Toward Pervasive Gait Analysis With Wearable Sensors: A Systematic Review

Shanshan Chen, *Member, IEEE*, John Lach, *Senior Member, IEEE*, Benny Lo, *Senior Member, IEEE*, and Guang-Zhong Yang, *Fellow, IEEE*

***Abstract*—After decades of evolution, measuring instruments for quantitative gait analysis have become an important clinical tool for assessing pathologies manifested by gait abnormalities. However, such instruments tend to be expensive and require expert operation and maintenance besides their high cost, thus limiting them to only a small number of specialized centers. Consequently, gait analysis in most clinics today still relies on observation-based assessment. Recent advances in wearable sensors, especially inertial body sensors, have opened up a promising future for gait analysis. Not only can these sensors be more easily adopted in clinical diagnosis and treatment procedures than their current counterparts, but they can also monitor gait continuously outside clinics – hence providing seamless patient analysis from clinics to free-living environments. The purpose of this paper is to provide a systematic review of current techniques for quantitative gait analysis and to propose key metrics for evaluating both existing and emerging methods for qualifying the gait features extracted from wearable sensors. It aims to highlight key advances in this rapidly evolving research field and outline potential future directions for both research and clinical applications.**

***Index Terms*—Free-living gait analysis, gait analysis, inertial sensors, insole pressure sensors, medical applications, quantitative gait analysis, wearable sensors.**

(a) (b)

Fig. 1. Gait analysis in common clinical settings: (a) observer-based timing and visual assessment of gait; (b) use of optical trackers for detailed motion capture and gait analysis.

I. Introduction

GAIT analysis is an established research area for many medical and healthcare applications [1]. These applications range from evaluating the efficacy of orthoses, prosthetics, surgical procedures, [2]–[5] or rehabilitation treatment (e.g., for knee surgery or stroke recovery), through aiding diagnosis and assessment of neuropathies [6]–[9], to monitoring gait degradation, assessing fall risks, and preventing falls for the elderly [10], [11].

The quality and validity of these gait analysis applications are dependent on the measuring instruments used [12]. In current clinical settings, gait analysis is usually performed by subjective and qualitative approaches, such as human observation [13] and patient self-reporting [see Fig. 1(a)]. In this way, the main quantitative measures that can be derived are cadence, gait speed, and distance covered. These are oversimplified measures for assessing human gait – a complex mechanism governed by the neuromuscular system. Although some severe gait disorders can be observed by human eyes, without quantitative measures, subtle changes can go unnoticed. Furthermore, these approaches typically involve significant inter- and intraobserver variabilities, thus affecting disease staging, severity assessment, and subsequent treatment planning [14].

Thus far, some specialized centers and clinics have adopted standard gait analysis tools based on optical motion capture systems, such as the Vicon (Oxford Metrics Limited, Oxford, United Kingdom) [see Fig. 1(b)] [15]. With infrared cameras capturing body motion defined by the reflective markers, these systems track spatial information and human motion, and provide high-precision data at a sampling rate of 100–200 Hz. Although such systems can deliver highly accurate human movement analysis, they are relatively expensive and require expert operation [12]. Furthermore, they are restricted to laboratory settings, so the information derived may not reflect gait in real-world settings [16]. They also involve an intrusive and cumbersome marker setup procedure, hindering normal movement of the patient [17]. Therefore, although such instruments have galvanized gait analysis research in the past, they are not pervasive enough among clinics for gait analysis to realize its full potential. Many studies continue to use goniometers for measuring joint angles. However, such tools are also cumbersome to use and can only provide limited types of information.

Manuscript received May 9, 2016; revised August 4, 2016; accepted August 25, 2016. Date of publication September 22, 2016; date of current version December 6, 2016.

S. Chen is with the Department of Biostatistics and the Department of Internal Medicine, Virginia Commonwealth University, Richmond, VA 23298 USA (e-mail: shanshan.chen@vcuhealth.org).

J. Lach is with the Department of Electrical and Computer Engineering, University of Virginia, Charlottesville, VA 22903 USA (e-mail: jlach@virginia.edu).

B. Lo and G.-Z. Yang are with the Hamlyn Centre, Imperial College London, London SW7 2AZ, U.K. (e-mail: benny.lo@imperial.ac.uk; g.z.yang@imperial.ac.uk).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/JBHI.2016.2608720

TABLE I
CURRENT QUANTITATIVE MEASURING INSTRUMENTS FOR GAIT ANALYSIS

	Kinematic Information		Kinetic Information		Muscle Activity
	Conventional	Wearable	Conventional	Wearable	Portable
Instrument Type	Optical Motion Capture Systems	Inertial Sensors	Force Plates	Insole Pressure Sensors	EMGs
Practicality	Pre-installation and expert operation	Easy to wear	Pre-installation	Easy to wear	Cumbersome or invasive to wear
System Cost	> $30000	< $2000	$200 ∼ $30000	∼$3000	∼$10000 (Wireless)
Continuous Monitoring	Less than 10 minutes	>2 hours	Less than 10 minutes	>2 hours	In-lab and out-of-lab
Accuracy & Precision	High	Sensor/Algorithm dependent	High	Sensor/Algorithm dependent	The only type of instrument for muscle activity
Measures	Kinematic measures	Capable of emulating optical motion capture	Kinetic measures	Capable of emulating force plates	Muscle activities and kinetic measures
Computation Cost	High (computing coordinate triangulation)	Low	Low	Low	Low
Real-time Potential	Limited	Implemented in Research	Limited	Yes	Yes

Force plates and electromyography (EMG) systems are two other quantitative gait analysis tools commonly used in those specialized centers together with optical motion capture systems. Force plates measure ground reaction forces (GRFs) during walking, and when synchronized with kinematic information recorded by optical motion capture systems, can provide kinetic information based on inverse dynamics. EMG systems capture the electrical activity generated by skeletal muscles, and can be used to study muscle activity. They are particularly useful for assessing gait disorders with symptoms such as severe muscle weakness. Traditional EMGs are inconvenient and cumbersome to wear, and force plates must be installed in dedicated laboratories. In order for gait analysis to gain popularity in clinics, it is essential to replace the current gait analysis systems that provide kinematic information and EMGs, with easier to use, more economical, and portable platforms.

Recent advances in wearable sensor technologies [18], especially inertial body sensors, insole pressure sensors, and wireless EMG sensors, have shown great promise for providing such a replacement. They are low cost, portable, versatile, and can supply rich information for real-time gait analysis in both indoor and outdoor environments, providing seamless gait analysis from clinics to free-living environments. To highlight the advantages of wearable sensors over the current laboratory systems, Table I compares the laboratory gait analysis tools and their wearable counterparts.

However, before wearable sensors can truly be adopted for clinical use, their effectiveness needs to be carefully assessed. To this end, we examine in this paper current gait analysis methods based on wearable sensors. First, we identify the clinical applications that could most benefit from portable gait analysis. Common diseases that are manifested by gait pathology are described with the corresponding gait characteristics. These abnormal gait patterns are then characterized and mapped into quantifiable gait measures. Next, we review existing methods that can extract such gait measures, demonstrating the feasibility of replacing current optical motion capture systems with wearable sensors. Finally, metrics for evaluating the methods in a clinical context are proposed.

