Wearable Gait Analysis – stepping towards the mainstream

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Abstract. Wearable technologies have transformed the accessibility of gait analysis, offering the opportunity to venture outside of the laboratory and into everyday life. This research article is concerned with investigating the progress that has been made, and the steps that remain in gait analysis becoming a mainstream activity. The evidence for the effectiveness of wearable gait analysis technologies was reviewed, indicating that these devices are capable of supporting gait analysis in a 'real-world' environment. Research into the application of wearable technology for gait analysis was found to limited in terms of scope, with progress still to be made in improving the perception of these devices. Challenges to be addressed within this field of research were identified: (1) Large scale data collection; (2) Broader scope of wearable gait analysis; (3) 'Real-world' gait analysis; (4) Case study research approach (5) Gait analysis as a service; (6) User testing/evaluation.

The development of wearable gait analysis systems, and the underlying research that supports their application, should be cognizant of how mainstream acceptance is contingent upon meeting these challenges. The path towards addressing them is considered in the context of the eZiGait portable gait analysis system, highlighting the value of collaboration with industry.

Keywords: Gait analysis, wearable devices, inertial measurement unit, smart insoles, clinical application, gait rehabilitation, industry perception.

1 Introduction

Gait Analysis is concerned with the study of human motion in order to develop an understanding of an individual's ability to walk. A normal gait pattern has a positive effect on quality of life by enabling a person to perform their everyday activities uninhibited [1]. This ability is assessed by analysis of specific characteristics that constitute their walk pattern. The analysis of the gait pattern of an individual involves the extraction of specific parameters, such as spatiotemporal parameters, that are associated with different characteristics of walking. The different phases of walking constitute an overall gait cycle that represents the activity between one foot contacting the ground and that same foot again contacting the ground. Depending on the level of granularity used, the gait cycle can be composed of up to eight phases [2]. At the coarsest level of granularity, the two main phases are the stance phase, where the foot remains in contact with the ground, and the swing phase where the foot is lifted off the ground. Identifying different phases of the gait cycle enables spatiotemporal parameters to be extracted e.g. walking speed, step time, step length etc. The use of pressure and force sensors enables kinetic parameters such as centre of mass and centre of pressure to be determined [3].

The development of gait analysis methods has largely been concerned with healthcare and rehabilitation. The role of analysing the gait of an individual in providing insight into their general health has long been established [4]. Conditions that have been determined to result in gait disorders include Cerebral Palsy [5], Parkinson's Disease [6] and Alzheimer's Disease [7]. For rehabilitation, gait analysis can contribute to improving an individual's limb movements to enable them to regain a normal walking function. The applications of gait analysis within sports include improving performance [8] and avoiding injury [9]. For security purposes, individual gait profiles have been demonstrated to provide the basis for identifying a person [10]. The range of applications continues to expand, with artificial gait for humanoid robots and more realistic computer-generated models for the entertainment industry among recent developments [11].

Traditionally gait analysis took the form of human observation of an individual subject walking. This observation was performed by a trained professional and could be complemented with self-reporting by the subject. General quantitative features such as walking speed, as well severe gait disorders, can be discerned through this approach. These judgements are inherently subjective in nature and thus limit their reliability in informing a medical diagnosis or treatment decision. More significantly, subtle deviations from 'normal' gait cannot be discerned from human observation limiting the insight that can be provided by this analysis. More sophisticated gait analysis approaches were developed to facilitate more objective analysis of gait. For example, motion laboratories incorporating such techniques as video imaging to record movements enable analysis of kinematic information. This generally involves the placement of markers on the body of the test subject, with marker-less systems yet to gain as widespread use [12]. The use of single or multiple cameras determines whether 2D or 3D motion analysis can be performed [13]. Force plates measure vertical ground forces exerted by an individual to enable analysis of kinetic information [14]. The primary downside of such approaches was the considerable cost incurred in setting up an appropriate laboratory to conduct the analysis. The prohibitive cost in turn ensured that access to this form of gait analysis was limited to specialist locations. The advent of wearable technology greatly reduced the barriers to use present with conventional technology, thus opening the possibility of widening access to gait analysis. Despite the breakthrough provided by these wearable devices mainstream acceptance of gait analysis remains a goal yet to be achieved. This research article considers the developments made within the field of wearable gait analysis and the barriers that remain in fully realizing its potential. Potential approaches that may be adopted to move towards mainstream acceptance are then discussed in the context of the eZiGait mobile gait analysis system that is currently being developed.

