FCEstimator: Self-Monitoring Foot Clearance App to Assess Risk of Falls Using a Smartphone

Maria Yousefian[*] [a], K.S. van Schooten[b], Parmit Chilana [a], Stella Atkins [a]
[a]School of Computing Science, Simon Fraser University, 8888 University Dr, Burnaby, BC V5A 1S6, Canada
[b]Dept of Biomedical Physiology and Kinesiology, Simon Fraser University, Burnaby & Centre for Hip Health and Mobility, University of British Columbia, Vancouver, BC, Canada;

ABSTRACT

Falls in the elderly and people with biomechanical abnormalities are a major public health issue due to associated mortality rates and social cost. The negative impact of falling has stimulated many researchers to study various tools to assess the risk and prevent falls. Maximum Foot Clearance (MaxFC) is the maximal foot height during the swing phase relative to the ground, and is a gait variable highly associated with tripping and falling. Analysis of gait to ensure appropriate interventions is now possible outside a laboratory through recent advances in sensor technology. We designed a smartphone application to estimate the MaxFC using the smartphone's built-in accelerometer and gyroscope to collect and analyze data when the phone is attached to the shank of the leg. Our method is based on double integration and drift cancellation of foot acceleration signals. An optical motion capture system was used as gold standard for validation, and the results show the mean error over all strides is less than 6%. These findings illustrate the feasibility of using a smartphone to estimate MaxFC. A small user study was conducted with seniors, showing that this application can be suitable for self-monitoring gait over time, and making users aware of increased risk of falls.

Keywords: Fall Prevention; Mobile Health application; Smartphone Foot Clearance; Accelerometer; Gyroscope.

1. INTRODUCTION

The risk of falling is an important factor that adversely affects seniors' quality of life [1], with as many one-third of seniors tripping while walking each year [2]. In addition to seniors, children and adults with biomechanical abnormalities are also at high risk of falling. This public health issue attracts many researchers to focus on designing and implementing fall prevention tools. One of the recent and promising approaches in fall prevention research and assessing associated risks is the wearable sensor-based method [3–5]. This approach facilitates early detection of risk of falls through gait analysis [6] to ensure appropriate interventions. Gait analysis is the study of human locomotion in terms of gait parameters such as walking cadence, velocity, step/stride length, step duration and foot clearance (FC) [5,7,8].

For years, the quantitative analysis of gait patterns has been studied in gait laboratories equipped with many complicated measurement and analysis devices. However, the use of such facilities requires specialized personnel, expensive equipment and set-up, and cumbersome data acquisition procedures [7,9]. Recently, inertial measurement unit (IMU) sensors have become convenient alternative devices and are being used widely for gait analysis [5,10]. Many researchers have explored external IMU sensors [2,5,10,11] to estimate gait parameters quantitatively that require offline processing of data. This is a significant disadvantage for using IMUs, as these analyses cannot be done without the help of trained experts or clinicians.

Smartphones have offered yet another alternative to IMU's and other commercial devices for studying gait patterns (e.g., [4,12,13]). Although smartphones collect data at lower frequencies than IMUs, smartphones allow for more immediate computational analysis and data processing using the sensor readings on the device [13]. A smartphone app can display and store gait parameters collected over time, which is useful for monitoring. Also, smartphones can be easily worn using sport armbands directly on the user's shank or above the ankle thus minimizing interference with normal gait conditions.

[*] myousefi@sfu.ca ; Phone 1 778 223-9207

Therefore, smartphones offer a unique opportunity for individuals to self-monitor their gait, independent of clinical practices and expensive laboratory equipment.

Despite the emerging research on gait analysis using smartphones, existing applications [4,12,13] have only explored a few gait parameters and have not focused on estimating and analyzing important foot clearance parameters, such as the MaxFC. In addition, existing applications either process motion data offline using an external server or only classify the gait rather than estimate the specific gait parameters quantitatively.

