Publication Date: 24 February 2025
Archs Sci. (2025) Volume 75, Issue 1 Pages 1-7, Paper ID 2025101.
https://doi.org/10.62227/as/75101

An Efficient Study Comparing the Measure of Spatiotemporal Gait Parameters Between Smartphone and Insole Sensors

Ali Dahir Alramadan[1], Maab Alaa Hussain[2], Ali S. Abed Al Sailawi[3,*] and Rasha Abed Hussein[4]
[1]Department of Petrolum Engineering, University of Misan, Iraq
[2]Electrical engineering department University of Misan,Iraq
[3]College of Law, University of Misan, Iraq
[4]Department Of Dentistry, University of Misan, Iraq

Corresponding authors: (e-mail: ali_sabah@uomisan.edu.iq).

Abstract Gait parameter evaluation is crucial while ascertaining the health status of participants and formulating therapeutic interventions. The design and application of the smartphone technique for evaluating and investigating participants' gait parameters are presented in this paper. New methodology to investigate the spatiotemporal parameters of healthy individuals: step time, stride time, cadence and walking speed, through insole sensors and smartphones is introduced in this work. The aim of this research is firstly to examine the performance of a couple of Android smartphones (one per leg) two Android smartphone compared to an insole sensor in estimating spatiotemporal gait parameters. Secondly, the research tests the validity of a tri-axial accelerometer of a smartphone to quantify gait features. Spatiotemporal gait parameters of twenty healthy subjects (10 male, 10 female, age >18) were measured using insole sensors and smartphones. Five trials of walking were requested from each subject. The data were obtained from the insole sensors and smartphones. Six statistic measures: Pearson correlation coefficient, linear regression, mean, standard deviation (SD), p-value, and Bland-Altman, were employed to compare the validity of the smartphones. The coefficient of correlation according to the developed approach was 0.79-0.92 for left and right legs, respectively. On the basis of the results obtained by the study using four parameters: step time, stride time, cadence, and walking speed, it was noted that there was consensus between smartphones and insole sensors in gait parameter measurement. In addition, these findings illustrated that the smartphone sensor is effective in measuring healthy adult participants' spatiotemporal gait parameters. Accordingly, it is capable of generating trustworthy data without having to invest in costly equipment. Lastly, the established technique could assist an expert in objectively and effectively assessing gait.

Index Terms smartphone, spatiotemporal, insole sensor, standard deviation (SD)

I. Introduction

The research of human gait is regarded as an important aspect of medical diagnosis concerning several aspects of individuals' health. The knowledge of human gait has numerous applications in exercise training and hence in rehabilitation and therapy [1]–[3]. Various factors, including pathological disease or traumas, can influence the individuals' walk or locomotion, either permanently or for a specific time period [4]. Spatiotemporal gait parameters are connected to negative health problems like falling risk [5], [6].

Gait analysis researchers in recent times employed various devices to analyze gait parameters to research the risk of falling. There are various technologies employing insoles in specially crafted shoes [7]. A sensor using an insole was found appropriate to calculate human movement parameters like stance and swing phases [8]. The insole sensor is also capable of measuring several spatiotemporal gait parameters, such as swing time, stride length, step time and cadence [9]. Other research employing an insole pressure sensor data allow for the planning of means to lower plantar pressure in diabetic patients [10]. A smartphone app has demonstrated that an accelerometer sensor can be employed for gait parameter analysis. The smartphone has been proven to be a good tool for the monitoring of human movement [11]. Other research has indicated that a smartphone-based fall detection system can be employed for such various issues as fall detection [12] and rheumatoid arthritis [13].

[14] created a procedure to confirm the smartphone accelerometer for measuring the spatiotemporal parameters of gait using other equipment like GAITRite. 34 volunteers were included in their research. Volunteers walked along a 10-m distance with slow and fast speeds while using a smartphone. Step length, step time, gait speed, and cadence were all measured using smartphones and then cross-validated by GAITRite. Their findings were assessed with the correlations coefficient (CC). A mean CC among the smartphone-based and GAITRite-based systems were 0.89, 0.98, 0.96, and 0.87 for step length, step time, gait velocity, and cadence, respec-

tively. [15] discussed a way to assess the concurrent validity of a smartphone. In that research, 16 healthy subjects were employed and the smartphone was placed first on the lower back and second on the sternum.