2 Review of Wearable Gait Analysis Research/Development

The review of developments within this area commences with a comparative overview of the main types of gait analysis technologies that have been developed thus far. The evidence for their effectiveness of wearable devices for enabling gait analysis is then considered. The contribution that these devices can make is then examined in terms of the scope of previous research and the potential users of such technology.

2.1 Comparative Overview of Gait Analysis Technologies

Table 1 provides an overview of the main types of technologies that are used to perform gait analysis. Optical Motion Capture systems represent the most accurate technology for capturing Kinematic information, but correspondingly incur the highest costs in terms of initial setup and subsequent operation. Force plates systems, that measure Vertical Ground Forces, can be implemented at varying levels of cost. Both systems are limited to use within a laboratory environment and only cater for recording data over limited durations. The application of gait analysis is therefore limited to controlled exercises that may not be reflective of the 'normal' walking patterns exhibited by an individual person. Gait Pressure mats have been developed as a more practical alternative, with medium costs incurred and some degree of portability. The relative bulk of such systems still inhibits their accessibility to some extent, and they remain suitable for indoor use only. The limited length of the mats means that they are unsuitable for extended recording durations. The development of wearable technologies represents the most significant breakthrough in terms of accessibility. The main types of inertial sensors provide measurements in up to 3 axes of motion and can be incorporated together in the form of an Inertial Measure Unit (IMU). Accelerometers provide measurements of the rate of change of velocity for an individual in their own real frame. Gyroscopes provide measurements of orientation and angular velocity. Magnetometers measure the direction and strength or relative change of a magnetic field at a location. These inertial sensors may be utilised within a standalone device or within other technology such as a smartphone. The presence of inertial sensors within smartphones provides the greatest degree of availability, although standalone IMU devices provide greater flexibility e.g. can be worn on different parts of the body. The location of the IMU device impacts both the measurement accuracy achievable and the level of comfort for the user. The costs of such devices can vary according to how they are implemented, but a significant reduction can be achieved relative to lab-based systems. The suitability for outdoor use and capacity for capturing sensor data over an extended duration provides a significant advantage in terms of measuring 'real-world' data.

Table 1. Comparison of Main Technology Types

Technology Type	**Key Characteristics**	**Practicality**
Optical Motion Capture System	- High Measurement Precision - High Technology Costs - High Computational Costs	- Lab-based System - Requires expert operation - Limited recording duration
Force Plates	- Low Measurement Precision - Low to High Technology Costs - Low Computational Costs	- Limited Portability (due to weight) and used mainly within Lab environment - Limited recording duration
Gait/Pressure Mat	- Variable Measurement Precision - Medium Technology Costs - Low Computational Costs	- Portable but suitable for indoor use only - Requires expert operation - Limited recording duration
Inertial Measurement Unit (Accelerometer, Gyroscope, Magnetometer)	- Low Measurement Precision - Low to Medium Technology Costs - Low Computational Costs	- Portable use both indoors and outdoors - Can be worn and operated by user - Level of comfort dependent upon design - Extended recording duration
Insole Pressure Sensor System	- Low Measurement Precision - Low to Medium Technology Costs - Low Computational Costs	- Portable use both indoors and outdoors - Can be worn and operated by user - Extended recording duration

Insole Pressure Sensor systems provide a more accessible alternative to Force Plates and at a significantly lower cost. These insoles deploy an array of sensors to record pressure at several locations on the sole of each foot. The number of sensors embedded into an insole can range from a few to over 40 depending on the design.

The level of availability of Insole Pressure Sensor systems is not as widespread as that of smartphone-based inertial sensors, but they otherwise retain the same benefits in terms of measuring ‘real-world’ data. Smart insole systems may combine the use of inertial sensors with pressure sensors, enabling a wider variety of application for any recorded data as well as the potential for fusion of the different types of data. In these systems, the inertial sensors may be attached to the insoles or embedded directly into the insoles. The development of these smart insole systems has addressed many of the shortcomings of previous gait analysis systems.

2.2 Clinical Application of Gait Analysis

Jarchi et al. [15] reviewed gait analysis involving accelerometery with a focus on how it is applied to clinical applications. The review included 159 research papers, starting from the year 2000, and defined three classifications for these studies. The most common category, at 38% of research papers, was the validation of gait parameters against more established approaches such as video analysis, force-plates etc. The other two categories were focused on applying gait analysis to clinical applications, with 32% of papers utilising an accelerometer and 30% of studies incorporating single or multiple configurations of sensors.

