED CONDITIONS AND ZUPT DETECTORS.

		ZUPT detector with fixed threshold		**Parametric ZUPT detector**	
Walking speed condition	***Speed range (m/s)***	***Mean ± standard deviation SL error (m)***	***Mean percentage SL error (%)***	***Mean ± standard deviation SL error (m)***	***Mean percentage SL error (%)***
Comfortable	1.11 – 1.19	-0.037 ± 0.080	3.8	-0.003 ± 0.014	1.9
Slow	0.64 – 1.12	0.004 ± 0.023	3.1	0.006 ± 0.010	2.5
Fast	1.41 – 2.13	-0.027 ± 0.062	2.6	-0.015 ± 0.040	2.6

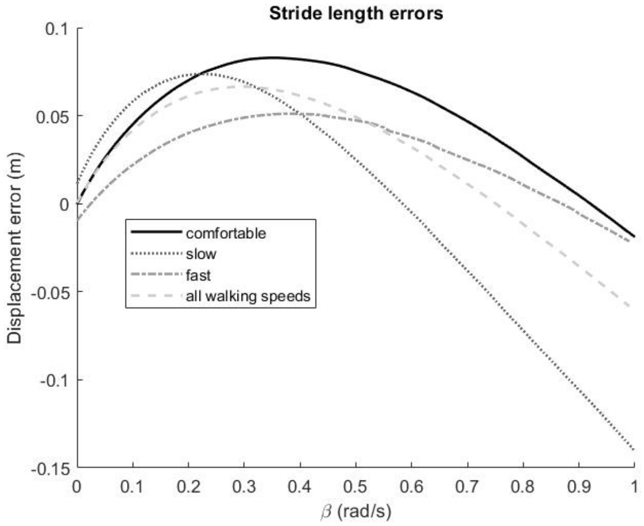

Fig. 3. Stride length errors according to β values from 0 to 1 rad/s at different walking speed conditions.

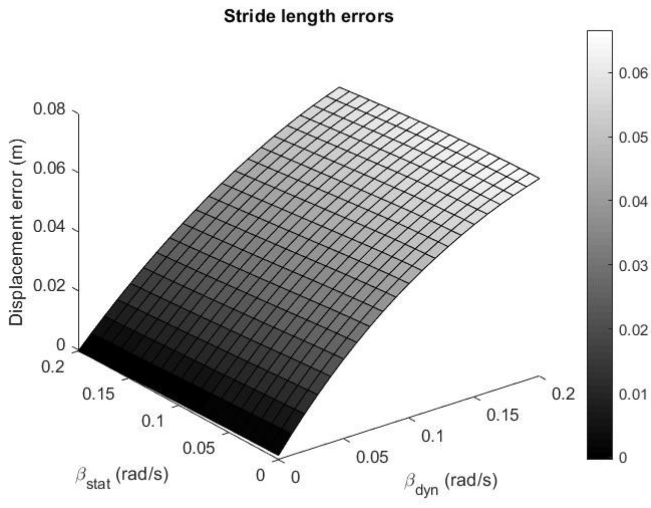

Fig. 4. Stride length errors according to the combinations of $\beta_{statics}$ (β_{stat}) and $\beta_{dynamics}$ (β_{dyn}). The reported errors are the mean values over all the trials.

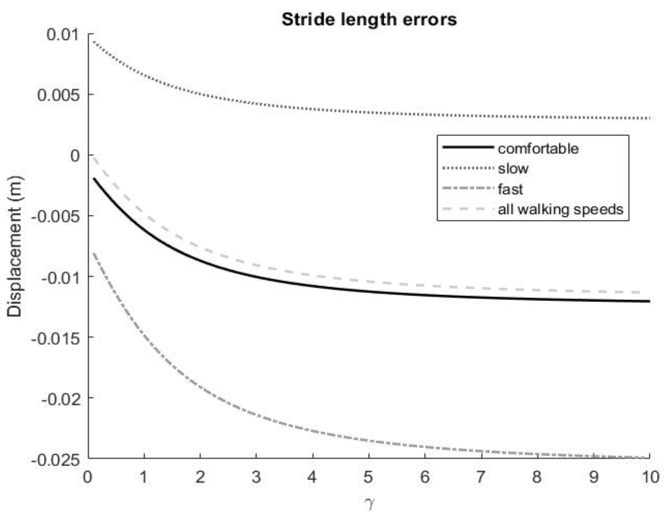

Fig. 5. Stride length errors according to different DRI parameter values.