The reference standard and the smartphone were then employed to measure vertical ground reaction forces and vertical acceleration. The proposed method was tested in this study using the correlation coefficient and standard error. Good reliability (ICC $\geq$ 0.75) was found, demonstrating Pearson correlation coefficients between vertical ground reaction forces and vertical acceleration. The authors determined that the smartphone might be considered a valid and reliable instrument to quantify the sit-to-stand movement in healthy elderly. Later on, [16], introduced a valid and effective way to determine spatiotemporal gait parameters from smartphone data, relying on an accelerometer and 3000E F-scan. In the current research, 10 young adults walked thrice with two smartphones and two insole sensors. Three parameters: cadence, step time, and stride time were estimated. The research indicated that the smartphone accelerometer sensor may be a valid and efficient gait assessment tool. Recent validation data for smartphone typically employ a single phone to measure gait parameter. In addition, these studies have utilized one or two measurement tools to test performance outcomes. Therefore, the aim of this study is to: (1) examine two Android smartphones for the measurement of spatiotemporal gait parameters (step time, stride time, cadence and walking speed) and (2) test the validity of a smartphone-based tri-axial accelerometer to measure gait features.

II. Description of Resarch Methodology

In this study, 20 healthy subjects were recruited for the outlined method to examine the spatiotemporal parameters: step time, stride time, cadence, and walking speed of the insole and smartphone in healthy individuals.

A. Participants

The twenty healthy adult subjects (10 males and 10 females) ranged in age from 20 to 40 years. The remaining parameters of the 20 participants were mass and height 60 to 95 kg and 156 to 180 cm, respectively. All of the participants had the capability of walking steadily for a minimum of ten meters with or without aid or assist devices. Demographic data was acquired from each subject; i.e., age, gender, height, weight and shoe size. All the subjects provided written permission at the initiation of the trials. A human ethics application was granted by the Human Research Ethics Committee of the University of Southern Queensland.

III. Equipment

During the research, every subject used an insole sensor 3000E F-scan inside properly fitting shoes, linked to a computer for collecting the data via the F-Scan research software. Simultaneously, both the subjects had two smartphones, each Samsung Galaxy S9 with the height of 5.81" (147.7 mm), width of 2.7" (68.7 mm), depth of.33" (8.5 mm), weight of 163 g and screen length of 5.8" (147.3 mm). The phones were held in both legs as displayed in Figure 1a and 1b. Smartphones were put here since the higher region of the body is complex; therefore, the method of collecting precise estimates is extremely challenging.

Figure 1: a and b show an example for one person who wore insole sensors and smartphones during the test

Figure 2 illustrates an example of one-step starting from the left side with heel strike, flat foot, midstance and toe off. All participants walked on a 9 m straight course, with all gait measuring equipment (insole shoes and smartphones) on, five times. Each time (trial), the data were collected separately for each device and each leg. Participants were instructed to walk normally, and to begin and end walking when they heard the tester's command.

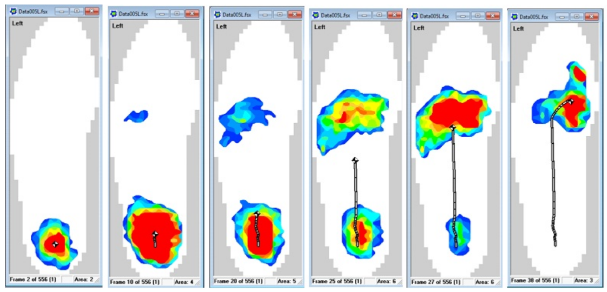

Figure 2: An example of flat foot, midstance and toe off pressure characteristics

A. Procedures

In this study, an effective approach was employed to investigate the spatiotemporal parameters of healthy individuals with the insoles and smartphones and compare and analyze spatiotemporal gait parameters in smartphone and insole sensors. The researcher applied a defined protocol. Every participant signed an agreement form. Then, describe the walking path, starting and ending point and how to hold the wires of the insole sensors to each person. Subsequently, information was taken for all the participants. They were requested to begin and end walking upon hearing the instructor provide the instruction.