Baker et al. [16] described four main reasons for performing clinical gait analysis. The first reason was the diagnosis of a specific disease, followed by the assessment of the severity of that disease or an injury. The other two reasons were concerned with either monitoring or predicting the progress of the disease or injury, with or without an intervention taking place on the patient. The success of clinical gait analysis can be judged according to the extent that it supports the desired outcomes for these intended uses i.e. its efficacy.

Table 2 shows how research involving the clinical efficacy of gait analysis has progressed over the past two decades. This research was focused on conventional three-dimensional instrumented gait analysis performed using laboratory methods such as motion capture and force plates. Two systematic reviews, conducted by the same authors [17] - [18], categorised the research studies published during their respective preceding decade according to the efficacy type that was addressed. For the second systematic review, a new efficacy type (2b) was introduced to reflect how the focus of research had evolved. This type 2b research was concerned with an evaluation of the efficacy of treatment at a group level, in contrast to individual patient outcomes addressed at type 5. In some cases, the research conducted in an individual study incorporated multiple adjacent efficacy types. The overall number of research studies had risen significantly in the latter decade, from 210 to 2712 papers, indicating the increased significance of this field of research. The level of efficacy that has been investigated most has also changed from type 1 to type 2, including the new type 2b. This may reflect the progress beyond evaluating the technical performance of gait analysis methods towards their clinical application. The efficacy type 2b research indicated the significance of being able to diagnose patients as being part of a group and consequently predicting treatment outcomes for that type of patient. The absence of any increase in research studies at higher efficacy types indicates the limitations on the understanding of how gait analysis can contribute at these levels. In particular, the question to be asked is whether the limitations on accessibility associated with laboratory gait analysis have themselves impacted the progress of research in this regard.

Table 2. Number of Research Studies Grouped by Efficacy Type

Efficacy Type	Number of Research Studies (Jan 2000 to Sept 2009)	Number of Research Studies (Sept 2009 to Oct 2019)
1 - Technical	116	313
2 - Diagnostic Accuracy	89	1466
2b - Outcome Prediction	-	927
3/4 - Diagnostic Thinking & Treatment	11	6
5 - Patient Outcome	7	3
6- Societal	1	0

The highest level of efficacy (type 6) was concerned with the cost effectiveness of gait analysis in terms of its impact on society. The need for such research was highlighted in a conference held amongst professionals within this field to establish a consensus on the general progress of gait analysis [19]. The absence of cost effectiveness studies on the use of motion laboratories was broadly agreed to be a significant problem. The absence of standardised procedures for gait analysis and publicly available data on 'normal' gait profiles was also identified as a problem to be addressed. The scientific evidence supporting the use of gait analysis was generally considered limited to a few medical conditions. The overriding conclusion of the conference was that the value of gait analysis as a research tool has thus far exceeded its value for clinical applications.

2.3 Overall Effectiveness of Wearable Gait Analysis Devices

Numerous research studies have examined the performance of wearable devices in the context of Gait Analysis. These studies have sought to demonstrate the feasibility of utilising wearable sensors for gait analysis and provide a means of evaluating them as a substitute for more conventional laboratory approaches.

Kobsar et al. [20] conducted a systematic review of studies on the validity and reliability of wearable inertial sensors. The context of this review was on healthy adults walking as opposed to individuals with any underlying medical conditions. The review covered research papers from 1998 to 2019 in terms of set parameters, rating each parameter according the quantity, quality and consistency of results across studies that addressed the parameter. For the step time and stride time parameters the results were rated as excellent. For step length, stride length, swing time and stance time the results were rated as good to excellent. For gait variability and gait symmetry parameters the results were only rated as poor to moderate. The issue with the lower performing parameters was more an issue of the limited number of studies, or their design, rather than the performance of the sensors themselves. The main weaknesses of the research studies were from a statistical perspective e.g. underpowered results, unjustified sample sizes, and inadequate statistical analysis in support of the evaluation of results. The meta-analysis undertaken within this review highlighted the difficulty in comparing results across studies. The large number of studies were completed without a standardised protocol and addressed different subsets of gait parameters. For each gait parameter there were typically between three to five studies that could be compared. Establishing a comprehensive appraisal of the validity and reliability of wearable inertial sensors was concluded to more a question of quality than of quantity in terms of future research studies.