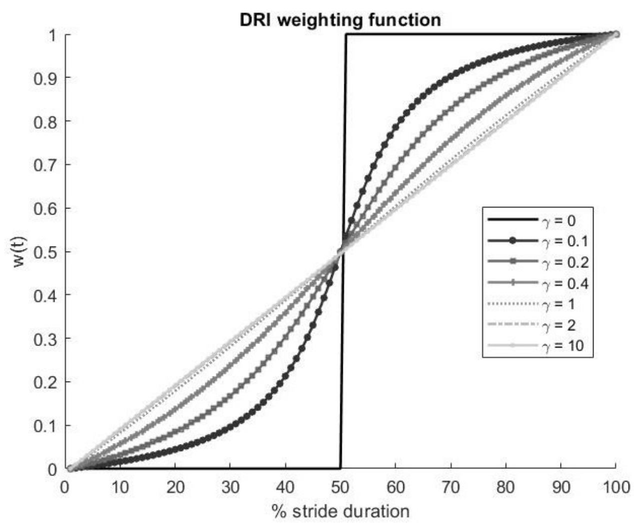

Fig. 6. Direct and reverse integration (DRI) weighting function w(t) according to different γ values. For γ equal to 0, w(t) is a step function. As γ value increases, the sigmoid becomes a line. w(t) with γ = 2 and γ = 10 are almost overlapped.

IV. Discussion and Conclusions

The study investigated the sensitivity parameters and provided a strategy for the optimization of the most relevant parameters involved in the algorithms for SL estimation using foot-mounted MIMUs [13-15] [18]. This work highlighted the importance of the customization of the SL estimation algorithms to ensure highly accurate results in the gait evaluation of different subjects and walking speed conditions. A proper setting of the involved parameters guaranteed percentage errors in the SL estimation ranging from 1.9% – 2.6% across different gait speeds (Table I). These errors are comparable with or slightly better than the results of previous studies that estimated the SL using ankle or foot-mounted MIMUs [8] [22-23].

Among the three parameters analyzed (ZUPT threshold φ, orientation parameter β and DRI parameter γ), the most significant for the SL estimation were φ and β. Especially at slower speeds (0.64 m/s – 1.12 m/s), choosing parameters not adequate for the specific subject's gait could increase the SL mean error by almost 14%. This occurred either with a ZUPT threshold set to 1 $(rad/s)^2$ or with β set to 1 rad/s.

Furthermore, the ZUPT threshold also affected the stride identification since the integration instants were selected within the ZUPT intervals to apply the hypothesis of zero-velocity as integration boundary condition. The risk of using a fixed threshold is to include part of the motion in the ZUPT interval, especially at lower walking speeds. As expected, the use of a ZUPT threshold of 0.5 $(rad/s)^2$, to ensure a correct ZUPT intervals detection regardless of walking speed, led to a higher performance at fast speed with respect to slow and comfortable trials (Table I). The proposed parametric solution showed a higher accuracy for slow and comfortable walking speeds and comparable performance for fast speed (Table I).

The orientation parameter β was also found to be notably influent. However, studying the combination of $\beta_{statics}$ and $\beta_{dynamics}$, it was evident that $\beta_{statics}$ did not affect the SL estimation considerably (Fig. 3). Further investigation of the range between 0 rad/s and 0.01 rad/s suggested that the choice of $\beta_{dynamics}$ within this limited interval was not crucial for any of the three walking conditions. There is not much advantage in introducing two different values of β (one for the flat-foot phases and one for the rest of the gait cycle) since an error in the detection of ZUPT intervals could lead to incorrect orientation estimation and gravity removal. Therefore, a single low β value (0 rad/s – 0.01 rad/s) is recommended. Furthermore, if the gyroscope is reliable, as in this study (Fig. 3), then β can be set to 0 rad/s, otherwise the use of data from the accelerometer and the magnetometer is recommended for improving the estimate reliability.