To address these drawbacks, we designed *FCEstimator*, a self-monitoring smartphone application that estimates the maximum foot clearance (MaxFC), an important gait parameter in assessing the ability to negotiate obstacles and risk of falls [14], such as to avoid tripping over the edge of a carpet. Furthermore, measurement of MaxFC over time is more useful than just a one-time evaluation, as it is the change in spatial gait parameters over time which is linked to the risk of falling [15,16]. The MaxFC is also used to recognize gait variations and can be especially useful for rehabilitation purposes [2,5].

Our *FCEstimator* application uses the smartphone's built-in sensors to collect, analyze and display the gait data. It provides an immediate calculation of MaxFC for the user over just a few steps, and by storing the results, the app allows convenient monitoring of the MaxFC over time. The main purpose of *FCEstimator* is to monitor the change in mean MaxFC over time, in addition to the variability of the MaxFC within a recording. These measures assess the magnitude of the deviations of the MaxFC with respect to each subject's MaxFC mean value. This app merely requires the user to wear the device for a few steps each day or week which takes only a few minutes; thus, we believe that it does not jeopardize the phone's usefulness.

We conducted a small feasibility experiment as a proof-of-concept and learned that our approach can be reliable compared to laboratory-based gait analysis. We also conducted a user study to design the graphical user interface (GUI) of *FCEstimator* based on feedback from seniors.

To the best of our knowledge, we are the first to use the built-in sensors of the smartphone to process the estimation of MaxFC and generate immediate data analysis to the user. Compared to commercial IMU devices, our approach to track MaxFC has no additional cost for users if they already own a smartphone, and they can carry out this analysis in the comfort of their own home. In addition, users do not need a clinician's help for obtaining and analyzing the data and do not need a server connection because the application generates, saves, and displays the mean MaxFC and variation for each test on the smartphone device. Hence, the *FCEstimator* app provides immediate feedback for the risk of falling based on the latest measure and the variability in the mean MaxFC.

Our key contribution is in designing and implementing a novel smartphone application to estimate and track the mean MaxFC and its variation for early detection of risk of falls independently, without the clinician's help, in the user's natural environment, and with immediate data analysis for use in long-term monitoring. While our *FCEstimator* application cannot replace the clinical laboratory measurements for MaxFC, it can be used as an effective screener to determine whether further analysis is necessary.

2. RELATED WORK

A person's walking pattern can be assessed by gait analysis to underline abnormalities as well as any significant variation in gait parameters and potential consequences of those abnormal patterns [17]. It has been reported that variability of gait parameters such as stride length, walking speed and FC are correlated with the risk of falls during walking [15,16]. FC is defined as the foot's height during the swing phase (i.e., when the foot is above the ground). Minimum foot clearance (MinFC) is the minimum vertical distance between the lowest point of the foot of the swing leg and the walking surface during mid-swing in the gait cycle [1]. Maximum foot clearance (MaxFC) is the maximal foot height during swing phase relative to the height at foot-flat [10]. During walking, insufficiency or fluctuations of FC could lead directly to tripping [2]. Researchers have shown that FC variability is the most discriminative parameter between young and elderly subjects and is an important gait parameter to estimate risk of fall in the elderly [1,10]. Gait deviations due to the MinFC increase the risk of trips and subsequent falls because of foot-ground contact [1,7] and deviations due to the MaxFC cause trips and subsequent falls over obstacles (any small uneven surface, such as edge of carpet) [14].

Benoussaad et al. [10] introduced a method for the robust estimation of foot clearance during walking, using external IMU placed on the subject's foot; however, all the data processing are offline and the method does not generate immediate feedback to the user. Majumder et al. [4] designed and implemented an application called iPrevention that uses the built-in accelerometer and gyroscope of the smartphone when it is in the user's pocket to identify abnormal walking patterns in users to prevent falls. They classified user's gaits rather than quantitative estimation. Pierleoni et al. [18] used a smartphone as a fall detection tool. They collected data from the accelerometer and magnetometer, and then classified events either as fall events or non-fall events by a machine learning method. This system is beneficial for patients who have fallen and been left immobilized for a period of time, but it cannot help prevent falls. Raknim et al. [19] used a smartphone to monitor and record patients' gait characteristics and identify those who are in their early stage of neurological disease, as these groups are high potential fallers. They focused on step length and cadence variations but not on FC. Capela et al. [12] proposed an algorithm to examine the 6MWT (six-minute walking test, a simple physical capacity test) on a smartphone application that uses the device accelerometer and gyroscope data to report the step length, step timing, gait symmetry, and walking changes over time. Qin et al. [6] measured gait parameters such as velocity, step length, and cadence by designing a smart-phone based gait monitor system, which worked by detecting current rate of acceleration using multi-axes accelerometer and rotational attributes using multi-axis gyroscope. In their system the smartphone is just used to collect data and processing is implemented offline on another system.