Overall, we aim to provide a roadmap for the future development of gait analysis based on wearable sensing, including highlighting current progress, identifying unmet clinical demands, and suggesting potential future research directions. The main contributions of this review paper are to:

1) establish intrinsic links between gait characteristics (of gait-manifested diseases) and quantifiable gait measures that can be captured by wearable sensors;
2) review existing methods for extracting gait measures from wearable sensors; discuss the feasibility of replicating the measures used in the laboratory systems; and finally, lay out a roadmap for extracting relevant gait measures from inertial sensors, pressure insole sensors, and EMG sensors;
3) propose tangible evaluation metrics for using wearable sensor platforms as clinical diagnostic tools.

II. GAIT ANALYSIS IN MEDICINE

As research and technologies evolve, quantitative gait analysis is proving to be beneficial for the assessment of patient outcomes. This section provides an overview of gait pathologies commonly seen in medicine, for which clinical research has proven gait analysis to be useful. These include, for example, poststroke rehabilitation, anterior cruciate ligament reconstruction, and prescribing orthopedic devices for severely gait-impaired patients. Quantitative gait analysis can also support clinical decisions and optimize treatment protocols [4], [19], [20]. As most neurological and neuropsychological diseases can be manifested by changes in gait, gait analysis can help to diagnose and assess the severity of these symptoms [21]. In psychiatrics, gait disturbance can reflect "cortical and subcortical dysfunction" [22], thus gait analysis can be highly informative in psychiatric diagnosis and assessment [22]. In geriatrics, gait analysis is playing a more important role [23]. A large body of research in sports medicine also studies running gait. However, since this paper focuses on patients and clinical outcomes rather than athletes and fitness, research work from sports medicine is not reviewed.

In general, gait pathologies can be classified into four major categories: rehabilitation-related gait patterns, neurological gait disorders, psychiatric gait abnormalities, and gait degradation due to aging. In each category, the gait characteristics

TABLE II
GAIT ANALYSIS USED IN MEDICAL RESEARCH

Disorders	Gait Measures to Monitor	No. of Related Papers on PubMed, Search Criteria
Orthopedics, Prosthetics & Rehabilitation		
Post-stroke	Gait velocity, time-distance measures, joint angles [24]	163, "gait"[title] AND ("post stroke"[title] OR "after stroke"[title])
Anterior cruciate ligament injury	Knee flexion, hip abduction-adduction [25]	98, "gait"[title] AND ("Anterior cruciate ligament"[title] OR "ACL"[title])
Knee replacement	Joint angle at different gait events, ground force reaction [26]	34, "gait"[title] AND ("knee surgery"[title] OR "knee replacement"[title] OR "knee operation"[title])
Lower limb osteoarthritis	Gait speed, knee joint angle, hip angle, peak moments of knee extension, hip flexion and ankle plantar-flexion [27]	181, "gait"[title] AND "osteoarthritis"[title] AND ("knee"[title] OR "ankle"[title] OR "lower limb"[title])
Spinal cord injury	Gait speed, cadence, stride length [28]	128, "gait"[title] AND ("Spinal cord injured"[title] OR "Spinal cord injury"[title])
Prosthetics	Range of motion, energy storing, energy cost [5]	86, "gait"[title] AND ("prosthetic"[title] OR "prosthetics"[title])
Orthoses	Ankle joint angle, stride length	392, "gait"[title] AND ("orthopedic"[title] OR "orthosis"[title] OR "orthoses[title]")
Neurological, Neuropsychological & Neurodegenerative Disorders		
Multiple sclerosis (MS)	Motor deficits in lower extremities, decreased gait speed, stride length and cadence [29]	131, "gait"[title] AND "Multiple sclerosis"[title]
Parkinson's disease (PD)	Posture instability, small steps, shuffling, difficulty in initiation, termed as 'Parkinsonian gait' [7]	846, "gait"[title] AND ("Parkinson"[Title] OR "Parkinson's"[title])
Huntington's disease	Uncoordinated, lurching [30]	32, "gait"[title] AND ("Huntington"[title] OR "Huntington's"[title])
Sydenham's chorea	Clumsiness, gait disturbance [31]	3, Sydenham's [All Fields] AND ("gait"[MeSH Terms] OR "gait"[All Fields]) AND ("analysis"[Subheading] OR "analysis"[All Fields])
Diabetic neuropathy	Slow gait speed, greater hip flexion, reduced hip extension, and reduced range of motion in knee and ankle [32]	81, "gait"[title] AND ("diabetic"[title] OR "diabetes"[title])
Amyotrophic lateral sclerosis (ALS)	Altered gait rhythm [33]	15, "gait"[title] AND ("Amyotrophic lateral sclerosis "[title] OR "ALS"[title] OR "MND"[title] OR "Motor Neurone Disease"[title] OR "Lou Gehrig's"[title])
Alzheimer's	Increased gait variability [34]	48, "gait"[title] AND ("Alzheimer's"[Title] OR "Alzheimer"[Title])
Normal pressure hydrocephalus (NPH)	Reduced foot to floor clearance, "poor balance, off balance, unsteady, wobbly, staggering" [35]	36, "gait"[title] AND ("normal pressure hydrocephalus"[title] OR "NPH" [title])
Spinal muscular atrophy	Excessive pelvic rotation [36]	3, "gait"[title] AND "Spinal Muscular Atrophy"[title]
Neurodevelopmental & Psychiatric Disorders		
Down syndrome	Posture stiffness, joint stiffness [37]	26, "gait"[title] AND ("Down syndrome"[title] OR "Down's"[title])
Attention deficit hyperactivity disorder	Deficit in gait regulation [38]	6, "gait"[title] AND ("Attention deficit hyperactivity disorder"[Title] OR "Attention deficit hyperactivity"[title])
Cerebral palsy (CP)	Hemiplegic or diplegic, toe-walking, crouch gait, abnormal adduction [4] [39] [40]	480, "gait"[title] AND ("Cerebral Palsy"[title] OR "CP"[title])
William's syndrome & Hyperkinetic gait	Reduced gait speed and stride length with disproportionate increase in cadence [41]	3, "gait"[title] AND ("Williams syndrome"[title] OR "William's syndrome"[title])
Autistic spectrum	Stiff, rigid, repetitive pattern, difficult to walk in a straight line [42] [43] [44]	14, "gait"[title] AND ("Autism"[title] OR "Autistic"[title] OR "Asperger"[title] OR "Asperger's"[title])
Schizophrenia	Slower gait speed, shorter stride length, disordered regulation of stride length [45]	6, "gait"[title] AND ("Schizophrenia"[title])
Depression	Slow, small gait steps [21]	15, "gait"[title] AND ("Depression"[title] OR "Depressed"[title])
Alcoholism	"Wide-based gait, poor tandem gait, and perhaps leg ataxia, but usually no arm ataxia" [22]	8, "gait"[title] AND ("Alcoholism"[title] OR "Alcoholic"[title])
Psychogenic disorder	Sudden buckling of knees, "walking on ice" pattern, excessive slowness [46]	24, "gait"[title] AND "Psychogenic"[title]
Geriatrics		
Mortality prediction	Slow speed (strongly associated with mortality) [23]	10, "gait"[title] AND "mortality"[title] AND ("geriatrics"[title] OR "elderly"[title] OR "older"[title] OR "old"[title] OR "gerontology" [title])
Fall risk assessment	Unstable gait [11] [47]	13, "gait"[title] AND "fall risk"[title] AND ("geriatrics"[title] OR "elderly"[title] OR "older"[title] OR "old"[title] OR "gerontology" [title])
Differential diagnosis	Different gait patterns from certain geriatric disorders	4, "gait"[title] AND "differential diagnosis"[title] AND ("geriatrics"[title] OR "elderly"[title] OR "older"[title] OR "old"[title] OR "gerontology" [title])
Dementia	Wide-based gait, circumduction – 'frontal gait' [48]	20, "gait"[title] AND "dementia"[title] AND ("geriatrics"[title] OR "elderly"[title] OR "older"[title] OR "old"[title] OR "gerontology" [title])
Quality of life	Slow speed [49]	23, "gait"[title] AND "quality of life"[All Fields] AND ("geriatrics"[title] OR "elderly"[title] OR "older"[title] OR "old"[title] OR "gerontology" [title])