Direct evidence for the performance of inertial sensor-based systems relative to that of conventional gait analysis approaches was reviewed for the time period from 2005 to 2017 [21]. In this systematic review, a total of 16 research articles were selected that compared gait parameters obtained using wearable or inertial sensors against those obtained using a motion laboratory. Meta-analysis was performed on seven different gait parameters addressed by multiple studies. Table 3 shows a summary of the results of this meta-analysis.

Table 3. Meta-Analysis of Gait Parameter Results

Gait Parameter	Number of Studies	Number of Subjects	Standardised Mean Difference	95% Confidence Interval (Leftmost value, Rightmost value)
Gait Speed	5	149	0.11	(-0.10, 0.33)
Step Length	6	245	0.14	(-0.14, 0.43)
Step Time	5	234	-0.03	(-0.24, 0.18)
Stance Time	3	140	0.50	(0.24, 0.76)
Stride Time	3	110	-0.03	(-0.29, 0.23)
Cadence	4	138	0.46	(-0.41, 1.34)
Swing Time	3	140	-0.63	(-1.32, 0.05)

Standardised Mean Difference (SMD) refers to the difference in the mean value of each group (IMU and motion laboratory) divided by the standard deviation. In this case, a positive SMD indicates that the IMU group had the greater mean value and a negative SMD indicates that the other group had the greater mean value. The leftmost and rightmost values of the 95% confidence interval for the SMD value provides an indication of the level of uncertainty associated with the value. Statistically significant differences between the groups are indicated when the 95% confidence interval does not contain zero. The results indicate that for gait speed, step length, step time and stride time there was a good level of agreement between the two groups. Only stance time demonstrated a statistically significant difference between the two groups.

Cadence and Swing Time had the greatest level of uncertainty regarding the SMD value, so caution is necessary in drawing any conclusions for those parameters.

The value of being able to obtain the gait parameters using relatively low-cost wearable devices in short walking exercises was noted by the authors of the review. Limitations on the understanding of the effectiveness of wearable inertial sensors that can be derived from this review were, however, identified. These included the different devices, algorithms and test procedures used by the studies. The use of wearable devices was not considered to be a substitute for motion laboratory gait analysis as the latter approach is necessary for identifying the locomotor strategy used by patients.

The use of Artificial Intelligence (AI) approaches such as machine learning for analysis of gait data has been a common research theme. The effectiveness of AI approaches to assist with gait analysis methods was considered by a systematic review of research studies focused on inertial sensors and adaptive algorithms [22]. The review, considering only Journal Papers, looked at research studies published between 1968 and 2016 that used IMUs and adaptive AI algorithms to classify gait events. The quality of results obtained from adaptive AI algorithms was reported to be above average, leading the authors to conclude that they are suitable for use in gait analysis. The lack of standardization in terms of the methods used was again highlighted as an issue moving forward. As most of the studies utilised healthy test subjects, the potential for improvements with patients whose gait is impacted by a medical condition was not discernible from the research.

The use of inertial sensors for gait recognition was reviewed by Sprager and Juric [23]. The performance of inertial sensor-based gait recognition was found to be more effective for large datasets, in the region of 200 people, with error rates of around 5% reported. These research studies generally used very short walking exercises, typically involving only a few steps, thus limiting the extent to which they would be replicated in practice. For those research studies that allowed for walking in an uncontrolled environment over a longer period the reported accuracy rates ranged from under 70% to above 90%.

2.4 Scope of Wearable Gait Analysis Devices

Chen et al. [24] conducted a systematic review of gait analysis research studies involving wearable sensors, examining how pervasive the technology could become. The authors asserted that only 0.2% of gait analysis papers both involved the use of inertial sensors and were conducted in real clinical settings. There was no indication that the total number of research papers accounted for those published before inertial sensors were developed so this relative proportion may be understated. The review included 2906 papers focused on applying gait analysis to medical conditions. The distribution of these studies was found to strongly favour some medical conditions with Parkinson's Disease (29%), Cerebral Palsy (17%), Orthoses (13%), Lower Limb Osteoarthritis (6%) and Post Stroke (6%) accounting for over 70% of the research papers. The remaining approx. 30% of research was distributed across 13 categories suggesting that research gaps remain to be addressed. Possible reasons suggested for this pattern of research were limited availability of affordable technology or a need to align technology advancements with the medical knowledge within those domains. A systematic review of the use of smartphone systems for physical rehabilitation revealed a similar narrow focus [25]. From the 74 research studies that were reviewed, the diseases that dominated the research were stroke, cardiac disease, balance impairment and joint/limb rehabilitation.