B. Data collection and processing

Consistent data were sought for the spatiotemporal parameters of gait: step time, stride time, cadence and walking speed employed in the study. Foot strike location for each subject was confirmed to be on the correct way in the shoes after selecting the appropriate shoes size. Each trial was the average of three middle steps (steps 5-7). From the Tekscan data-acquired foot pressure map and from the smartphone accelerometer plots, step 3 of the middle steps was utilized in order to measure the stride time, step time and cadence, as represented in Figure 3.

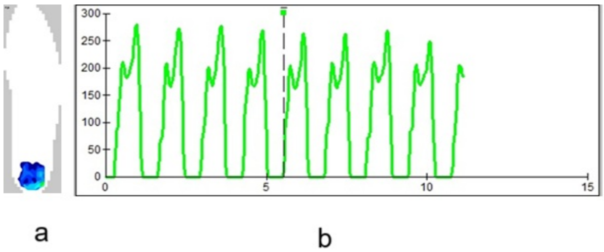

Figure 3: a and b show the heel strike insole sensor and heel strike for the fifth step, respectively

The nine steps acceleration data for normal walk are shown in Figure 4. The device, smartphone and insole sensors test were performed simultaneously. The variation between them was noticed. We saw this variation in the insole sensor and accelerometer sensor patterns like noise and negative signal in accelerometer sensors but nothing similar to that in the insole sensors reading.

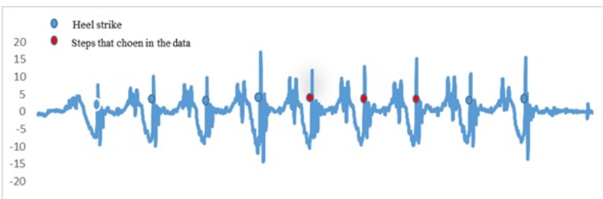

Figure 4: Heel strike start with the positive peaks acceleration from smartphone accelerometer

C. Statistical analysis

Blind-Altman plots were employed to present the bias and limit of agreement (LOA) between smartphone sensor and insole sensor data as well as to assess the constructed study method.

In order to analyze the validity between insole sensors and smartphones for every trial, Pearson correlation was employed for this analysis. We utilized the following value to verify the consistency between the device results: .90 to 1.00 as very high, 0.70 to 0.90 as high, and 0.50 to 0.70 as moderate, 0.30 to 0.50 as low, and below 0.30 as insignificant. These measures and ranges have been utilized by several studies [17]–[19]. According to Figure 4, it was observed that the insole pattern in the forward and upward directions was relatively more stable for most of the time since it relies on the leg pressure sensor.

But with the smartphone, the most of the patterns had relatively more stable steps in 5-7 since the accelerometer data relies on the walk action. That is, walking speed varies at the start of walking and while preparing to halt. Further, the accelerometer data from the smartphone in the direction of movement and upwards revealed a little noise and negative readings in the pattern, even though we utilized only the positive readings. The sign change of the positive peak in the acceleration signal in the anterior-posterior direction is considered as the moment of the foot contact [20]. In step time and stride time, the mean of the time of the three middle steps (5-7) steps was computed.

That is, in this paper, we calculated the time of three steps and then divided it by 3, and likewise for stride time but for three strides. Cadence processing was done in a similar way as [21] but we changed the time to seconds since the time of both devices (smartphone and insole sensor) was in seconds. To test the accelerometer's capacity to identify the steps taken, the subject walked 10 meters based on lap distance on a flat indoor floor.

IV. Experiment Results and Discussions

The aim of this study was to compare and measure the validity of insole sensor and smartphone sensors' spatiotemporal gait parameters. For that aim, in this paper, a series of experiments were performed to assess the performance of the smartphone device to investigate the spatiotemporal parameters.

In this experiment twenty participants: healthy young adults (10 males and 10 females; aged between 20 and 40 years; mass and height 60 to 95 kg and 156 to 180cm, respectively), were recruited and they completed the testing in the laboratory setting successfully. Various sets of parameters: step time, stride time, cadence and walking speed, were obtained in this study. 5 trials were performed by each subject. Subsequently, spatiotemporal gait parameters were obtained and using two smartphones and two insole shoes sensors. In trials, the smartphone displayed comparable results with that of the insole. The findings of every subject (left and right) were presented as mean and standard deviation (SD), as is evident from Tables 1 and 2. These are the statistical terms that have been employed by the majority of the researchers to check their methodology [14], [22].