associated with each gait pathology are listed in Table II. Meanwhile, to gauge the distribution of research efforts in each area, papers regarding each pathology are counted by a systematic search on PubMed. The total numbers returned, along with the search criteria, are also listed in Table II, which details the most commonly seen gait pathologies and their related gait characteristics. Overall, Parkinsonian gait has attracted the most research attention thus far, with about 850 related papers showing up on

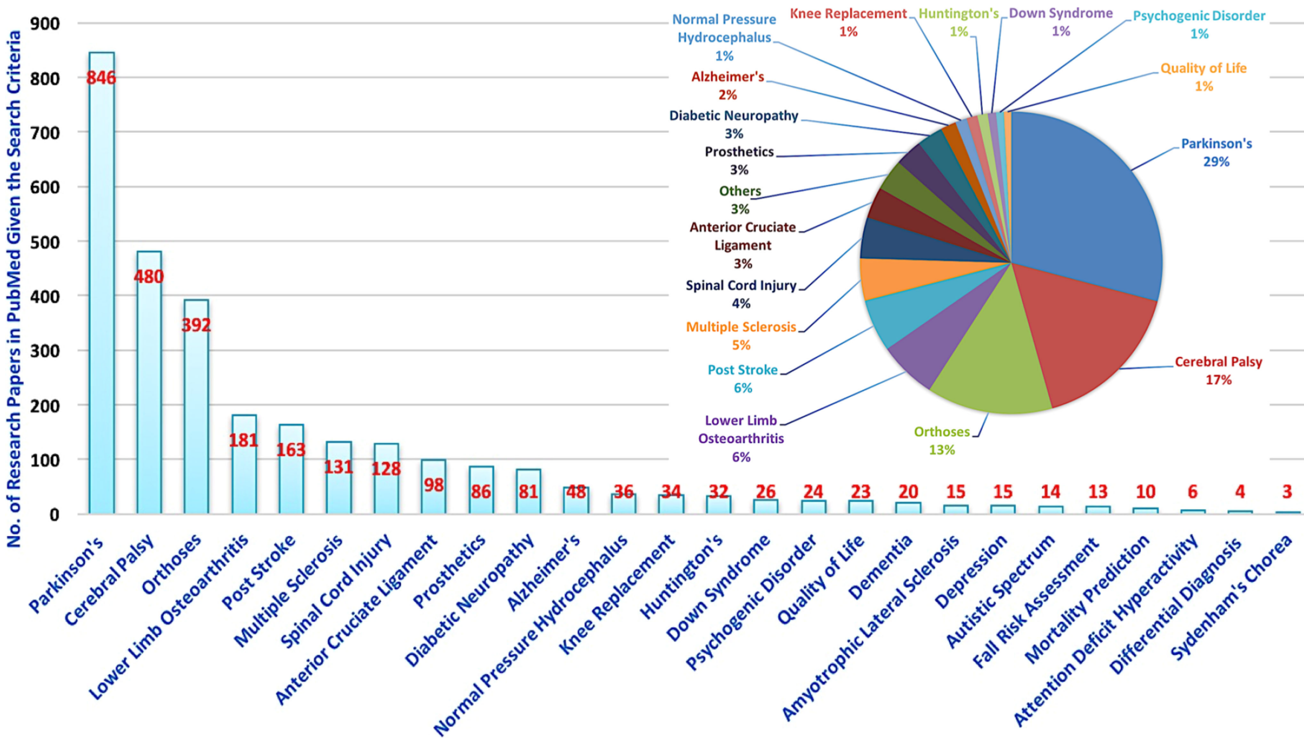

Fig. 2. Distribution of research efforts on different gait pathologies for papers published between 1970 and 2016.

TABLE III
SUMMARY OF CLINICAL GAIT DISORDERS

Classification of Gait Disorders	Conditions	Typical Description of Gait Characteristics
Peripheral Sensory	Visual	Tentative, uncertain
	Vestibular	Unbalanced, weaving, drunken
	Peripheral nerves	Stomping gait (due to the lack of sensation, foot is slammed hard onto the ground in order to sense it landing), worsens when patients cannot see their feet (in the dark)
Peripheral Motor	Myopathy or muscular dystrophy	Waddling gait, excessive lateral trunk movement (pelvic girdle weakness), Trendelenburg gait
	Neuropathy	Steppage gait (high stepping), foot drop (weakness of foot dorsiflexion)
	Arthritis	Antalgic gait, avoiding weight-bearing on the affected side, very short stance phase
Spasticity	Hemiplegia (paralysis affecting one side of the body) or paraplegia (paralysis affecting the lower extremities)	Circumduction on one side (leg swing outwards in semi-circle), excessive plantar-flexion in ankle
	Diplegia (paralysis affecting symmetrical parts of the body) or quadriplegia (paralysis affecting all four limbs)	Abnormally narrow base, scissor gait, circumduction on both sides, foot drop
Parkinsonian	Particularly seen in Parkinson Disease	Small shuffling steps, festination (involuntary inclination to quicken and shorten normal strides), propulsion, retropulsion, en bloc when turning, arm swing absent, rigidity and bradykinesia
Cerebellar (Ataxic)	Most commonly seen in cerebellar diseases	Uncoordinated, staggering, wide-based gait, increased trunk sway, not able to walk in a straight line, resembling gait of acute alcohol intoxication.
Choreiform (Hyperkinetic)	Certain basal ganglia disorders and athetosis or dystonia	Irregular, jerky, involuntary movements in all extremities

PubMed. The most frequently researched gait pathologies are summarized in the bar chart in Fig. 2. Despite the wide spectrum of gait pathologies in medicine, only seven types of gait pathologies have attracted the majority of research attention (comprising 80% of the 2906 papers found on gait analysis). The summary of gait pathologies shown in Table III and Fig. 2 highlights the gaps in current gait research, possibly due to a lack of portable gait analysis tools and accessible specialized equipment, and translation between technology advancement and medical domain knowledge.