In order to provide the greater accessibility within standardised medicine that wearable sensors are intended to provide it is necessary to gain acceptance within the medical community. In terms of research, using established gait analysis procedures ensures generalisability for the results. Numerous research studies have shown that standard clinical tests such as the Timed Up and Go (TUG) test and the 6-Minute Walk test, can be successfully administered using low cost sensors in mobile or wearable devices [26], [27]. The Standardised procedure outlined for the TUG test has also been successfully adapted towards use with wearable devices [28]. The usage of wearable devices for standard tests of a longer duration, as with the 6-Minute Walk test, has also enabled a more detailed analysis of gait features to be performed. For example, sensor data obtained from turning during the test provides a clearer indication of impaired gait than may be obtained from regular walking in a straight line.

Research into the use of wearable devices for gait analysis outside of the laboratory environment was reviewed by Benson et al. [29]. The research papers were comprised of 43 walking studies, 13 running studies and a single study incorporating both forms of exercise. While the outcomes of the studies were assessed as being sufficiently reported they generally did not adequately describe the statistical power of their results. There was some progress towards using larger number of participants within walking studies, but it was recommended further improving this by monitoring gait over longer periods of time and in natural environments. The need to address the usability of wearable sensors was also highlighted. For long term use, the location the device is to be worn and its size/weight need to be as unobtrusive as possible without compromising the validity of the measurements that can be obtained.

3 Adoption of Wearable Gait Analysis Devices

Investigating the perception of wearable devices provides insight into the progress that has been made towards achieving mainstream acceptance. The development of wearable technology has been largely driven by potential medical applications, but in terms of impact the main market has been the general fitness industry [30]. The medical field represents a higher barrier to entry in terms of performance in comparison to the general fitness market. The level of accuracy acceptable for a consumer-oriented device would not generally be considered sufficient for supporting medical decisions. In contrast, familiarity with gait analysis is much less prevalent within general consumers.

Issues affecting the adoption of wearable gait analysis tools are discussed in the following sections. This considers the perception of wearable devices amongst both professional users, interested in adopting them into their work practices, and individuals that would have their gait characteristics analysed. An example of how gait analysis can be integrated into the wider healthcare system is then provided.

3.1 Perception of Wearable Devices

In a survey of the adoption of wearable sensors in the workplace [31], 90.4% of respondents that wore a device at work did so for monitoring general physical activity. The most popular devices that respondents expressed confidence in, such as "Fitbit", were typically providing easy to understand data such as step counts. Doubts were commonly expressed by respondents about the validity and efficacy of more sophisticated uses of wearable technology.

Mobile phone health apps have experienced substantial growth, but a systematic review of the scientific evidence behind their diagnostic performance was underwhelming [32]. Even when including research focused on symptom monitoring, for supporting diagnosis, it was found that studies were lacking both in terms of quantity and quality.

The need for a patient-centred focus has been promoted as a response to the increasingly complex delivery of healthcare. In the context of physical rehabilitation, several themes have been identified within research [33]. It is important that treatment is individualized for the patient and that they have a good understanding of their symptoms and treatment path. Goal setting and establishing a feeling of empowerment for the patient were reported as having a positive effect in helping them cope with their condition. The use of wearable devices offers the potential for providing patients with this patient-centred treatment both in and outside of physiotherapy sessions.

Morris et al [34] conducted a survey of clinicians concerning their perspectives on the use of mobile health and rehabilitation applications. Over 500 clinicians were surveyed, drawn from a range of professions such as physical, occupational and psychological therapists. While a large proportion of the respondents reported prescribing specific out of clinic exercises and interventions to patients, it was clear that acceptance of mobile solutions continues to be a challenge. Only 51% of respondents expressed comfort in integrating mobile technology into their clinical practice. In addition, only 23% of respondents considered themselves to be knowledgeable about the available technology. The top barrier to their use, identified by 72% of respondents, was the inability of patients to learn and correctly use mobile technology.

The perspectives of physiotherapists on the use of wearable or mobile health technology were investigated by Blumenthal et al. [35] In this study a simplified version of the popular Technology Acceptance Model (TAM) framework [36] was used to investigate the willingness of 76 participating therapists and students to implement these types of technology into their clinical practice. The primary motivation of the research was to investigate why the usage of this technology remained low within the physiotherapy industry. The study found no evidence that early adopter behaviour was influenced by age or previous experience with technology. It was suggested that the perceived usefulness of the technology was an important determinant of early adoption. Encouraging physiotherapists to invest their time and resources in implementing this technology requires a clear demonstration of how it would add value to their practice. Increasing patient engagement and improving how progress is communicated were rated as highly important by the study participants. The importance of the user experience was therefore proposed as an important design consideration for mobile health technologies.