Despite the availability of these mobile applications, not all gait analysis parameters, such as FC, have been explored in smartphones. Our main motivation was to provide users with a tool that analyzes the MaxFC data independent of clinicians and immediately processes the data to display feedback after each test recording (unlike other tools with offline processing of data).

3. DESIGN OF FCESTIMATOR

In this research, we present a new approach for estimating the MaxFC when the phone is attached to the shank. In addition, we present the user interface we designed to make it convenient for users to utilize the application.

3.1 Foot Clearance Algorithm on smartphone

A previous study suggested the foot dorsum as a proper location on the body to estimate MinFC [2], because the MinFC is estimated by tracking the movement of the toe of the swing leg. However, considering the size of smartphone, the best location to mount the smartphone is on the user's shank which is suitable for detecting the movement of the heel and estimating the MaxFC. Therefore, we focused on estimating the MaxFC rather than the MinFC.

The algorithm presented in this paper, uses the iPhone7Plus's built-in 3D-accelerometer and 3D-gyroscope to estimate the MaxFC. This algorithm is based on filtering the signals, detection of temporal cycles and foot flat phase, and computation of foot orientation from accelerometer and gyroscope sensor's signal data fusion at each timestamp. Next, the gravity-compensated translational acceleration is double integrated over time during the swing phase in each stride. The ankle joint clearance is first estimated and then one bias is added in terms of the distance between the ankle joint and the heel [10].

Data acquisition frequency of 51HZ was chosen to avoid data missing and make sure the application keeps up with the updates. To remove noise from the sensor's signals, the 3D acceleration data was low-pass filtered with 8-Hz cut-off frequency, and the 3D gyroscope data was band-pass filtered between 0.08 Hz and 6 Hz to remove constant and high frequency components.

3.1.1 Sensor Tilting

The initial angle of the smartphone to the foot must be considered when the phone is mounted to the shank, shown in Figure 1. The orientation of the smartphone can be defined by its pitch (θ), roll (φ) and yaw (ψ) rotations from an initial position about the x, y and z axes respectively. As suggested by [10,12], the misalignment angles can be estimated by projection of the gravity vector (S_G) on three axes measured by accelerometers during the stationary period, prior to the start of movement. (G_{R0}) is the initial transformational matrix.

$$G_{R0} = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} S_{Gx} \\ S_{Gy} \\ S_{Gz} \end{bmatrix} = G_{R0} * \begin{bmatrix} 0 \\ -1 \\ 0 \end{bmatrix} \tag{2}$$

$$\psi_0 = \arctan\left(\frac{-S_{Gx}}{S_{Gy}}\right) \quad ; \quad \theta_0 = \arctan\left(\frac{-S_{Gz}}{\sqrt{S_{Gx}^2 + S_{Gy}^2}}\right) \tag{3}$$

3.1.2 Rotation

The measured raw acceleration (acc) corresponds to the acceleration in the device sensor frame, and contains user acceleration as well as gravity. During the movement, the orientation angles must be calculated by integrating the relative angular velocity (ω) plus initial estimated angles [8,20].

$$\theta(t_i) = \int_{t_{i-1}}^{t_i} \omega(t)\,dt + \theta_0 \tag{4}$$

$$\psi(t_i) = \int_{t_{i-1}}^{t_i} \omega(t)\,dt + \psi_0 \tag{5}$$

In order to remove the gravity, we need to estimate the transformational matrix (G_{Rt}) at each time stamp and apply it to the raw acceleration at the device reference frame. Gravitational acceleration can then be removed to obtain the gravity-free acceleration in the global frame G_a.

