Exploratory Gait Analysis using Wearable Technology

Richard Davies[1][0000-0002-2663-3979], Paul McCullagh[1][0000-0002-9060-6262], Huiru Zheng[1][0000-0001-7648-8709] and Joan Condell[1][0000-0002-3517-2182]

[1] School of Computing, Ulster University, Jordanstown BT37 0QB, Northern Ireland

Abstract. Gait analysis is a rapidly expanding and evolving research area with application to biomechanics and rehabilitation. Current wearable technology that can be used to collect gait information is becoming more accessible in terms of cost and usability compared to lab counterparts which can be expensive and require training to setup and use. This paper provides an exploratory analysis of knee angle versus angular velocity of the lower leg for six healthy participants for at four walking speeds (1.8 km/h, 2.7 km/h, 4.5 km/h, 5.4 km/h) on a treadmill and walking over the ground at 3.9 km, using the Xsens Inertial Measurement Unit. These phase portraits provide a rich data source for qualitative comparison. In future objective gait analysis based on suggested gait parameters can aid with rehabilitation of dysfunctional gait.

Keywords: gait analysis, wearable technology, inertial motion capture, accelerometer, Xsens.

1 Introduction

Gait Analysis (GA) is an area of research that is continually expanding and evolving across a wide range of domains such as, healthcare, sport science and surveillance. There are a plethora of medical gait applications such as the evaluation of prosthetics, assessment of surgical procedures [1] [2], treatments plans, fall risk in the elderly [3] and assessment of neuropathies [4]. In addition GA has achieved further significance in the monitoring of elite athletes [5] and identification of individuals for forensic biometric purposes [6] [7].

During the past four decades the measurement and assessment of gait has evolved rapidly; tools and technology now provide an objective, quantitative evidence-based approach. Current clinical practice for motor assessment of the lower limb in stroke survivors is based upon a battery of tests, such as the two-minute walking test, timed-up and go, berg balance scale, fugl-meyer assessment, motor assessment scale, rivermead motor assessment of movement, motricity index and stroke rehabilitation assessment of movement. All of the aforementioned motor assessment scales predate the year 1997 and have an average age of 31 years. Although they provide a quantitative score they are based upon human clinical observation and are subject to inter- and intra-rater variability. Additionally, the majority of these assessment approaches are not capable of detecting subtle changes in motor function particularly at the top end of assessment scales as a ceiling effect often occurs [8].

Advances in technology used to measure gait have been instrumental in the evolution of GA. Biomechanical movement of the human body is complex and therefore effective GA requires information such as kinematics, ground reaction forces and influence of muscle activity. Motion Capture (MC) strives to measure kinematic data in an accurate, valid and unobtrusive manner. There are two competing MC technologies: optical capture and the use of force plates to measure plantar pressure. Each offers advantages and disadvantages depending on the context of the application being considered [9] [10].

1.1 Optical motion capture and force plates

Optical Motion Capture (OMC) systems use cameras based upon active or passive markers to accurately detect the position of body worn markers within a 3-dimensional space. There are a number of commercial OMC systems available such as Vicon, Qualysis and Codamotion. These systems tend to be very accurate at sensing marker position to within the sub-millimeter range, however this accuracy heavily relies on the ability of a researcher to place markers accurately and repeatably. Various protocols exist to help locate joint centers but these differing conventions can produce a varied set of results [11]. Due to the complexity involved in camera setup and the configuration of software, OMC systems require a considerable amount of setup time and a need for specialised training. Hence OMC systems are more suited to static deployment in a dedicated gait laboratory, thus impacting upon the information derived as it may not be representative of gait in a real-world context [12]. OMC systems are expensive and occupy a static laboratory space which can restrictive for particular applications. However, they do offer unparalleled accuracy when configured by a trained Biomechanist and serve as a gold standard or reference point for other less accurate systems.

Traditionally force plates were designed to record single steps with high accuracy and resolution. Pressure sensing technology has evolved through the incorporation of this technology into instrumented walkways such as the GAITRite mat facilitating GA of a sequence of steps [9] [10].