TABLE IV
QUANTIFIABLE GAIT MEASURES FOR CLINICAL USE

Quantifiable Gait Measures	Gait Disorders
Gait speed	Slow walking
Step length	Parkinson gait, small steps, marche à petits pas (gait with little steps)
Step frequency (cadence)	Slow walking, gait efficiency
Stride-stride variability	Abnormal rhythm of gait
Step width	Cerebellar gait (ataxic gait), wide base, extremely narrow base
Step height	Peripheral neuropathic gait, foot drop, high stepping gait
Transverse plane signal amplitude	Hemiplegic gait, diplegic gait, circumduction, scissor gait
Knee joint angle	Crouch gait, drop foot, equine gait, stiff knee
Ankle joint angle	Equine gait, crouch gait
No. of steps during turning	Difficulty with turning
Hip flexion	Myopathic gait, waddling gait, excessive hip sway, drop of pelvis
Heel-strike amplitude, ground reaction forces	Sensory gait, stomping, stamping
Motion signal distribution	Tremor
Stance time	Antalgic gait, hesitation
Swing time	Difficulty in clearing off at toe off, difficulty in swinging
Double support time	Steadiness
Bilateral sensor comparison	Gait asymmetry
Gait stability measure	Wobbly gait, unstable gait
Gait complexity measure	Choreiform gait, hyperkinetic gait, jerky gait
Gait regularity measure	Reduced gait variability
Moment	Weakness during toe off
Muscle force from EMG	Muscle weakness, abnormal muscle activity

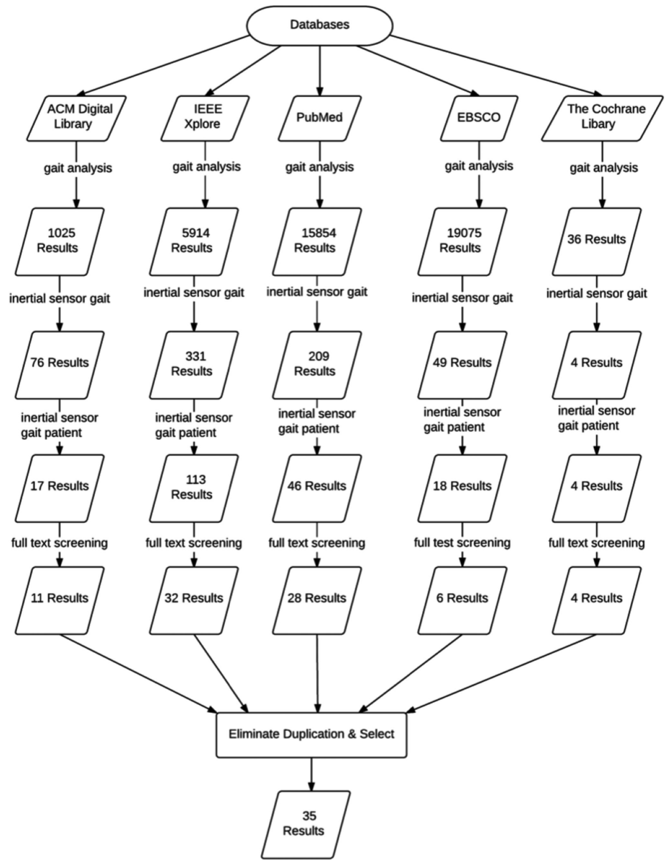

Fig. 3. Systematic search for current research on gait analysis using inertial sensors.

As most of the medical literature [50], Hook *et al.* [51] tend to provide a qualitative description of gait based on the observation of clinicians, it is important to quantify these descriptions with measuring tools. Thus, a translation from medical descriptions to quantified gait measures that could be tracked by measuring tools is summarized in Table IV.

III. Methods for Extracting Relevant Gait Features From Wearable Sensors

In this section, we review current research employing wearable sensors for gait analysis in clinical settings. First, a systematic approach is used for literature review. Then, the methods for extracting commonly used gait features such as double stance time, gait speed, gait stability, etc. are reviewed. More general features, such as gait asymmetry – a comparison between more specific bilateral gait features – can be derived from the basic gait features. Finally, flowcharts are presented to outline the feature extraction processes.

A. Literature Search

For the literature review, five major databases on biomedical engineering and computing were searched up to June, 2016: PubMed, IEEE Xplore, ACM Digital Library, EBSCO, and The Cochrane Library. The search process and criteria are shown in Fig. 3. Only the search process for papers using inertial sensors is shown in this figure. However, by using the same approach, current research using other types of sensors can also be found.

In this systematic search, first the key words "gait analysis" were used in order to get an overview of research on gait analysis from each database. Next, the key words "inertial sensor gait" are used to identify how many papers have studied human gait using inertial sensors. Then, the key word "patient" is added to "inertial sensor gait" in order to select papers that have applied inertial sensors to gait-related clinical applications. Next, these papers (i.e., searched by the key words "inertial sensor gait patient") are manually screened to eliminate work that has not yet been applied to patient studies. Finally, all of the manually screened papers from all five databases are selected again to eliminate duplication and papers that have not provided enough insight into gait pathologies.

Fig. 3 allows us to glimpse the distribution of research efforts in gait analysis. Overall, gait analysis has already become an established field, given that over 40 000 papers from the five databases are associated with gait analysis. However, gait analysis using inertial sensors (669 papers) is no more than 2% of the entire research field. Of these 2%, although 30% (roughly 200 papers) claim the research is related to patients, less than 90 papers are from real clinical settings. This is only about 0.2% of gait analysis papers. In other words, despite the extensive use of gait analysis in medicine as shown in Section II, the majority of the research has not yet been applied to patient populations.

Fig. 3 reveals both the great potential in this research field and the long process involved in applying such research to routine clinical practice. On the one hand, gait analysis using wearable sensors must be evaluated in the target patient population to prove its clinical value, since algorithms developed from control subject data may not be generalizable to the pathological gait. On the other hand, only by studying the real pathological gait, using wearable sensors, researchers can discover and capture subtle gait abnormalities, which may have been overlooked in the previous gait studies done using conventional tools. In any case, although current research is embracing wearable technologies, there is still a long way to go in terms of their clinical adoption.

The 35 papers detailing research using inertial sensors for gait analysis are summarized in Table V. The second column of this table lists the total number of inertial sensors mounted on the body as a measure of convenience. The clinical applications and the gait measures extracted in each paper are listed in the fourth and the third columns, respectively.

Table V is a representative yet not exclusive list of current research using wearable sensors up to June, 2016. In line with the more general search results in Section III-A, see Table II, Parkinson's gait is also the most studied gait in the field of wearable inertial sensors.

B. Kinematics

Kinematic information is a well-established set of gait measures in biomechanical analysis [85]. Accurate orientation tracking using inertial sensors has been a major research focus in the field. Although it may seem intuitive to obtain kinematic information from inertial sensors, accurate spatial information on body kinematics is still challenging to obtain. This is caused by several factors as follows:

1) Signals sensed by inertial sensors are defined in the inertial frame. In other words, inertial sensors are oblivious to the global frame. In practice, when mounting inertial sensors on the human body, it is common to have the inertial frame and the global frame misaligned, causing a discrepancy (also known as mounting error) between the information obtained under the inertial frame and the information obtained under the global frame. Various mounting error correction methods have been proposed using vision [86] or prior knowledge (e.g., posing the subject in a predefined posture).
2) Signals sensed by inertial sensors are derivatives of displacement, i.e., acceleration and angular velocity. This will inevitably cause integration drift when converting the acceleration to velocity and position, or the angular velocity to angular displacement. Signal processing techniques, such as high-pass filtering [87], complementary filtering [88], and Kalman filtering [89]–[91], have been used to remove the drift. Among these techniques, Kalman filtering and its variations (e.g., extended Kalman filtering and unscented Kalman filtering) are frequently used. This approach characterizes the noise in accelerometers and gyroscopes, and updates the integration process accordingly.