$$F_{acc}(t) = G_{Rt} * acc(t) \quad ; \quad G_a = F_{acc} - \begin{bmatrix} 0 \\ g \\ 0 \end{bmatrix} \tag{6}$$

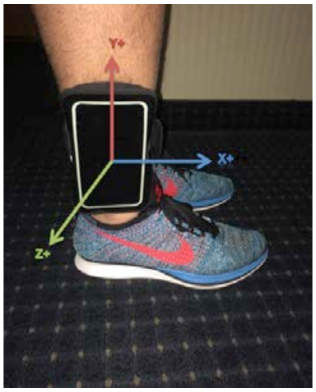

Figure 1. Acceleration and Gyroscope readings in directions of x, y and z- axes when iPhone is attached to the shank.

3.1.3 Stride Phase Detection

The continuous walking motion must be segmented into a series of stride cycles to compute the vertical movement in each stride and perform drift cancellation. The gyroscope signal is used to determine the shank vertical event and thereby bounds each cycle [11,20] as shown in Figure 2.

According to Laudansky et al. [11] and Li et al. [20], when the IMU is attached to the shank, the start point of each gait cycle is from mid-stance where the shank is parallel to the direction of gravity; thus, this point is considered as the start point of any new stride cycle. The mid-stance time corresponds to the period of time between heel-strike and heel-off in which the angular rate about the Z-axis (ω_z) is close to zero, as the foot is almost motionless.

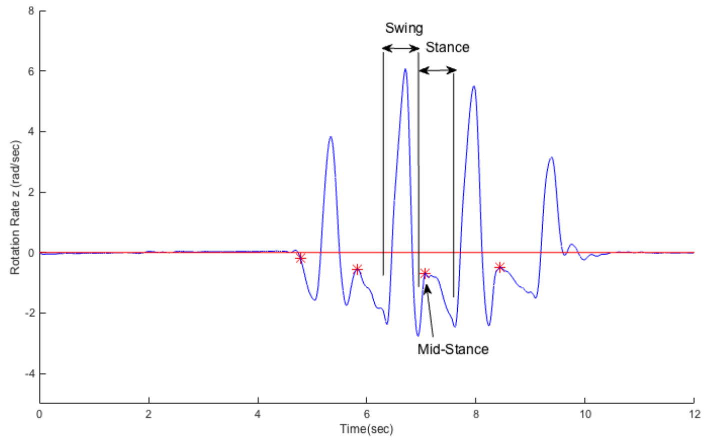

Figure 2. Angular velocity (rad/s) of the shank during four strides.

3.1.4 Trapezoidal Integration

The sensor bias directly affects the estimating velocities when duration of integration is long. Gait segmentation can be used to avoid the accumulation of drift error between different strides. Moreover, at the start of each cycle the orientations are reset to the initial orientations in order to compensate the orientation bias. To calculate the vertical displacement, the transformed gravity-free acceleration around the y-axis should be double integrated in each gait cycle.

$$V_y(t) = \int_{t_0}^{t_{end}} G_{ay}(t)\,dt + V_y(0) \tag{7}$$

Where ($V_y(t)$) is the vertical velocity and ($V_y(0)$) is the initial vertical velocity computed from shank angular velocity based on assumption that the shank is approximately rotating about the ankle joint in the stance phase and L is the distance between the iPhone location on the shank and ankle joint.

$$v(0) = \omega(0) * L \tag{8}$$

The same method is used to calculate the end vertical velocity ($v(T)$). Using the initial and end shank velocities, the shank velocity drifts bias were compensated [10,20]:

$$V_{y-corrected}(t) = V_y(t) + \frac{V(T) - V_y(t_{end})}{t_{end} - t_0} * (t - t_0) \tag{9}$$

To estimate the vertical foot displacement, we first integrated the corrected vertical velocity ($V_{y-corrected}(t)$) and then applied the same drift cancellation on this vertical foot displacement, assuming zero displacement at the end of the stride [10].

$$X_{y-corrected}(t) = X_y(t) - \frac{X_y(t_{end})}{t_{end} - t_0} * (t - t_0) \tag{10}$$

Where $X_y(t)$ is the vertical foot displacement obtained by trapezoidal integration of the corrected velocity and $X_y(t_{end})$ is the calculated displacement at the end of the stride phase. The maximum of the $X_{y-corrected}(t)$ in each stride plus the distance between the ankle joint and the heel is our considerable MaxFC.