Guillen-Gamez and Fernández [37] investigated the perceptions of the subjects involved in wearable technology research. The study included a total of 606 patients and relatives, comprised of 60.2% female and 39.8% male participants. The attitude of the participants towards the usefulness of wearable devices was reported as being medium high, with a slightly higher level reported for males. In particular, the participants viewed the devices as being more useful for caring for the health of elderly people than for themselves. While men were generally more accepting of the use of wearable devices there was a greater contrast across age for female participants. Women under 30 owned more wearable devices than any other group, but women over 45 had the lowest level of acceptance for the use of such devices. In terms of the acceptance expressed for the location of the wearable device, on the wrist had the highest level (Male 52.7%, Female 50.19%) out of five options. The option of wearable devices placed in shoes, relevant for Smart Insole technology, was ranked third for Male (48.77%) and fourth for Female (45.30 %) participants.

Evaluating usability and accessibility of mobile heath apps has been identified as an important consideration for achieving a patient-centred focus in improving rehabilitation outcomes [38]. In this review, usability was reported to be high for those apps that were educative and supported self-reporting of symptoms. For apps focusing on intervention, the most positive effects were found with functional outcomes such as gait and self-management skills. Positive effects were also found with health outcomes such as pain and quality of life. Evaluating the impact of mobile health systems requires consideration of both types of outcomes. Investigating functional outcomes from using these systems outside of the controlled laboratory environments is therefore as important as investigating their accuracy.

3.2 Integration of gait analysis into clinical practice

The acceptance of gait analysis within mainstream clinical practice is contingent upon successful integration into the wider healthcare system. Research on how to achieve this integration has been limited, but an in-depth study on the design of a gait test within clinical rehabilitation provided instructive guidelines [39]. This study adopted a service-oriented approach to design in contrast to viewing gait analysis as a technological challenge. The multiple stakeholders in this service include patients (and their relatives), doctors, and therapists. Each of these stakeholders present different needs that must be met and therefore they must be considered in the design process. The design in this study was comprised of three main phases. Firstly, 'User-product proximity effect' where the gait test is performed in a motion laboratory and the effects on the various stakeholders are observed. Secondly, 'Effect and value in the service' where an overview is obtained of the path followed by the patient through the service e.g. diagnosis, care and treatment decisions. Thirdly, 'User interactions' that define the information flows between stakeholders that are necessary to facilitate implementation of the gait test. The design recognised the need to treat the patient as an individual that will respond in their own way to treatment. Providing guidance to the patient at each stage of the service being provided is essential in enabling them to view the gait test as a motivational tool within their overall treatment.

4 Towards Mainstream Adoption of Wearable Gait Analysis

The review conducted in the preceding sections enabled the identification of the challenges to be addressed for wearable devices. The eZiGait system is introduced as an example of a wearable gait analysis system, with consideration then given to how future development of this system can be directed towards addressing the challenges that have been identified.

4.1 Future Challenges for the adoption of Wearable Gait Analysis Devices

The issues to be addressed on the path towards mainstream acceptance of Wearable Devices for gait analysis can be summarised as follows:

1. **Large scale data collection:** in order to achieve a greater understanding of normal and abnormal gait profiles it is necessary significantly increase the size of datasets. The accessibility and cost of wearable sensor systems needs to be considered if they are to enable the establishment of datasets on a large scale. The increase in the adoption of these systems could potentially decentralise the establishment of these datasets from researchers to the users.
2. **Broader scope of wearable gait analysis:** to facilitate the acceptance of gait analysis it is necessary to broaden the nature of the data collected. Instead of focusing on a limited selection of pathological conditions research should explore whether an individual's gait profile is affected by other conditions. In terms of the sports and leisure industries it should be investigated whether gait analysis can benefit the more 'casual' athlete rather than being restricted to professional athletes. The impact of wearable gait analysis should be to move gait analysis beyond being restricted to relatively niche markets.
3. **'Real-world' gait analysis:** the development of wearable sensor devices has enabled the collection of subject data in 'real-world' conditions. It is imperative for research to increase efforts to engage in the collection of data in these conditions. Wearable sensor technology provides the basis for users to record data in their own time and location.
4. **Case study research approach:** increasing the quality of research includes the adoption of in-depth research studies. Case studies involving the progress of patients through the treatment/rehabilitation process are necessary to understand both how gait analysis can inform decisions made at each stage and how it impacts recovery for a patient.