All of the experiments were analyzed using SPSS. Tables 1 and 2 present the mean (for 20 subjects) of four parameters for left and right insole sensor and smartphone, computed on the basis of mean and SD. The mean and SD for every subject according to the four parameters were calculated. The average for every parameter for insole sensors and smartphones was calculated. According to the findings in Tables 1 and 2, the mean and SD for smartphone and insole according to four parameters gave almost the same results. The findings proved that the smartphone can study the spatiotemporal parameters for healthy individuals.

To emphasize further analysis of the suggested study in terms of comparison between the smartphone and insole sensors, 25 trials were also employed in this study to analyze the relationship between smartphone and insole. The outcome of each subject relies on four parameters: step time, stride time, Cadence and walking time, and they are expressed as mean

± standard and afterwards the average of mean ± standard was obtained for all subjects, as represented in Table 3. The outcome of smartphone shows that the current study out-performed with respect to comparing smartphone and insole sensors. Among the four parameters, the step time results gave the best performance in terms of average of mean and SD across all subject relative to the other parameters. It can be seen from Table 3 that the smartphone pair gave satisfactory results relative to that of the insoles. P-value was utilized to establish significance by reporting the concordance between the smartphones and insoles. The disparities between the data obtained from the insole sensor and smartphone weren't-significant for all measures (P-value >0.05), indicating the resemblance between these two devices, as provided in Table 4. Outcomes verify the hypotheses made before this research and hence are in favor of higher use of smartphones for gathering spatiotemporal data rather than insole sensors.

Variable	Insole		Smartphone	
	Mean	SD	Mean	SD
Step time	0.68	0.03	0.67	0.03
Stride time	1.22	0.06	1.22	0.06
Cadence	50.05	0.92	49.35	1.03
Walking time	1.03	0.05	1.02	0.05

Table 1: The performance of the proposed method based on four parameters - left insole sensor and smartphone for five trials m/s

Variable	Insole		Smartphone	
	Mean	SD	Mean	SD
Step time	0.68	0.02	0.69	0.03
Stride time	1.21	0.05	1.21	0.05
Cadence	49.81	0.78	49.41	0.96
Walking time	1.01	0.05	1.01	0.05

Table 2: The performance of the proposed method based on four parameters - right insole sensor and smartphone for five trials m/s

Parameters	Insole		Smartphone	
	Right	Left	Right	Left
	mean ± standard	mean ± standard	mean ± standard	mean ± standard
Step time	0.76 ± 0.03	0.74 ± 0.03	0.78 ± 0.03	0.73 ± 0.03
Stride time	1.30 ± 0.05	1.31 ± 0.05	1.27 ± 0.24	1.31 ± 0.05
Cadence	45.41 ± 1.75	45.78 ± 1.62	45.75 ± 1.60	45.73 ± 1.74
Walking time	0.92 ± 0.09	0.89 ± 0.08	0.90 ± 0.06	0.89 ± 0.07

Table 3: The results for mean ± standard of 25 trials

Variable	Right		Left	
	Pearson r	P-value	Pearson r	P-value
Step time	0.79	0.42	0.79	0.26
Stride time	0.92	0.31	0.88	0.08
Cadence	0.80	0.47	0.88	0.08
Walking time	0.82	0.46	0.80	0.94

Table 4: Summary of result agreement between smartphones and insoles for two subjects with 25 trials

Table 4 shows the summary of results based on the Pearson correlation coefficient (r) and P-value between the smartphones and insole sensors for all subjects with 25 trials. For (r) values 0.90-1.00 considered very high, 0.70-0.90 high, 0.50-0.70 moderate, 0.30-0.50 low and less than 0.30 considered negligible. The P-value was calculated for all parameters through insole and smartphone (Left and right). The results in Table 4 show that each parameter of insole and smartphone could be presented by a specific set of P-value.