3.2 Feasibility Study

For validation of our foot clearance estimation method, we performed a feasibility study with eight healthy participants. Each participant was asked to stand upright, remain still for two seconds and then walk a distance of approximately 7 m (this short walk was due to space limitation in the laboratory). The smartphone was mounted to the shank above the ankle joint by sport armbands as shown in Figure 1. Each participant covered this distance five times with the smartphone attached on the left foot. Simultaneously, the participants were observed by a Qualisys motions capture system, using reflective markers located on the heel, ankle joint and smartphone. This system was considered highly accurate and would serve as a gold standard for calculation of the FC. We set up 8 cameras to capture the 7m walkway (based on start and end markers). Data for each participant were collected from the smartphone's accelerometer and gyroscope using the Apple CoreMotion framework. The MaxFC was estimated by our algorithm inside the mobile phone. The collected data were automatically segmented into stride cycles, and the peak of each cycle was compared one by one to the MaxFC provided by the motion capture system's heel reflective marker. The L was set to 15cm for all participants. After each test, the app generated immediate feedback to the user about their estimated MaxFC. In addition, the collected data could be saved as a CSV file in the app to be analyzed offline. This file could easily be transferred via email from the app to any clinician for deep gait analysis purposes, if there was any concern with the user's walking pattern. The results of each test were saved in the application using Apple CoreData framework to provide the opportunity for the user to track any significant changes in MaxFC.

Table 1 . Information on video and audio files that can accompany a manuscript submission.

Participant (ID)	Motion Capture System MaxFC±SD (cm)	Mean Error Estimation Using iPhone on the Left Shank MaxFC±SD (cm)	RMSE (cm)	NRMSE (%)
1	30.6±0.3	30.3 ±1.8	1.3±1.0	4.2%
2	24.9±0.6	24.3 ±0.9	1.0±0.6	4.0%
3	25.1±0.7	27.7±1.5	2.6±1.3	10.3%
4	25.8±0.5	26.2±1.0	1.0±0.9	3.9%
5	23.4±0.3	22.5±1.7	1.1±1.3	4.7%
6	23.1±0.6	24.1 ±1.2	1.2±0.7	5.2%
7	24.3±0.5	24.5±1.0	0.6±0.4	2.5%
8	22.7±0.7	25.5±1.6	2.8±1.4	12.3%
Average	25.0±0.5	25.7±1.3	1.4±0.9	5.8%

In total 217 strides from participants were computed and compared one by one to the ground truth system. The RMS value of MaxFC errors (RMSE) was quantified for the evaluation of MaxFC estimation performance, using the following criterion:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum(X_m - X_a)^2} \tag{11}$$

$$\text{NRMSE} = \frac{RMSE}{X_m} * 100 \tag{12}$$

Where X_m and X_a are respectively the measured MaxFC for each stride by motion capture system's marker on the heel of participants and the estimated MaxFC for each stride by our smartphone application. Table 1 shows results for MaxFC estimation and the RMSE obtained from both systems for all eight participants on their left foot. In 75% of all cases on the left foot, the RMS errors remained less than 1.3 cm with an average of RMS errors around 1cm with the mean error over all strides less than 6%.

3.3 Iterative UI Design

Figure 3. Screen Shot of (a) Current test (b) Weekly result (days) (c) Monthly result (d) Yearly result

To investigate user preferences in estimating the MaxFC on their own, we followed a user-centered iterative approach process to design the user interface (UI) of the *FCEstimator* application. We carried out a pilot user study to understand how our target users perceived the application, what their expectations were and how we could improve the initial design. We recruited five seniors between the ages of 55-66 (one female and four male) and allow them to explore our first prototype. We solicited their feedback through questionnaires and brief interviews.