5. **Gait analysis as a service:** the value of wearable sensor systems is to be derived from the service they provide to the various user groups. The objective is therefore to identify the needs of each user group, such as patients, medical professionals, athletes etc., and incorporate them into the services provided by the system. Achieving this objective requires including each user group as stakeholders and having them guide the direction of development of these services.
6. **User testing/evaluation:** to ensure the suitability of wearable sensor systems to fulfil their intended role, they must be subjected to appropriate evaluation by the intended users so that their design can be refined accordingly. For the wearable devices, it is necessary to ensure that the size/weight and location of the technology remains comfortable for the patient. For the supporting software, the gait analysis reports produced must be both be understandable to the users and convey information that is of value to them.

The path towards addressing these challenges would include collaboration with organisations with a vested interest in the growth of wearable gait analysis, such as medical and rehabilitation organisations. The patients/customers of such organisations represent prospective users that need to be reached in order to achieve the goal of wearable technology i.e. to improve their quality of life.

4.2 eZiGait System Overview

The architecture of the eZiGait system is shown in Fig 1. The main components of the system are the Smart Insoles, the AI Gait Assistant mobile application, and the Cloud-based Analytics. The Smart Insoles used in previous research studies [40] - [41] were provided by TreeHouse Technology Ltd in China. There are eight separate pressure sensors built into each insole, providing readings of Vertical Ground Forces for eight locations within each foot. A pressure map is thus obtained for each foot, charting the distribution of weight exerted across each foot during the Gait cycle. An attached electronic device, that is worn around the ankle, is equipped with an IMU. This IMU provides a 3-axis accelerometer, 3-axis gyroscope and 3-axis magnetometer. By simultaneously sampling data in three axes, the test subject's movements are effectively monitored.

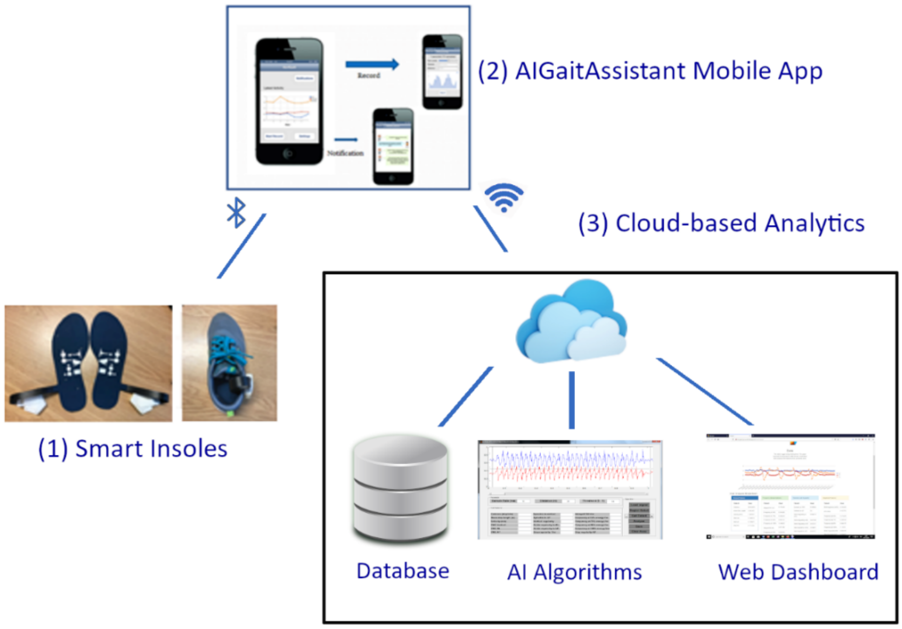

Fig. 1. Overview of eZiGait System

The electronic device is equipped with a rechargeable battery that allows sensor data to be recorded over prolonged exercise sessions. The battery for this device is charged using any standard USB connection. The sensor readings are streamed in real-time and transmitted via Bluetooth to any paired device, such as a smartphone. An API is provided for the Smart Insoles that facilitates communication with other applications. A mobile app, AIGaitAssistant, has been developed for Android based smartphones. This app serves as the intermediary between the Smart Insoles and the Cloud-based Analytics, analysing the gait characteristics of the test subject. The following main functionality is included within the smartphone app:

- Connect to Bluetooth paired Smart Insoles to receive real-time sensor data on test subject movements.
- Display of real-time sensor data from each of the sensors within the GUI. This enables the user to verify that each of the sensors is functioning correctly prior to performing any exercise.
- Record sensor data for a specified exercise session. Each session is defined by the user in terms of a label to identify that session, the type of exercise to be completed, automatic or manual upload and generation of a gait report. The recorded session data is automatically saved locally on the smartphone as a CSV file.
- Upload the sensor data to a web server via a Wi-Fi connection for subsequent cloud-based analysis.