C. Temporal Features

Current methods for extracting kinematic information from inertial sensors preserve the time-series nature of the signal at a high sampling rate. To relate this to clinical outcomes, more in-depth information needs to be extracted. As human gait typically involves repetitive motion, gait signals usually have a pseudoperiodic nature. This means that repetitive events in a cycle can be detected and extracted to examine the temporal features that are characteristic of human gait [92]–[97]. Extracting and analyzing such features helps to segment gait motion in time. In this section, methods of detecting critical gait events are presented.

Fig. 4 illustrates the decomposed gait events for a normal gait. Taking the left leg on both figures as an example, to move forward, the subject lifts her/his left heel off, then pushes backwards on the ground in order to provide a counterforce as the body leans forward until she/he can completely lift her/his toe up in the air (left Toe-Off). It is worth noting that Toe-Off is a more widely accepted term, and a broader term used in clinics is terminal contact, denoting the moment when the foot leaves the ground (whereas Toe-Off is a special case of terminal contact when terminal contact is made with the toe). The left leg continues to swing backward in order for the shank to maximize its potential energy as a pendulum. Then, after reaching that point, the left leg swings forward while transforming the potential energy to kinetic energy without extra effort (left swing phase). When the left leg reaches the lowest point, the left foot hits the ground (left Heel-Strike, also known as initial contact), lands to support the body weight, and waits for the other leg to swing. This cyclic motion can also be found for the right leg, as the two legs alternate.

To detect these gait events, a peak detection algorithm is usually employed [7], [98]. Others have used hidden Markov models (HMM) and also achieved good accuracy [99]. For signal waveforms with less prominent peaks, HMM can be a better solution for extracting gait phases. With the gait events successfully detected, temporal features – such as double stance time, swing time, etc. – can be extracted based on the timestamps of the events. The critical gait phases can be extrapolated, as shown in Fig. 4.

Fig. 4 illustrates the relationship between the three critical temporal features: swing time (SWT), double stance time (DST), and stance phase time (SPT). SWT is the duration between the Toe-Off gait event and the Heel-Strike gait event of one leg inside one gait cycle. During this time, the leg first pushes backward and then swings forward, transforming the potential energy into kinetic energy, and resulting in the highest values in the acceleration and angular velocity signals. To find the duration, a sorting algorithm can be used to label the two sequential, adjacent Toe-Off and Heel-Strike events, and count the number of samples between these two timestamps to get swing time, as stated in (1). It is worth noting that this feature only relies on one leg's inertial sensor data.

$$\mathrm{SWT} = T_{\text{Toe-Off}} - T_{\text{Heel-Strike}} \tag{1}$$

Another temporal feature worth mentioning is single support time (SST), which is also the duration between the Toe-Off gait

TABLE V
CURRENT RESEARCH ON GAIT ANALYSIS USING WEARABLE SENSORS

References	Setup (No. of sensors/sensor type/sensor location	Gait Measures Extracted	Medical/Clinical Applications
[52]	4/3D accelerometer/both thighs and shanks	Range of motion of ankle and knee	Patients with ankle fractures
[53]	1/3D accelerometer/lower back	Improved local dynamic stability	Stability to differentiate fallers and non-fallers
[54]	7/3D accelerometer + 3D gyroscope/waist, both thighs, both shanks and both feet	Hip, knee and ankle joint angles, joint trajectories	Osteoarthritis patients
[55]	1/3D accelerometer + 3D gyroscope/waist	Local stability of trunk measured by Lyapunov Exponent	Gait assessment of ataxic patients
[56]	2/3D accelerometer + 3D gyroscope/bilateral shanks	Statistical features of signals during TUG test	Classification of Multiple Sclerosis
[57]	1/3D accelerometer + 3D gyroscope/shoe	Statistical features and linear gait features during pull test	Postural instability in Parkinson's
[58]	1/3D accelerometer + 3D gyroscope/dorsal spine	Autocorrelation coefficient and walking speed from accelerometers	Walking speed and symmetry assessment after hip arthroplasty
[59]	5/3D accelerometer + 3D gyroscope/both wrists, both shanks and waist	Causality matrix	Differentiation of Multiple Sclerosis
[60]	1/3D accelerometer + 3D gyroscope/shoe	Stride length, stride time	Geriatric patients
[61]	1/3D accelerometer/ear	Swing time, stance time, double stance time	Mobility score for post-operative recovery assessment
[62]	1/3D accelerometer+3D gyroscope/shoe	Swing width, path length	Parkinson's disease
[63]	1/3D accelerometer/ear	Swing time, stance time, double stance time	Parkinson's disease
[64]	1/3D accelerometer+ 3D gyroscope/shoe	Statistical features of signals	Classification of Parkinson's gait
[65]	1/3D accelerometer+3D gyroscope/waist	Total time of transition, jerk, fluency, root mean square of rotational speed	Lie-to-sit-to-stand-to-walk transition in patients in geriatric rehabilitation
[66]	1/3D accelerometer+3D gyroscope/pelvis	Speed, cadence, step time, step length, step irregularity, step asymmetry, range of motion	Gait, sit-to-stand transfers and step-up transfers in patients after knee operations
[67]	1/3D accelerometer+ 3D gyroscope +3D magnetometer/waist	Angular velocity in the global frame, turn duration, turn angle	Detection of turning in Parkinson's disease
[68]	1/3D accelerometer+3D gyroscope/posterior trunk	Sway dispersion, sway velocity, frequency of sway, jerkiness of sway	Postural sway in Parkinson's patients
[69] [70]	1/3D accelerometer+ 3D gyroscope +3D magnetometer/one shank	Cadence, step length, similarity between strides	Detection of freezing of gait episode in Parkinson's disease
[71]	1/3D accelerometer+ 3D gyroscope +3D magnetometer/waist	Trunk angles (pitch, yaw and roll)	Lower trunk angle in Parkinson's gait and post-stroke gait
[72]	1/3D accelerometer/right foot	Time, no. of strides, stride length and frequency, gait speed, cadence, stance phase variability	Gait analysis for Alzheimer's patients
[9]	5/3D accelerometer + 3D gyroscope/both wrists, both shanks and waist	Cadence, double stance time, gait speed, gait stability	Differential diagnosis for Normal Pressure Hydrocephalus
[73]	2/3D accelerometer+3D gyroscope/both shoes	Step duration, gradient of swing phase signal and other statistical features	Early diagnosis in Parkinson's disease
[74]	2/3D accelerometer + 3D gyroscope +3D magnetometer/both shoes	Reconstructed gait trajectory, walking speed, stride length, foot swing time, stance time	Characterizing hemiplegic gait in post-stroke patients
[75]	1/3D accelerometer + 3D gyroscope + 3D magnetometer/back	Step and stride length, gait speed, stride duration, stance and swing time, double support time, stride length and height ratio, cadence, symmetry	Assessing the potential benefit of ankle-foot orthoses for patients with hemiplegia
[76]	3/3D accelerometer + 1D gyroscope + 2D gyroscope/shoes and waist	No. of strides, walking time, stride length, cadence, swing time, stance time	Gait and balance test for patients with Alzheimer's disease
[39]	4/3D accelerometer + 3D gyroscope/bilateral shanks and both feet	Ankle joint angle, range of motion	Assessing efficacy of ankle-foot orthoses for children with cerebral palsy
[77]	4/3D accelerometer + 3D gyroscope + 3D magnetometer	Average arm acceleration,	Bradykinesia and hypokinesia in Parkinson's patients
[78]	4/1D gyroscope on both shanks + 2D gyroscope on both wrists	Symbolic symmetry index	Detecting movement symmetry in early Parkinson's gait
[79]	4/3D accelerometer+ 3D gyroscope +3D magnetometer/right thigh, right shank and both feet	Cadence, step length, thigh and knee angle of right leg, gait events (mid-swing, heel-strike, toe-off, heel-off, feet-adjacent, tibia-vertical)	Gait phase detection for dementia patients
[80]	5/3D accelerometer +3D gyroscope/both wrists, both shanks and waist	Temporal features, gait complexity, gait stability, gait speed	Assessment of Multiple Sclerosis
[81]	6/3D accelerometer+ 3D gyroscope +3D magnetometer/both thighs, shanks and feet	Flexion/extension angle, gait cycle, balance level measured by joint angle at particular gait events	Balance and knee extensibility of hemiplegic gait
[82]	2/insole pressure sensors/prefabricated in both insoles	Peak pressure, total contact area, forefoot pressure time integral, duration of load at the site of highest peak pressure of forefoot loading	Testing whether insoles can help to reduce foot ulceration
[83]	2/insole pressure sensors/both insoles	Features extracted from center of pressure data	Assessing gait deviation in children with cerebral palsy
[84]	2/insole pressure sensors/both insoles	Average of peak pressure, plantar pressure distribution	Reducing plantar pressure on diabetic patients in the early stage