Based on this user feedback, we carried out another design iteration and simplified the presentation of the MaxFC estimation and improved our UI design (samples shown in Figure 3) to inform people if their walking pattern is degrading. Figure 3 shows screen shots from the *FCEstimator* app to monitor the gait parameter over time. The tabs in the app correspond to the tabs in the pre-loaded iHealth app on iPhones. Fig 3a shows a typical test result, Fig 3b shows the weekly result, Fig 3c shows a monthly result and Fig 3d shows a year result, where the user is alerted to improve their gait to prevent falling. The feedback may suggest referring to a doctor, thus enabling appropriate intervention in time to avoid possible falls. We also provided a link to useful exercises to improve stability and balance, as gait variability is associated with strength and balance [15].

4. CONCLUSION AND DISCUSSION

In this paper, we introduced *FCEstimator*, a new approach to estimate the MaxFC and provide feedback to users by using smartphone sensors. We validated the proposed MaxFC calculation algorithm using a motion capture system and found satisfying correspondence between MaxFC values estimated with our method and those measured with the ground truth system as a reference. This work is a proof of concept and consistent with recent studies [2,10,14] that showed error estimation by IMU to be between 4%-10%, giving us confidence that our measurement is good enough to detect MaxFC variation.

Our experiments showed that iPhone distance to the ankle (L) has an acceptable range between 13-15 cm, confirming other studies such as [11] that the MaxFC calculation is not sensitive to the exact positioning of the iPhone on the shank, provided the center of the phone is positioned to sit flat against the shank, approximately two-thirds of the distance to the knee from the ankle.

Our main contribution is in introducing a new approach that allows people to self-monitor variations in foot clearance and assess risk of falls using just a smartphone. The availability of smartphones makes *FCEstimator* a convenient tool for at-home monitoring of walking patterns with immediate data analysis which can play a key role in helping prevent falls or facilitate rehabilitation, especially among seniors and others with biomechanical abnormalities.

4.1 Limitations and Future work

Despite the overall positive results, our study has limitations which could be addressed in future work. For example, we observed performance degradation in some of the trials mainly due to how tightly the smartphone was fastened to the shank. The lack of an available armband which fits to any shank size caused unnecessary movements in trials where the participant's shank was very thin. This limitation could have affected mid-stance detection in gait cycle algorithm. The small walking area in the kinesiology lab limited the number of strides we could gather from our participants, to analyze the steady walking.

While the smartphone presents a significant advantage over IMUs or other devices, there is still potential for future work to explore simplifying the communication between the user and the application for starting and stopping the test, possibly by defining a body gesture such as double tapping of the heel or toe to the ground as a notification to activate or deactivate the sensors to collect the data and do the immediate processing.

Finally, although we carried out an iterative user interface design with seniors to develop our application, we strongly believe that future work has to focus more on user needs, especially of seniors, in designing new applications for self-monitoring gait analysis. Clearly, the needs of seniors in self-monitoring differs from clinicians or other analysts and more investigations are needed to determine how the same data can be presented to different audiences at appropriate levels of granularity.

REFERENCES

[1] Barrett, R. S., Mills, P. M.., Begg, R. K., "A systematic review of the effect of ageing and falls history on minimum foot clearance characteristics during level walking," Gait Posture **32**(4), 429–435 (2010).

[2] Mariani, B., Rochat, S., Büla, C. J.., Aminian, K., "Heel and toe clearance estimation for gait analysis using wireless inertial sensors," IEEE Trans. Biomed. Eng. **59**(11), 3162–3168 (2012).

[3] Kitagawa, N.., Ogihara, N., "Estimation of foot trajectory during human walking by a wearable inertial measurement unit mounted to the foot," Gait Posture **45**, 110–114 (2016).

[4] Majumder, A., Rahman, F., Zerin, I., Ebel, W.., Ahamed, S., "iPrevention: Towards a Novel Real-Time Smartphone-Based Fall Prevention System," Proc. ACM Symp. Appl. Comput. (2013).