1.2 Wearable technologies and inertial motion capture

Over the last 5 years, there have been significant advances in technologies for inertial motion capture (IMC) systems; in particular insole pressure sensor recording and the measurement and wireless transmission of the electromyogram (EMG). Insole pressure sensing technology has benefited from [13]advancements in microelectronics, wireless charging, energy harvesting, smaller batteries and low power wireless communication. These advancements have made insole technology more pervasive, embedding all of the technology within the insole e.g. Moticon [14]. These developments have paved the way for wearable technologies to replace gait laboratory equipment in the measurement of human kinematics, ground reaction forces and muscle activity. These wearable technologies offer a lower cost, portable, versatile, real-time and highly usable system to provide rich gait information in free-living environments for clinical GA [15], [16].

Inertial Motion Capture (IMC) systems offer benefits over OMC systems due to their portability, wearability and decreasing costs. IMC sensor units provide the opportunity for more practical, untethered data capture free from the constraints of an indoor observation area. Deploying outside a gait laboratory environment can facilitate diverse spatial settings such as stairs, open space, more natural terrain or other indoor areas. The setup time is shorter repeatability for measurement of joint angles during walking [17] is better than OMC systems for both in-day and between-day recording sessions.

The fundamental assumption of an underlying rigid body such as the human skeleton can be violated by the movement of overlying soft tissue known as skin artefact. This is particularly evident when there is an excess of soft tissue or during highly dynamic movements [18]. Skin artefact is a common issue with IMC and OMC, however, it may be more pronounced with IMC systems as their sensor units are of greater physical size and mass leading to greater displacement. Skin artefact is an important factor in the context of clinical research as a higher than average body-fat index is more common in people suffering from stroke [17]. Ground reaction forces as measured by force plates provide an alternative or complementary means to perform GA.

2 Methodology

In this study we conducted exploratory GA on healthy participants (n=6) using data gathered from a wearable IMC system. The GA focuses on a subset of parameters to assess feasibility, validity and diversity of gait amongst a healthy cohort. Baseline data were collected to establish a normal set of gait parameters. Factors that may contribute to variations in the data relate to but are not limited to gender, age, height and weight. Walking therapies are part of the rehabilitation pathway as defined by the NICE guidelines [19]; therefore the focus of this study is on walking on a treadmill and walking over ground while incorporating a turn.

In a data driven approach the quality and volume of the data being collected plays a vital role in the capability of a computational model to provide accurate, objective and repeatable assessment of gait. Therefore, it is import to control the recording of activities by applying a consistent clinical protocol. Although the number of participants is low (n=6) the size of the dataset can still be adequate to provide sufficient quality of data as the number of steps can reach 2,400. In addition each step can provide further information angle, velocity for 7 locations on the lower body.

Participants wore an IMC system and a pair of smart insoles to collect kinematic and ground reaction forces during walking activities. Participants were required to complete a short anonymous questionnaire that provided information on their age, gender and weight.

Inertial Motion Capture Configuration. The IMC system was configured to investigate lower limb which involved donning 7 Inertial Measurement Units (IMUs) using a velcro based strapping system as shown in Fig. 1. The IMUs were attached to the pelvis (sacrum), left/right upper leg (thigh), left/right lower leg (shank) and left/right foot. A number of anatomical measurements (body height, shoulder width, arm span, hip height, hip width, knee height, ankle height, foot size, shoe sole height) were taken from the participant to help complete the calibration. The IMC was re-calibrated before each recording session.

Fig. 1. Xsens inertial capture system showing sensor positions for foot, lower and upper limb.

Participants. A group of 6 healthy adults participated in the study. A summary of demographic information is provided in Table 1.

Table 1. Demographic information of participants

Participant ID	Gender	Age	Height (cm)	Weight (Kg)
1	Male	61	179	68.7
2	Female	52	158	N/A
3	Male	26	186	N/A
4	Male	71	172	73.0
5	Female	71	164	64.0
6	Male	N/A	177	N/A

Initial feasibility testing was conducted to evaluate at an observational level that the wearable systems were fit for purpose in terms of robustness, reliability, usability, comfort, repeatability and set-up time. Walking activities have been designed to include walking at differing speeds, walking on a treadmill versus over the ground. The study also included turns as this is an important constituent of GA.