Conversely, the DRI parameter γ did not appreciably affect the SL estimations (Fig. 5). In this study, γ was set to 0.4, as a trade-off between the errors obtained in slow and fast trials.

Hence, the crucial sources of errors may be:

- the incorrect definition of the integration interval, due to the erroneous identification of ZUPT intervals, which leads to merge two strides or to split a stride;
- the incorrect amount of gravity subtraction due to erroneous orientation estimation.

In conclusion, we suggest adopting a single β value between 0 rad/s and 0.01 rad/s, according to gyroscope reliability. As for the ZUPT detector, there is not a unique φ value that ensures optimal performance in the SL estimation for comfortable, slow, and fast walking speeds. So, the ZUPT detector based on a fixed threshold is not always reliable, especially if the gait speed range is not known a priori or if it is variable (e.g., free-living conditions). Hence, the proposed parametric ZUPT detector is preferable to target the methods on the subject's way of walking (Table I) and to avoid a threshold's fine-tuning.

Future work should primarily focus on a similar optimization process *i)* enrolling a higher number of healthy subjects, including older adults and elderly, and *ii)* considering more complex walking tasks (i.e., paths with turns and/or steps) and outdoor acquisitions. Also, pathological gaits will be investigated assuming that the influence of the parameters' setting in estimating SL is expected to be more relevant.

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References

[1] S.R. Simon, ''Quantifcation of human motion: gait analysis—benefts and limitations to its application to clinical problems,'' J Biomech. 2004;37(12):1869–80, doi: 10.1016/j.jbiomech.2004.02.047.

[2] F. Horak, L. King, M. Mancini, ''Role of body-worn movement monitor technology for balance and gait rehabilitation recent advances in body-worn sensors,'' Phys Ther. 2015;95:461–70, doi: 10.2522/ptj.20140253.

[3] A.K. Rao, L. Quinn, K.S Marder, ''Reliability of spatiotemporal gait outcome measures in Huntington's disease,'' Mov Disord 2005, 20:1033–1037.

[4] C.K. Balasubramanian, R.R Neptune, S. Kautz, ''Variability in spatiotemporal step characteristics and its relationship to walking performance post-stroke,'' Gait & Posture, April 2009, 29:408–414, doi: 10.1016/j.gaitpost.2008.10.061.

[5] O. Bello, J.A. Sánchez, C. Vazquez-Santos, M. Fernandez-Del-Olmo, ''Spatiotemporal parameters of gait during treadmill and overground walking in Parkinson's disease,'' J Parkinson's Dis, 2014;4(1):33-6, doi: 10.3233/JPD-130251.

[6] A. Cereatti, D. Trojaniello, U. della Croce, ''Accurately measuring human movement using magneto-inertial sensors: techniques and challenges,'' IEEE International Symposium on Inertial Sensors and Systems (ISISS), 2015.

[7] A. M. Sabatini, ''Estimating three-dimensional orientation of human body parts by inertial/magnetic sensing,'' Sensors, vol. 11, no. 2, pp. 1489–1525, Jan. 2011, doi: 10.3390/s110201489.

[8] A. Peruzzi, U. Della Croce, A. Cereatti, ''Estimation of stride length in level walking using inertial measurement unit attached to the foot: A validation of the zero velocity assumption,'' Journal of Biomechanics, 44:1991-1994, 2011.

[9] D. Trojaniello, A. Cereatti, E. Pelosin, L. Avanzino, A. Mirelman, J. M. Hausdorff et al., ''Estimation of step-by-step spatiotemporal parameters of normal and impaired gait using shank-mounted magneto-inertial sensors: Application to elderly, hemiparetic, parkinsonian and choreic gait,'' Journal of NueroEngineering and Rehabilitation, 11(1):152, 2014, doi: 10.1186/1743-0003-11-152.

[10] U. Della Croce, A. Cereatti, M. Mancini, ''Gait parameters estimated using inertial measurement units.'' In: Müller B, Wolf SI, Brueggemann G-P, Deng Z, McIntosh A, Miller F, et al., editors. Handbook of human motion. Cham: Springer International Publishing; 2017. p. 1–21, doi:10.1007/978-3-319-30808-1_163-1.