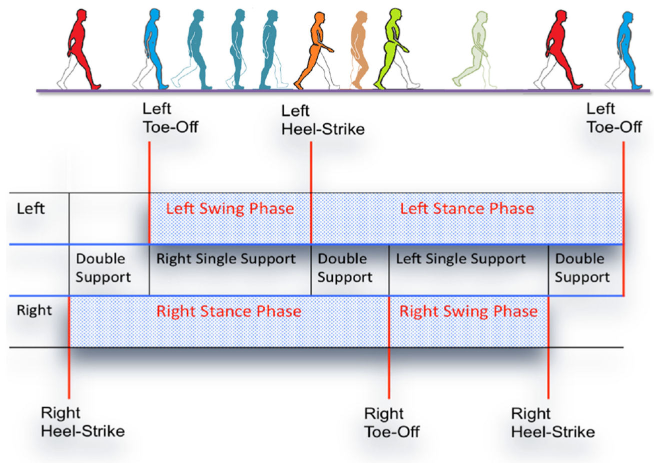

Fig. 4. Gait events and gait phases explained.

event and the Heel-Strike gait event of one leg. In fact, one leg's single support time is exactly the same as the swing time of the other leg, as stated in (2). Note that this feature only relies on one leg's inertial sensor data.

$$\begin{cases} \mathrm{SST}_{\mathrm{LeftLeg}} = \mathrm{SWT}_{\mathrm{RightLeg}} \\ \mathrm{SST}_{\mathrm{RightLeg}} = \mathrm{SWT}_{\mathrm{LeftLeg}} \end{cases} \tag{2}$$

SPT is the duration between the Heel-Strike gait event and the Toe-Off gait event of one leg inside one gait cycle. During this phase, the foot lands on the ground and the leg gradually rotates, centered around the foot, until the center of mass of the whole body moves forward. To find the duration, a sorting algorithm can be used to label the two sequential, adjacent Heel-Strike and Toe-Off events, and count the number of samples between these two timestamps to get single support time, as stated in (3). The difference between single support time and stance phase time is that the latter includes the double support time where both feet are on the ground. Note that this feature only relies on one leg's inertial sensor data.

$$\mathrm{SPT} = T_{\text{Heel-Strike}} - T_{\text{Toe-Off}} \tag{3}$$

DST is the phase where both feet are in contact with the ground during walking. Fig. 4 shows that double stance time is the duration between the Heel-Strike event of one leg and the Toe-Off event of the other leg. As this involves coordination from both legs, the information is tricky to obtain accurately since its accuracy depends on timestamps from both legs instead of one. Here, the synchronization between the nodes becomes critical. However, with a careful examination of Fig. 4, this feature can be extrapolated as shown in (4).

$$\begin{cases} \mathrm{DST} = \mathrm{SPT}_{\mathrm{LeftLeg}} - \mathrm{SWT}_{\mathrm{RightLeg}} \\ \mathrm{DST} = \mathrm{SPT}_{\mathrm{RightLeg}} - \mathrm{SWT}_{\mathrm{LeftLeg}} \end{cases} \tag{4}$$

Fig. 4 defines these temporal features by incorporating the gait events and phases, providing a map of the temporal features depicted. With modern inertial sensors sampled at a frequency beyond 50 Hz, these gait events can be captured relatively accurately in time and the temporal features can be extrapolated accurately too. These temporal features can be considered to be the most accurate features that can be extracted from wearable sensors.

D. Gait Speed Extraction by Inertial Sensors

Gait speed is an important measure in gait analysis. In geriatrics especially, gait speed has become the number one predictor of mortality in adults over 65 years old, with differences of just a couple of tenths of a meter per second predicting statistically significant outcome differences [23]. Therefore, accurate gait speed estimation from inertial sensors has interested researchers in the field [98], [100]–[111].

Laudanski *et al.* [104] reviewed the current research (16 papers in total) on gait speed estimation using inertial sensors, classifying the current gait speed estimation model into three categories: abstraction model (i.e., machine learning approach), human gait model, and numerical integration, shown in Fig. 5.

Previously, work using inertial sensors to estimate gait speed tended to model human gait as an inverse pendulum [7], [100], [106], [112]. Miyazaki [100] was the first to devise the method of using a single-axis gyroscope to estimate stride length and gait speed, with a single pendulum model. The paper intuitively explained how to use a geometric model to extract gait speed from inertial sensors and achieved an accuracy with relative errors of 15–25% over a speed range of 0.5–1.7 m/s. Salarian *et al.* [7] proposed a more precise model using both shank- and thigh-mounted inertial sensors with a better defined geometric model, achieving a root-mean-square error (RMSE) of 0.06 m/s at a constant treadmill speed (1.11 m/s). While the initial efforts in [100] seemed to provide an oversimplified model, the more refined model in [7] requires thigh nodes, which are more invasive to wear (an issue of both node location and number). By simplifying the double pendulum model in [7] and improving on the gait model presented in [100], Chen *et al.* [98] used only a shank-mounted inertial sensor and achieved better accuracy; Salarian *et al.* [108] also tried to reduce the thigh nodes required in the double pendulum model in [7] by predicting thigh measures based on underlying biomechanics. Chen *et al.* [98], Nagaragna *et al.* [106], and Salarian *et al.* [113] also employed the double pendulum model, with a Kalman filter to cancel drift in the gyroscope-integrated signal, achieving a stride length RMSE of 0.05 m per stride.