A. Performance of the study based on Bland Altman plots

Bland Altman plots were used to assess this study's ability to investigate the effectiveness of the variables (step time, stride time, cadence, and walking speed). Bland Altman plots are another way to examine the agreement and systematic error between the smartphones and insoles [19].The x-axis represents the average of the two systems' values while the y-axis represents the difference between the two values. The Bland Altman graph has three horizontal lines that provide more information about the acquired data. The solid line, called the bias, represents the average differences between the two values and the two dashed lines represent the limit of agreement (LOA). Bland Altman plots provide bias and 95% limits of agreement when comparing the spatiotemporal gait parameters derived from the smartphones and insole sensors, as shown in Figure 5. If 95% of the values fall between the dashed lines, the difference is normally distributed [23]. Based on the obtained results in Figure 5, we can observe that there are no big differences in the obtained results when the smart-phones and insole sensors were used, indicating that there is an agreement between both devices. From these results, it is evident that the smartphone has the ability to determine spatiotemporal gait parameters, and to evaluate the validity of a smartphone-based tri-axial accelerometer to assess gait characteristics.

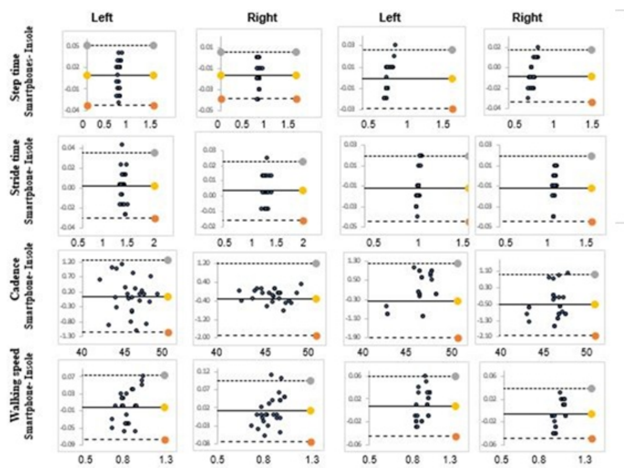

Figure 5: Bland-Altman plot for the Samsung smartphone attached to subject body and insole sensors for two subjects with 25 trials. Each dot represents a single step. The solid line is the bias, with dashed lines representing the upper and lower of error LOA

B. Performance of the proposed study based on 25-cross validation

To investigate the effectiveness of the smartphones as opposed to the insole sensors in determining spatiotemporal gait parameters (step time, stride time, cadence, and walking speed), box plots were used based on the Pearson correlation coefficient. The box plots consist of three parts: upper, lower, and middle Figure 6. The upper part of the plot box denotes the 75th percentile, and the lower part presents the 25th percentile, while the central part refers to the median 50th percentile which is sometimes called the centre. The highest and lowest values in the box plot are marked using a line extending from the top to the bottom of the box. The box plot shows agreement between smartphones and insole sensors at the same time point based on the Pearson correlation coefficient. In further investigations, the performance of the proposed method through 25- cross validation using smartphone device was used in this study. The proposed method was tested 25 times and all the results were recorded. From Figure 6 a and b we can see that Pearson correlation coefficient ranged between 0.79 and 0.92 for left and right. In the results in Figure 6a, the value of the maximum Pearson correlation coefficient was 0.98% for stride time left, while the minimum value was 0.68% for walking speed left. On the other hand, the maximum and minimum Pearson correlation coefficient for the right limb was 0.98% and 0.65% for stride time and step time, respectively. For further evaluation of the study, the behaviours of the smartphones and insole sensors were analysed and tested for spatiotemporal gait parameters using R-squared (R2). Figure 7 shows the scatterplot of the insole sensor (Gse) vs smartphone device (Gsd) with the least square regression, line, [y (GIsd)= aGIse +b], and correlation of determination (R2) which is used to evaluate as well as to show the agreement between smartphones GIsd and insole sensors GIse for all gait parameters. The constant values of a and y-intercept b were used outline the model's performance, with the correlation of determination (R2), was employed. Reliable results were found for all four parameters: step time, stride time, cadence and walking, based on the value a, b and R2. Furthermore, it was noticed that there is agreement between the smartphones and insole sensors, which reported the same or similar results. The results for the left leg were R2= 0.81%, 0.88%, 0.87% and 0.80% for step time, stride time, cadence and walking, respectively, while results for the right leg were R2= 0.85% ,0.96%,0.87% and 0.81% for step time, stride time, cadence and walking, respectively. Finally, the experimental outcomes indicate that the proposed method is capable to study the spatiotemporal parameters of healthy people: step time, stride time, cadence, and walking speed, using both insole sensors and smartphones.