Given that the potential use case scenario for this research will be typically elderly post-stroke survivors some slower walking speeds were included. Participants performed two walking activities. The first involved walking indoors over the ground on a flat smooth surface within a gait laboratory environment for a distance of 10m and turning. This activity was repeated for 2.5 mins at a comfortable walking speed, self-selected by the participant. The second activity required participants to walk for 2.5 minutes at 4 different speeds on a treadmill with zero incline for a total walking time of 10 minutes. The four speeds using the treadmill were: very slow (0.5m/s), slow (0.75m/s), medium (a comfortable speed self-selected by the participant, either 1m/s or

1.25m/s) and fast (1.5m/s). The fastest walking speed test is similar to the 2-minute walking test which is a clinical assessment.

3 Results

The Xsens system has already been well validated against OMC systems and has been reported to have a coefficient of multiple correlation > 0.96 for all joints during flexion/extension for level walking activities [20]. However, configuration, calibration and positioning sensors can have varying effects on the quality of the data collected. Repeatability was explored for in-day testing of the Xsens without doffing/donning the sensors.

The two phase portraits shown in Fig.2 are highly correlated and present knee angle against angular velocity of the lower limb for participant 1. These phase portraits show the dynamic nature of the knee during walking on a treadmill at a 5.4 m/s for 2 minutes. A single gait cycle is represented by one phase which can be seen as a closed loop. The phases are plotted on top of each other as each gait cycle is repeated, it shows high levels of correlation but with some dynamic and chaotic variations. The variation between gait cycles in the first test can be seen in red while the blue lines show the variation of gait cycles in the second test. Since both tests were recorded within 30 minutes and under the same conditions the variation which is expected to be minimal between walks can be observed by comparing red and blue lines.

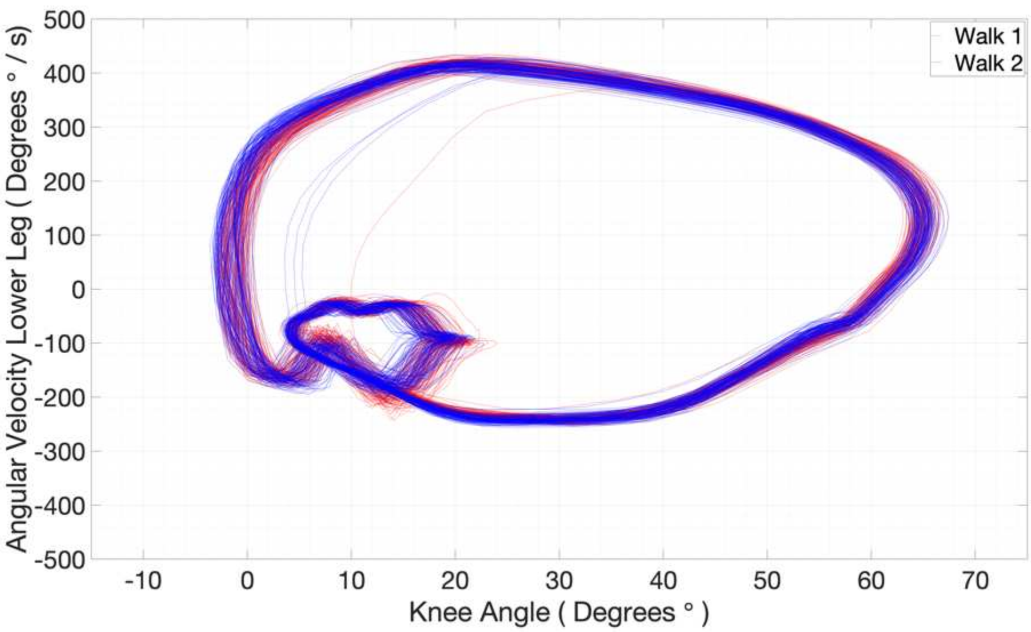

Fig. 2. A highly correlated phase portrait of knee angle versus angular velocity of the lower right leg for Participant 1 during two separate tests while walking on treadmill at 5.4 m/s for 2 minutes.