[11] M. Bertoli, A. Cereatti, D. Trojaniello, L. Avanzino, A. Pelosin et al., ''Estimation of spatio-temporal parameters of gait from magneto-inertial measurement units: multicenter validation among Parkinson, mildly cognitively impaired and healthy older adults,'' Biomedical Engineering Online, 17(1), 58, 2018.

[12] R. Rossanigo, S. Bertuletti, M. Caruso, M. Knaflitz, U. Della Croce, A. Cereatti, ''Estimation of the base of support during gait with an unobtrusive wearable system,'' Proceedings of Seventh National Congress of Bioengineering, Trieste, Italy, 2020, in press.

[13] B. Mariani, C. Hoskovec, S. Rochat, C. Büla, J. Penders, K. Aminian, ''3D gait assessment in young and elderly subjects using foot-worn inertial sensors'', Journal of Biomechanics, 43(15):2999–3006, 2010.

[14] I. Skog, P. Händel, I. Skog, P. H. Andel, ''Zero-Velocity Detection — An Algorithm Evaluation,'' IEEE Transactions on Biomedical Engineering, 2010.

[15] M. Zok, C. Mazzà, U. Della Croce, ''Total body centre of mass displacement estimated using ground reactions during transitory motor tasks: Application to step ascent,'' Medical Engineering and Physics, 26(9 SPEC.ISS.):791–8, 2014.

[16] Multi Sensor Inertial Chameleon – Descriptions and Specifications, https://www.221e.com/wp-content/themes/221e-theme/pdf/products_overview.pdf.

[17] A. Salarian, H. Russmann, FJG. Vingerhoets, C. Dehollain, Y. Blanc, PR. Burkhard, et al., ''Gait assessment in Parkinson's disease: Toward an ambulatory system for long-term monitoring'', IEEE Transactions on Biomedical Engineering, 51(8):1434–43, 2004.

[18] S.O. Madgwick, A.J. Harrison, A. Vaidyanathan, ''Estimation of IMU and MARG orientation using a gradient descent algorithm,'' IEEE Int Conf Rehabil Robot. 2011;2011:5975346. doi: 10.1109/ICORR.2011.5975346.

[19] M. Caruso, A. M. Sabatini, M. Knaflitz, M. Gazzoni, U. Della Croce, and A. Cereatti, "Accuracy of the orientation estimate obtained using four sensor fusion filters applied to recordings of magneto-inertial sensors moving at three rotation rates," Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS, pp. 2053–2058, 2019, doi: 10.1109/EMBC.2019.8857655.

[20] M. Caruso, A. M. Sabatini, M. Knaflitz, M. Gazzoni, U. Della Croce, and A. Cereatti, "Orientation estimation through magneto-inertial sensor fusion: A heuristic approach for suboptimal parameters tuning," IEEE Sens. J., vol. 21, no. 3, pp. 1–1, 2020, doi: 10.1109/jsen.2020.3024806.

[21] M. Caruso, A.M. Sabatini, D. Laidig, T. Seel, M. Knaflitz, U. Della Croce, A. Cereatti, ''Analysis of the accuracy of ten algorithms for orientation estimation using inertial and magnetic sensing under optimal conditions: One size does not fit all,'' Sensors. 2021; 21(7):2543, doi: 10.3390/s21072543.

[22] W. Teufl, M. Lorenz, M. Miezal, B. Taetz, M. Fröhlich, G. Bleser, ''Towards inertial sensor based mobile gait analysis: Event-detection and spatio-temporal parameters,'' Sensors (Basel). 2018;19(1):38, doi:10.3390/s19010038.

[23] L. Donath, O. Faude, E. Lichtenstein, C. Nüesch, A. Mündermann, ''Validity and reliability of a portable gait analysis system for measuring spatiotemporal gait characteristics: Comparison to an instrumented treadmill'', J. Neuroeng. Rehabil. 2016, 13, 6, doi:10.1186/s12984-016-0115-z.