[5] Mariani, B., Hoskovec, C., Rochat, S., Büla, C., Penders, J.., Aminian, K., "3D gait assessment in young and elderly subjects using foot-worn inertial sensors," J. Biomech. **43**(15), 2999–3006 (2010).

[6] Qin, D.., Huang, M.-C., "A Smart Phone Based Gait Monitor System," Proc. 10th EAI Int. Conf. Body Area Netw., 32–38, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), ICST, Brussels, Belgium, Belgium (2015).

[7] Begg, R., Best, R., Dell'Oro, L.., Taylor, S., "Minimum foot clearance during walking: strategies for the minimisation of trip-related falls," Gait Posture **25**(2), 191–198 (2007).

[8] Sabatini, A. M., Martelloni, C., Scapellato, S.., Cavallo, F., "Assessment of walking features from foot inertial sensing," IEEE Trans. Biomed. Eng. **52**(3), 486–494 (2005).

[9] Mills, P. M., Barrett, R. S.., Morrison, S., "Toe clearance variability during walking in young and elderly men," Gait Posture **28**(1), 101–107 (2008).

[10] Benoussaad, M., Sijobert, B., Mombaur, K.., Azevedo Coste, C., "Robust Foot Clearance Estimation Based on the Integration of Foot-Mounted IMU Acceleration Data," Sensors **16**(1), 12 (2015).

[11] Laudanski, A., Yang, S.., Li, Q., "A concurrent comparison of inertia sensor-based walking speed estimation methods," Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf. **2011**, 3484–3487 (2011).

[12] Capela, N. A., Lemaire, E. D.., Baddour, N., "Novel algorithm for a smartphone-based 6-minute walk test application: algorithm, application development, and evaluation," J. NeuroEngineering Rehabil. **12**, 19 (2015).

[13] Cheng, Q., Juen, J., Li, Y., Prieto-Centurion, V., Krishnan, J. A.., Schatz, B. R., "GaitTrack: Health Monitoring of Body Motion from Spatio-Temporal Parameters of Simple Smart Phones," Proc. Int. Conf. Bioinforma. Comput. Biol. Biomed. Inform., 897:897–897:906, ACM, New York, NY, USA (2013).

[14] Trojaniello, D., Cereatti, A.., Croce, U. D., "Foot clearance estimation during overground walking and vertical obstacle passing using shank-mounted MIMUs in healthy and pathological subjects," 2015 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBC, 5505–5508 (2015).

[15] Hausdorff, J. M., Rios, D. A.., Edelberg, H. K., "Gait variability and fall risk in community-living older adults: a 1-year prospective study," Arch. Phys. Med. Rehabil. **82**(8), 1050–1056 (2001).

[16] Maki, B. E., "Gait changes in older adults: predictors of falls or indicators of fear," J. Am. Geriatr. Soc. **45**(3), 313–320 (1997).

[17] Chan, H. K. Y., Zheng, H., Wang, H., Gawley, R., Yang, M.., Sterritt, R., "Feasibility study on iPhone accelerometer for gait detection," 2011 5th Int. Conf. Pervasive Comput. Technol. Healthc. PervasiveHealth Workshop, 184–187 (2011).

[18] Pierleoni, P., Pernini, L., Belli, A., Palma, L., Valenti, S.., Paniccia, M., "SVM-based fall detection method for elderly people using Android low-cost smartphones," 2015 IEEE Sens. Appl. Symp. SAS, 1–5 (2015).

[19] Raknim, P.., Lan, K.-C., "Gait Monitoring for Early Neurological Disorder Detection Using Sensors in a Smartphone: Validation and a Case Study of Parkinsonism," Telemed. J. E-Health Off. J. Am. Telemed. Assoc. **22**(1), 75–81 (2016).

[20] Li, Q., Young, M., Naing, V.., Donelan, J. M., "Walking speed estimation using a shank-mounted inertial measurement unit," J. Biomech. **43**(8), 1640–1643 (2010).