- Generation of a Gait Report for the completed exercise session. This report is comprised of the following detail
  - Overall summary of the gait session e.g. time, step count etc.
  - Gait Phase Distribution for each foot, with the overall gait cycle divided into Loading, Foot-Flat, Pushing and Swing Phases
  - Temporal Symmetry between each foot for Step Time, Stance Time, Swing Time and Stride Time
  - Pressure Symmetry between each foot for Heel Region, Mid-foot Region, Toe Region and Overall Foot.

The Cloud-based Analytics are hosted on a web portal that enables further examination of the recorded sessions by healthcare/rehabilitation professionals. For example, the progress of an individual in terms of their gait characteristics can be tracked over the course of their uploaded sessions. The analysis provided by this web portal continues to be developed with the aim of applying advanced machine learning approaches to establish a greater understanding of an individual gait.

4.3 eZiGait and the Future of Wearable Gait Analysis

The several challenges to be addressed for wearable gait analysis to gain more mainstream acceptance are being considered during the development of eZiGait.

eZiGait is being developed in conjunction with related research projects concerned with gait analysis. It has been utilised within previous research studies [40] - [41] in addition to internal data collection and validation. This provides a mechanism for conducting user testing and refining both functional and non-functional user requirements. It also presents opportunities for collaborating with external parties in 'real-world' environments. For example, the Smart Insoles and smartphone app have been utilised during rehabilitation sessions with a local physiotherapist. This provided the opportunity to learn from prospective users of the system and refine the user experience based on the feedback obtained. This ongoing collaboration will provide the opportunity to collect data from both healthy subjects and rehabilitation subjects. The healthy subjects include individuals participating in regular sports exercises within a gym environment. This enables data related to 'normal' gait to be collected in a 'real-world' situation in contrast to a lab-controlled environment with specific exercises. The access to rehabilitation subjects presents a learning opportunity that addresses multiple challenges.

- The physiotherapist is one the few specialists available in Ireland that provides the use of an exoskeleton as part of the rehabilitation process. The range of conditions affecting patients undergoing rehabilitation therefore presents the opportunity to collect data outside of the common conditions more regularly addressed within research. This will enable an understanding to be developed of how these conditions impact the gait profile of the subjects.
- The collection of data at successive stages of the rehabilitation process will enable the subsequent effect of the treatments on the subject's gait profile to be assessed.

The in-depth case-study approach presents the opportunity to learn how gait analysis can form part of the rehabilitation process.

- The input from the physiotherapist throughout the research can guide the development of the gait analysis system by communicating which information is of use to the rehabilitation process and identifying potential new aspects of gait to be investigated.
- The needs of both the physiotherapist and the rehabilitation subjects, in terms of the service that is being provided, can be analysed and subsequently specified. This includes an understanding of the expectations held by these users prior to each gait analysis session and the level of satisfaction achieved upon completion of the session. Designing the service is as important to its success as the performance of the technology.
- The deployment of the system in a 'real-world' environment enables user testing and evaluation of the system to be performed. This will enable the system to be refined in order to enhance the accessibility of software. The presentation of information is integral to user understanding and subsequently them benefitting from their experience with the system.
- The benefits and costs of using the system can be investigated. The impact upon the rehabilitation process in terms of the extent of the recovery and the timeframe involved can establish what benefits, if any, that gait analysis provides. The cost incurred, such as the provision of the technology and the learning time required, can also be established, enabling an assessment to be made on the value that is provided.

5 Conclusion

Wearable gait analysis has provided a significant breakthrough in terms of the accessibility and affordability of such technology. This technology provides the potential for enabling gait analysis to become commonplace within mainstream healthcare systems and both the sports and leisure industries. Realising this potential is dependent upon directing the technology towards the needs of these users and demonstrating clear and cost-effective benefits. Research within this field should include investigating wearable gait analysis systems within the context of those industries that it aspires to benefit in order to further understand the role that this technology can fill. Bringing wearable gait analysis research out of the lab environment should enable the technology to follow suit and step forward into the mainstream.

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