To provide a statistical measure of correlation an average gait cycle was computed for both walks and a correlation coefficient calculated by comparing both average gait cycles. The average phase portraits can be seen in **Fig. 3**, these are highly correlated as expected (r=0.9993), this is the Pearson correlation coefficient as reported by MATLABs 2-dimensional correlation function.

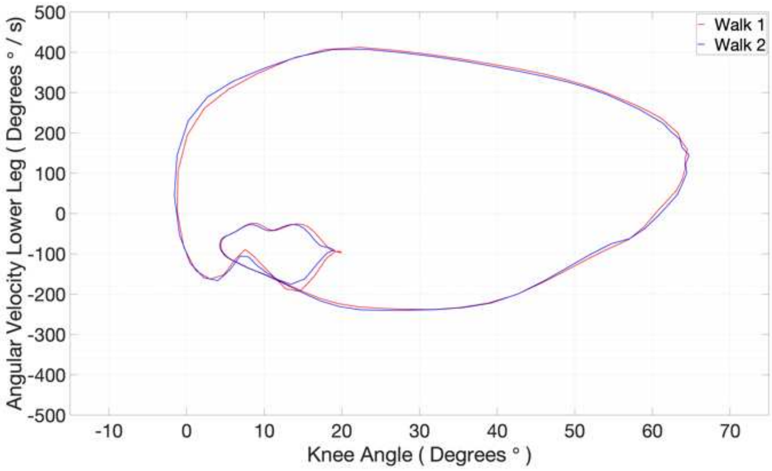

Fig. 3. A highly correlated (r=0.9993) phase portrait, it represents an average gait cycle from two walks by participant 1.

The next stage of GA was to compare all of the walking activities for participants across a number of different walking speeds; this involved 2 minute treadmill walks at 1.8 km/h, 2.7 km/h, 3.6 km/h or 4.5 km/h and 5.4 km/h and a final 2 minute walk over the ground for 10 metres with a turn. The phase portraits of these walking activities can be seen in **Fig. 4** for participant 1. Initial observations show correlation between walking speed and the area enclosed within the phase portraits. A greater range of motion and increased angular velocity should result in an increased area within the curves. Additionally, as the speed increases the variability in the phase portraits reduces to produce a more rhythmic and stable gait cycle, this is particularly for true for walking activities on the treadmill. It seems that this effect is caused by a combination of the treadmill and higher walking speeds.

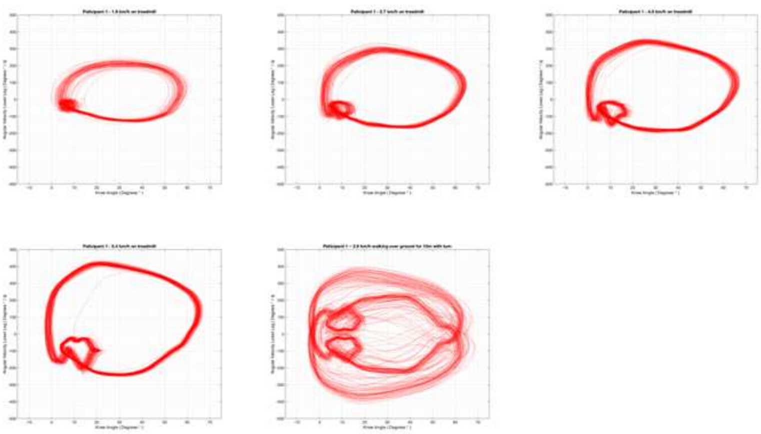

Fig. 4. Phase portraits of knee angle versus angular velocity of the lower right leg for Participant 1 at four walking speeds (1.8 km/h, 2.7 km/h, 4.5 km/h, 5.4 km/h) on a treadmill walking over the ground at 3.9 km/h.

To quantify the relationship between the area of the phase portraits and speed an average phase portrait was computed for each walk. These were then used as a basis to calculate an average area of each phase portrait and to plot these against speed to quantify any relationship and how it may change across the cohort. Observation of **Fig. 5** shows a common pattern of increased area equating to increased speed. Participants 4 and 5 were both in their early seventies and yet it is interesting that they were able to maintain walking speeds of 1.8 km/h, 2.7km/h and 3.3km/h with a reduced area, this may imply a greater sense of control by reducing the stride length.