Regarding the validation study, [15] proposed the same method of validation as our study; a smartphone device used to compare the motion capture systems. In their study, 22 healthy young adults were assessed with a smartphone application and a motion capture system. The reliability of the proposed method was evaluated using the correlation coefficient and standard error. The validity of the smartphone application and motion capture-derived values were compared with the Pearson correlation coefficient and Bland-Altman limits of agreement. They demonstrated that there was agreement in the obtained results of the systems. Another study was presented by [24] in which the reliability and validity of a smartphone-based accelerometer in quantifying spatiotemporal gait parameters of stroke patients when attached to the body were confirmed. In their study, the gait parameters were measured and evaluated using a smartphone accelerometer and GAITRite analysis.

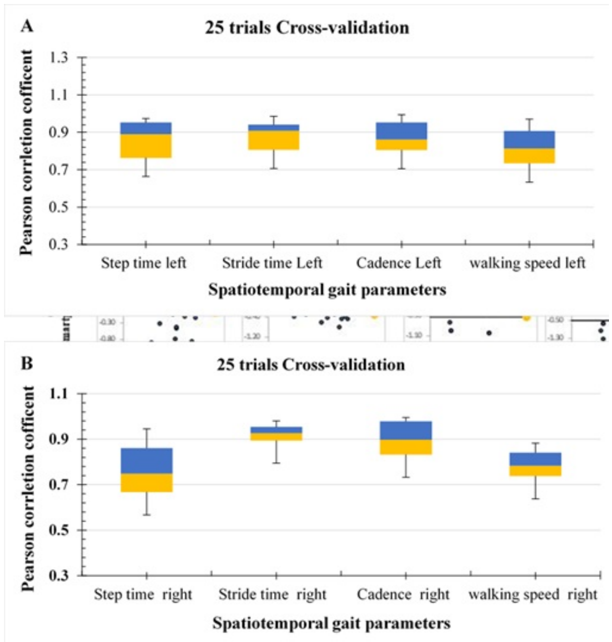

Figure 6: Box plot for Pearson correlation coefficient of smartphones and insole sensors: A present the left leg and B show the right leg

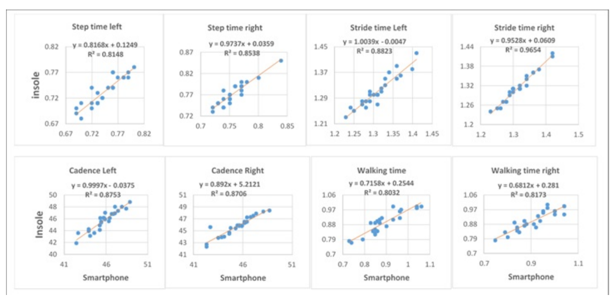

Figure 7: shows the scatterplot of the smartphone device (Gsd) vs Insole sensor (Gse) for the left and right legs

Thirty participants were asked to walk 10 meters. Then three parameters: gait velocity, cadence, and step length were computed using smartphone-based accelerometers. The results were validated with a GAITRite analysis system. Average excellent reliability (ICC2, 1≥.98) of correlation coefficient was reported. They observed that the high correlation between the smartphone-based gait parameters and GAITRite analysis system-based gait parameters was achieved.

Following [25], we used step time, stride time, cadence, and walking speed for a comparison of spatiotemporal gait parameters between smartphone and insole sensors. Furthermore, the Bland-Altman 95% bias and limits of agreement, linear regression and statistical analysis using mean and standard deviation were also employed to evaluate the obtained measures and to assess the agreement between the two systems. The comparison between the devices showed excellent agreement. In summary, from all the obtained results above, we can notice that specific opportunities exist for smartphone-based gait assessment as an alternative to conventional gait assessment. Furthermore, a smartphone-based gait assessment could provide reliable information about changes in the spatiotemporal gait parameters.