Vathsangam *et al.* [105], [107], [110], [111], [114] resorted to machine learning approaches for estimating gait speed. Vathsangam *et al.* [105] adopted Gaussian process regression (a nonlinear regression approach) to estimate gait speed from frequency-domain features, achieving an average RMSE of 0.027 m/s in one subject's data. Martin [107] and Martin *et al.* [110] used the decomposed wavelets from accelerometer signals as features, and used a linear regression approach to estimate gait speed, achieving an average error below 5%. Panagiota *et al.* [111] estimated gait speed as a feature for energy expenditure estimation. With a hip-mounted accelerometer tracking cadence, it achieved an average error of 0.18 m/s. This early work using statistical learning methods laid the groundwork for the field to move from first principles modeling to machine learning for gait speed estimation. Chen and Lach [101] proposed a novel feature that is rooted in biomechanics and strongly correlated

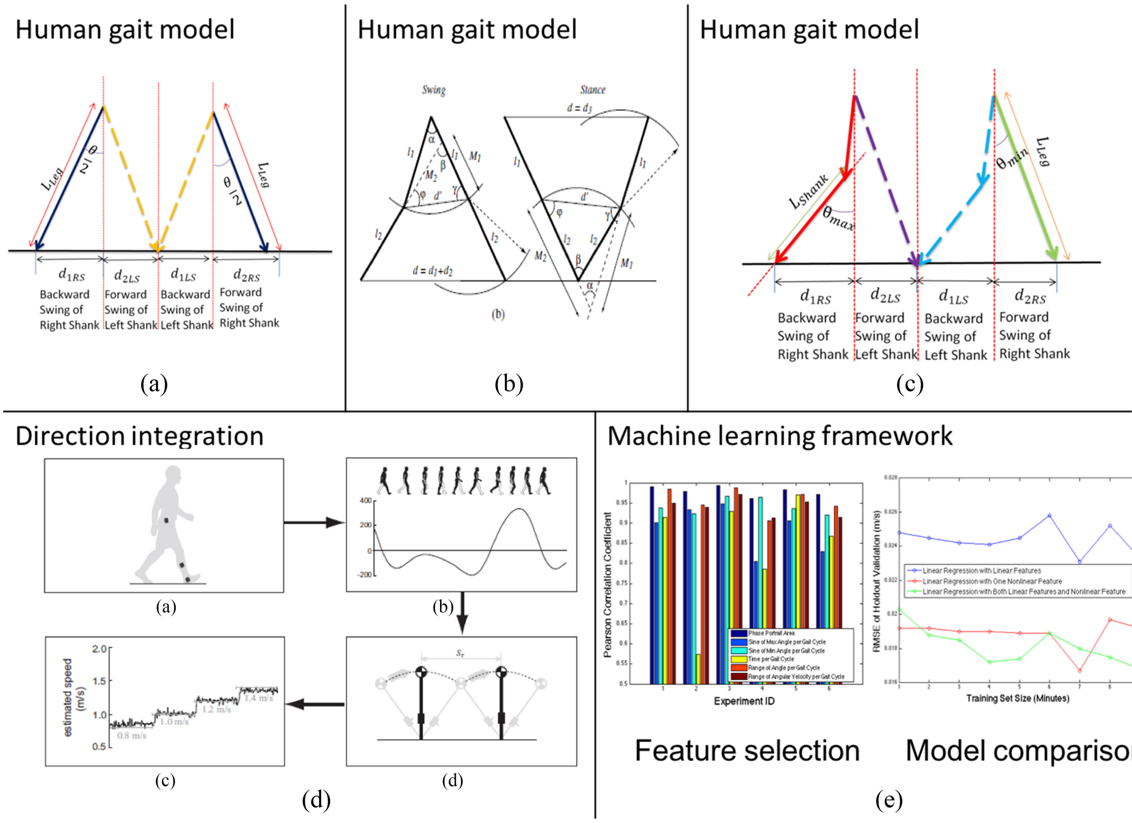

Fig. 5. Methods for gait speed estimation using inertial sensors (see details in Section III-D). Different types of human gait models: (a) Single pendulum model [100]; (b) Double pendulum model [7]; and (c) Simplified double pendulum model [98]. (d) Direct integration [111]. (e) Machine learning framework [101].

with gait speed, then compared the most commonly used features for gait speed estimation by adopting a unified machine learning framework, showing great estimation accuracy and the potential for combining features extracted from biomechanical knowledge and machine learning methods.

Sabatini *et al.* [102] explored the possibility of using foot-mounted inertial sensors to obtain linear velocity from accelerometers by leveraging the gyroscope-integrated angular information, achieving RMSEs across five subjects ranging from 0.03 to 0.06 m/s. Li *et al.* [112] took a similar approach, but instead of mounting the sensors on the foot, they used shank-mounted inertial sensors and achieved an RMSE of 0.05 m/s. Although integrating acceleration to obtain distance and velocity seems an intuitive approach, the accuracy can be worse because the gravitational force is difficult to separate from the inertial force. Moreover, accelerometers are susceptible to both mechanical and thermal noises. To achieve accurate results using the methods described in [7] and [112], careful noise reduction and integration drift cancelation are required, rendering the method less robust in implementation. The most robust method for gait speed estimation using inertial sensors needs to be confirmed by carrying out experiments over a much longer time span in the free-living environment.

E. Novel Features Extracted Using Nonlinear Analysis Techniques

Dingwell and Cusumano [115] pointed out that nonlinear analysis techniques might "provide insight into the neuromuscular control processes that govern locomotion" and demonstrated that the variability in certain temporal gait features must be carefully distinguished from the "gait stability," i.e., greater variability does not necessarily indicate less stability. Therefore, it is important to investigate nonlinear analysis techniques from which the measures for analyzing the dynamic characteristics of a pseudoperiodic system (like human gait) can be borrowed for gait analysis.

Most of these nonlinear analysis techniques center around one important presentation of gait signals – phase portrait. A phase portrait is a geometric representation of the trajectories of a dynamical system in the phase plane [116]. In this representation, the position information is often plotted against its first time derivative. Certain gait measures can then be extracted by quantifying this geometric shape, including for example: gait regularity, gait mechanical energy, gait complexity, and gait stability. Besides, it is a great visualization tool for data presentation and clinical interface.

A shank segment phase portrait of one healthy gait cycle is plotted in Fig. 6(a). The gait events are plotted sequentially clockwise in the figure as the arrows indicate. The closed curve form reveals the periodic nature of a healthy gait and the sharp turning point indicates the sudden change in motion [117], which are the critical gait events detected in the time series, as discussed in Section III-C.