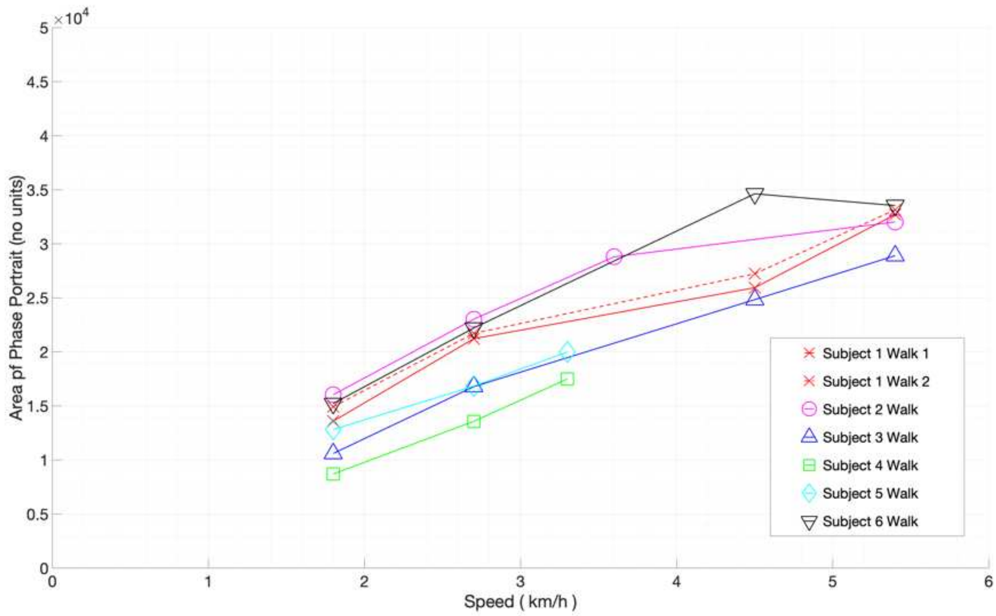

Fig. 5. Walking activity for six participants showing average phase plot area against speed.

Comparing treadmill walking activities against over the ground walking in **Fig. 4** shows that the variation in knee angle is more apparent while walking over ground. As the walking over the ground activity included turning 180 degrees every 10 metres there are a significant amount of turns (n~=16) within a 2 minute period. Therefore it makes it more difficult to attribute the increased knee angle variation as a direct result of walking over the ground. The second noticeable feature of the phase portraits for walking over the ground is that there is a mirroring effect which results in two prominent distinct phases. These are a direct result of walking in two opposite directions and may be combined into a single phase if it is possible to adjust the data to accommodate walking direction. This would be a useful analysis feature as it would allow all walking activities to be analyzed and compared irrespective of walking direction.

4 Future Work

This paper provided a demonstration that repeatable and interpretable gait analysis is possible using wearable IMC technologies. Phase cycles and repeatability were assessed by observation and quantitative measurement. Further work will be conducted

with more healthy participants and incorporate between-day and inter-rater reliability. There is a significant opportunity to quantify GA through the measurement of spatial, temporal, spatiotemporal and other phasic parameters, as listed in Table 2. Additional features that can be used in assessing the repeatability of normal gait can be derived from the normative dataset. Using these measurements and features will facilitate gait modelling for a healthy population. A gait model for a healthy population can be used to provide a reference to any new gait information that should be compared from a disease specific cohort such as stroke survivors.
There are a number of use cases where gait analysis can be beneficial for both the clinician and patient such as Parkinson's disease, cerebral palsy, lower-limb osteoarthritis, post-stroke and diabetic neuropathy. The authors propose to develop a computational gait model based on intelligent data analysis using non-linear techniques to provide an objective and quantifiable assessment of pathological gait for post-stroke that is accurate, robust and repeatable.

Table 2. List of gait features for future work.