V. Conclusion

The characteristics of a smartphone application were used to study the spatiotemporal parameters: step time, stride time, cadence and walking speed of both insole sensors and smartphones for healthy people. In this work, an innovative method was used to extract the most important features from 20 subjects. One of the most important findings was that the measures of the smartphone device agree with the insole shoe sensors when measuring spatiotemporal parameters. The effectiveness of the proposed model was tested with two Android smartphones and 20 healthy adult participants. The study used different statistical methods (ANOVA, Bland-Altman, linear regression, and Pearson correlation coefficient) to measure the reliability and validity of smartphone use. Smartphone use was also compared with four other existing methods. It was demonstrated that the developed model achieved the best performance in terms of a correlation coefficient.

The obtained results showed that, by using two Android smartphone devices with Insole shoe sensors, a high level of agreement was obtained, allowing for a good range of acceptable alternatives to assess spatiotemporal parameters. Our findings also demonstrated that the smartphone can be used as a reliable and valid tool in spatiotemporal gait analysis of healthy adults. This method can help a clinician to work more efficiently and to objectively evaluate gait with easy to use and interesting work as well as to reduce cost. In the future, additional studies will be needed to investigate the ability of smartphones to detect the differences between adult and older people in their way of walking and to ascertain whether it is sensitive enough to detect differences in gait patterns. Furthermore, we can apply big data and different devices to study the spatiotemporal parameters of the insole sensors and smartphones for healthy and non-healthy people.

Acknowledgements

The first author would like to thank Dr Wessam Al-Salman for his help.

References

[1] Mirek, E., Filip, M., Chwała, W., Szymura, J., Pasiut, S., Banaszkiewicz, K., ... & Szczudlik, A. (2018). The influence of motor ability rehabilitation on temporal-spatial parameters of gait in Huntington's disease patients on the basis of a three-dimensional motion analysis system: An experimental trial. *Neurologia i Neurochirurgia Polska*, 52(5), 575-580.

[2] Bernardes, D., & Oliveira, A. L. R. (2017). Comprehensive catwalk gait analysis in a chronic model of multiple sclerosis subjected to treadmill exercise training. *BMC Neurology*, 17, 1-14.

[3] Braun, B. J., Osche, D., Rollmann, M., Orth, M., Mörsdorf, P., Histing, T., ... & Herath, S. C. (2019). Increased therapy demand and impending loss of previous residence status after proximal femur fractures can be determined by continuous gait analysis–A clinical feasibility study. *Injury, 50*(7), 1329-1332.

[4] Lin, F., Wang, A., Zhuang, Y., Tomita, M. R., & Xu, W. (2016). Smart insole: A wearable sensor device for unobtrusive gait monitoring in daily life. *IEEE Transactions on Industrial Informatics, 12*(6), 2281-2291.

[5] Kalron, A., & Achiron, A. (2014). The relationship between fear of falling to spatiotemporal gait parameters measured by an instrumented treadmill in people with multiple sclerosis. *Gait & Posture, 39*(2), 739-744.

[6] Bang, D. H., & Shin, W. S. (2016). Effects of robot-assisted gait training on spatiotemporal gait parameters and balance in patients with chronic stroke: A randomized controlled pilot trial. *NeuroRehabilitation, 38*(4), 343-349.

[7] Howell, A. M., Kobayashi, T., Hayes, H. A., Foreman, K. B., & Bamberg, S. J. M. (2013). Kinetic gait analysis using a low-cost insole. *IEEE Transactions on Biomedical Engineering, 60*(12), 3284-3290.

[8] Martínez-Martí, F., Martínez-García, M. S., García-Díaz, S. G., García-Jiménez, J., Palma, A. J., & Carvajal, M. A. (2014). Embedded sensor insole for wireless measurement of gait parameters. *Australasian Physical & Engineering Sciences in Medicine, 37*, 25-35.