Spatial	**Temporal**	**Spatiotemporal**	**Phasic**
Step Length (cm)	Cadence (steps/min)	Gait Speed (m/s)	Stance Time (%GC)
Stride Length (cm)	Step Time (s)	Stride Speed (m/s)	Swing Time (%GC)
Step Width (cm)	Stride Time (s)	Stride variability	SST (%GC)
Step Height (cm)	Stance Time (s)	Smoothness	DST (%GC)
Knee Angle (°)	Swing Time (s)	Centre of Pressure	
Hip Angle (°)	Single Support Time (s)		
Ankle Angle (°)	Double Support Time (s)		

5 Conclusion

Gait analysis of the normal population and of different pathologies is an area of research that is expanding rapidly. There are a number of competing technologies that can provide gait information, two such competing sets are research gait lab technology and wearable technology. The former tends to be more expensive, less flexible and with longer setup times often requiring specialised training. With recent advances, wearable technology can offer a cheaper, more accessible, less restrictive and easier to use option without comprising on the accuracy or quality of the information. This is particularly true of recent advances of IMC systems.

The Xsens IMC system captured kinematic data from walking. Due to the exploratory nature of this study only the dynamic nature of knee angle during walking was considered; the gait variation across a number of walking speeds on a treadmill and walking over the ground and gait variation across the population were assessed. Future research aims to build a computational model that can be used to assess a user's gait during ambulation. A large set of features will be generated to serve as input to the model and as such can be configured in multiple ways via feature selection to ascertain the optimal model and as a result what are the optimal features, technologies and sensors. There is a significant body of research to suggest that spatial temporal gait parameters provide such a feature set [21], [22], [23].

6 Acknowledgements

The authors would like to acknowledge the School of Computing at Ulster University and SENDoc (www. Sendocnpa.com) project in the ongoing support of this doctoral research.

References

1. A. Heikkilä, N. Sevander-Kreus, A. Häkkinen, M. Vuorenmaa, P. Salo, P. Konsta and J. Ylinen, "Effect of total knee replacement surgery and postoperative 12 month home exercise program on gait parameters," *Gait & Poature,* vol. 53, pp. 92-97, 2017.
2. P. Ornettia, J.-F. Maillefert, D. Laroche, C. Morisset, M. Dougados and L. Gossec, "Gait analysis as a quantifiable outcome measure in hip or knee osteoarthritis: A systematic review," *Joint Bone Spine,* vol. 77, pp. 421-425, 2010.
3. M. Zagoa, C. Sforza, D. R. Bonardi, E. E. Guffanti and M. Galli, "Gait analysis in patients with chronic obstructive pulmonary disease: a systematic review," *Gait & Posture,* vol. 61, pp. 408-415, 2018.
4. M. E. Fernando, R. G. Crowther, P. A. Lazzarini, K. S. Sangla, P. Buttner and J. Golledge, "Gait parameters of people with diabetes-related neuropathic plantar foot ulcers," *Clinical Biomechanics,* vol. 37, pp. 98-107, 2016.
5. B. Hanley, C. B. Tucker and A. Bissas, "Differences between motion capture and video analysis systems in calculating knee angles in elite-standard race walking," *Journal of Sport Science,* vol. 36, no. 11, pp. 1250-1255, 2018.
6. I. Bouchrika, M. Goffredo, J. Carter and N. Mark, "On Using Gait in Forensic Biometrics," *Journal of Forensic Sciences,* vol. 56, no. 4, pp. 882-889, 2011.
7. Y. He, J. Zhang, H. Shan and L. Wang, "Multi-Task GANs for View-Specific Feature Learning in Gait Recognition," *IEEE Transactions on Information Forensics and Security,* vol. 14, no. 1, pp. 102-113, 2019.
8. D. J. Gladstone, C. J. Danells and S. E. Black, "The Fugl-Meyer Assessment of Motor Recovery after Stroke: A Critical Review of Its Measurement Properties," *Neurorehabilitation and Neural Repair,* vol. 16, no. 3, pp. 232-240, 2002.
9. S. S. Kuys, S. G. Brauer and L. Ada, "Test-retest reliability of the GAITRite system in people with stroke undergoing rehabilitation," *Disability and Rehabilitation,* vol. 33, no. 19-20, pp. 1848-1853, 2020.

10. A. Scully and D. Tan, "Within-Assessment Variability of the GAITRite System in People With Stroke," *Physical Medicine & Rehabilititation,* vol. 98, no. 6, pp. 446-449, 2019.
11. A. Ferrari, M. G. Benedetti, E. Pavan, C. Frigo, D. Bettinelli, M. Rabuffetti, P. Crenna and A. Leardini, "Quantitative comparision of five current protocols in gait analysis," *Gait Posture,* vol. 28, no. 2, pp. 207-216, 2008.
12. A. Ali, K. Sundaraj, B. Ahmad, N. Ahamed and I. Anamul, "Gait disorder rehabilitation using vision and non-vision based sensors: A systematic review," *Bosnian journal of basic medical sciences,* vol. 12, no. 3, pp. 193-202, 2012.
13. T. P. Kakarla, K. A. Varma, P. S. P. Jayaraj Joseph and M. Sivaprakasam, "Accuracy Enhancement of Total Force by Capacitive Insoles," in *IEEE International Symposium on Medical Measurements and Applications*, Istanbul, 2019.
14. M. S. Oerbekke, M. J. Stukstette, K. Schütte, R. A. de Bie, M. F. Pisters and B. Vanwanseele, "Concurrent validity and reliability of wireless instrumented insoles measuring postural balance and temporal gait parameters," *Gait & Posture,* vol. 51, pp. 116-124, 2017.
15. J. Lee, S. Y. Shin, G. Ghorpade, T. Akbas and J. Sulzer, "Sensitivity comparison of inertial to optical motion capture during gait: implications for tracking recovery," in *IEEE 16th Internal Conference on Rehabilitation Robotics*, Toronto, 2019.
16. C. Cao, M. I. Rodríguez-Ferradas, A. Cazón-Martin and P. Morer, "Development of a Low-Cost Wearable Prevention System for Musculoskeletal Disorders Using Inertial Measurement Unit Systems," in *Advances on Mechanics, Design Engineering and Manufacturing II. Lecture Notes in Mechanical Engineering*, Cham, Springer, 2019.
17. T. Cloete and C. Scheffer, "Quantification of human motion: gait analysis—benefits and limitations to its application to clinical problems," in *Quantification of human motion: gait analysis—benefits and limitations to its application to clinical problems*, Quantification of human motion: gait analysis—benefits and limitations to its application to clinical problems, 2010.
18. A. Cappozzo, F. Catani, A. Leardini, M. G. Benedetti and D. U. Croce, "Position and orientation in space of bones during movement: experimental artefacts," *Clinical Biomechanics,* vol. 11, no. 2, pp. 90-100, 1996.
19. "National Institute for Health and Care Excellence Stroke rehabilitation: long-term rehabilitation after stroke. Clinical Guideline 162," NICE, 2013. [Online]. Available: www.nice.org.uk/guidance/cg162. [Accessed 31 08 2020].
20. J.-T. Zhang, A. C. Novak, B. Brouwer and Q. Li, "Concurrent validation of Xsens {MVN} measurement of lower limb joint angular kinematics," *Physiological Measurement,* vol. 34, no. 8, pp. 63-69, 2013.
21. J. H. Hollman, M. K. Watkins, A. C. Imhoff, C. E. Braun, K. A. Akervik and D. K. Ness, "A comparison of variability in spatiotemporal gait parameters between treadmill and overground walking conditions," *Gait & Posture,* vol. 43, pp. 204-209, 206.
22. O. Beauchet, G. Allali, H. Sekhon, J. Verghese, S. Guilain, J.-P. Steinmetz, R. W. Kressig, J. M. Barden, T. Szturm, C. P. Launay, Grenier, L. Bherer, T. Liu-Ambrose, V. L. Chester and M. L. Callisaya, "Guidelines for Assessment of Gait and Reference Values for Spatiotemporal Gait Parameters in Older Adults: The Biomathics and Canadian Gait Consortiums Initiative," *Frontiers in Human Neuroscience,* vol. 11, p. 353, 2017.

23. R. Briggs, D. Carey, P. Claffey, T. McNicholas, O. Donoghue and S. P. Kennelly, "Do Differences in Spatiotemporal Gait Parameters Predict the Risk of Developing Depression in Later Life?," *Journal of the American Geriatrics Society,* vol. 67, no. 5, pp. 1050-1056, 2019.