[9] Noshadi, H., Ahmadian, S., Hagopian, H., Woodbridge, J., Dabiri, F., & Terrafranca, N. Mobile Balance and Instability Assessment System. https://pdfs.semanticscholar.org/baba/874a54ea01e3096d0cfe4d525e2d945ea73d.pdf

[10] Zequera, M. L., & Solomonidis, S. (2010, August). Performance of insole in reducing plantar pressure on diabetic patients in the early stages of the disease. In 2010 *Annual International Conference of the IEEE Engineering in Medicine and Biology* (pp. 2982-2985). IEEE.

[11] Del Rosario, M. B., Redmond, S. J., & Lovell, N. H. (2015). Tracking the evolution of smartphone sensing for monitoring human movement. *Sensors, 15*(8), 18901-18933.

[12] Carletti, V., Greco, A., Saggese, A., & Vento, M. (2017). A smartphone-based system for detecting falls using anomaly detection. In *Image Analysis and Processing-ICIAP 2017: 19th International Conference, Catania, Italy, September 11-15, 2017, Proceedings, Part II 19* (pp. 490-499). Springer International Publishing.

[13] Yamada, M., Aoyama, T., Mori, S., Nishiguchi, S., Okamoto, K., Ito, T., ... & Ito, H. (2012). Objective assessment of abnormal gait in patients with rheumatoid arthritis using a smartphone. *Rheumatology International, 32*, 3869-3874.

[14] Silsupadol, P., Prupetkaew, P., Kamnardsiri, T., & Lugade, V. (2019). Smartphone-based assessment of gait during straight walking, turning, and walking speed modulation in laboratory and free-living environments. *Ieee Journal of Biomedical and Health Informatics, 24*(4), 1188-1195.

[15] Furrer, M., Bichsel, L., Niederer, M., Baur, H., & Schmid, S. (2015). Validation of a smartphone-based measurement tool for the quantification of level walking. *Gait & Posture, 42*(3), 289-294.

[16] Mnati, M. N., & Chong, A. K. (2020, April). Reliability and validity of smartphones to record and study the assessment of gait characteristics. In 2020 *IEEE 10th Symposium on Computer Applications & Industrial Electronics* (ISCAIE) (pp. 141-144). IEEE.

[17] Mukaka, M. M. (2012). A guide to appropriate use of correlation coefficient in medical research. *Malawi Medical Journal, 24*(3), 69-71.

[18] Muheidat, F., Tyrer, H. W., Popescu, M., & Rantz, M. (2017, March). Estimating walking speed, stride length, and stride time using a passive floor based electronic scavenging system. In *2017 IEEE Sensors Applications Symposium* (SAS) (pp. 1-5). IEEE.

[19] Howell, D. R., Lugade, V., Taksir, M., & Meehan III, W. P. (2020). Determining the utility of a smartphone-based gait evaluation for possible use in concussion management. *The Physician and Sportsmedicine, 48*(1), 75-80.

[20] Ducharme, S. W., Sands, C. J., Moore, C. C., Aguiar, E. J., Hamill, J., & Tudor-Locke, C. (2018). Changes to gait speed and the walk ratio with rhythmic auditory cuing. *Gait & Posture, 66*, 255-259.

[21] Silsupadol, P., Teja, K., & Lugade, V. (2017). Reliability and validity of a smartphone-based assessment of gait parameters across walking speed and smartphone locations: Body, bag, belt, hand, and pocket. *Gait & Posture, 58,* 516-522.

[22] Hollman, J. H., Watkins, M. K., Imhoff, A. C., Braun, C. E., Akervik, K. A., & Ness, D. K. (2016). A comparison of variability in spatiotemporal gait parameters between treadmill and overground walking conditions. *Gait & Posture, 43*, 204-209.

[23] Myles, P. S., & Cui, J. (2007). I. Using the Bland–Altman method to measure agreement with repeated measures. *British Journal of Anaesthesia, 99*(3), 309-311.

[24] Park, J., & Kim, T. H. (2018). Reliability and validity of a smartphone-based assessment of gait parameters in patients with chronic stroke. *Journal of the Korean Society of Physical Medicine, 13*(3), 19-25.

[25] Clark, R. A., Bower, K. J., Mentiplay, B. F., Paterson, K., & Pua, Y. H. (2013). Concurrent validity of the Microsoft Kinect for assessment of spatiotemporal gait variables. *Journal of Biomechanics, 46*(15), 2722-2725.