Visualization: As a visualization tool, phase portrait can represent a certain dynamic system with unique geometric patterns. It can characterize the dynamic system in the absence of detailed equations of motion, when the experimental data for position

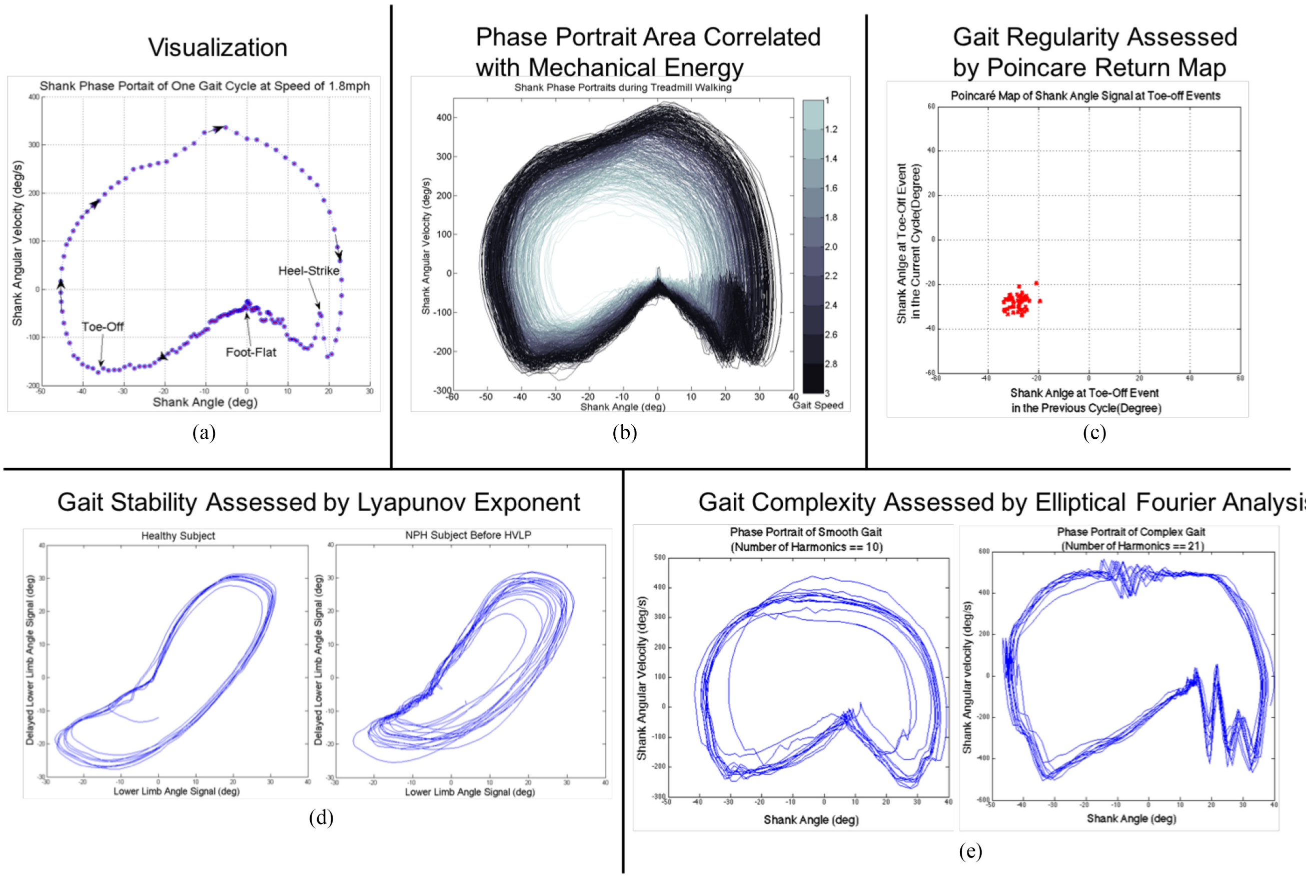

Fig. 6. Gait analysis using phase portrait representation of inertial sensor data (see details in Section III-E). (a) Visualization [80]. (b) Phase portrait area correlated with mechanical energy [101]. (c) Gain regularity accessed by poincare return map [80]. (d) Gain regularity accessed by Lyapunov exponent [80]. (e) Gait complexity accessed by elliptical Fourier analysis [80].

and its derivative are known – such as the kinematic information presented by inertial sensors. More specifically, by directly displaying both positional information and its first time derivative simultaneously, it becomes possible to correlate the two variables. For example, gait motion range is usually of interest in studies of motion constraints and amplitude [118]. Also, as pointed out in [101], the area enclosed inside the phase portrait represents the mechanical energy [see Fig. 6(b)].

Visualization tools, such as phase portrait, can play a vital role in promoting pervasive gait analysis. First, current gait analysis results can only be understood by gait experts by reading critical gait measures from a lengthy report. Since humans interpret images better than data, a visualization of gait can provide a vivid and memorable impression of the severity of gait abnormalities for clinical staff. Second, these phase portraits can even be quantified to provide more sensitive and precise characterization of gait patterns.

Gait Regularity: A Poincaré return map (also known as a first return map) has been used to analyze orbital stability [47], and can be applied to assess variability between gait cycles as well. A Poincaré return map samples a particular event in every cycle in a cyclic signal. In gait analysis in particular, gait events occur repetitively in gait cycles. Since the data obtained from inertial sensors are discrete time series, in order to obtain the map, the magnitude of a gait signal at a particular event of interest can be sampled as a means of assessing the orbital stability of this signal, after identifying the critical gait events in the time domain as described in Section III-C. Taking the shank angle signal, for example, the mapping shown in Fig. 6(c) plots the shank angle at the Toe-Off moment in the previous gait cycle, against the shank angle at the Toe-Off moment of the current cycle. The more clustered the return points are [the red dots in Fig. 6(c)], the more orbital stability the signal possesses. Therefore, the regularity can be quantified by the sum of the distances from the points to the center of the cluster.

Gait Stability: Gait instability is a major risk factor leading to falls, and has been recognized as a measure for identifying potential fallers [119]. In clinics today, the gait stability test is still largely done by subjective observation, pulling the patients' shoulders during walking [120]. However, studies usually show no correlation between an abnormal pull test and a future fall risk [120]. Therefore, it is important to assess gait stability with objective and quantifiable measures.

With quantitative data captured by inertial sensors and nonlinear analysis techniques, gait stability can be characterized by the Lyapunov exponent (LyE), which describes how a pseudoperiodic dynamic system (e.g., human gait function) responds to "very small perturbations continuously in real time" [121].

Chen *et al.* [9] demonstrated that this metric exhibits better sensitivity to the subtle gait differences pre- and postmedical intervention in the elderly group. Fallah *et al.* [122] have used long-term LyE and short-term LyE to assess recovery from knee replacement surgery.

LyE can be computed by two types of numeric methods: either the W-algorithm [123] or the R-algorithm [124]. In gait analysis, the R-algorithm is more commonly used due to claimed accuracy with short-term data. However, [125] has argued that the W-algorithm is more appropriate for assessing local dynamic stability because of its sensitivity in estimating LyE. Both algorithms quantify the divergence rate between trajectories in the phase portrait [see Fig. 6(d)]. The faster the trajectories diverge, the larger the Lyapunov exponent is and the less stable the gait is. Therefore, gait instability can be quantified and its severity assessed using LyE extracted from inertial sensor data.

Gait Complexity: The idea of complexity analysis lies in analyzing the jerkiness of a motion. As approximated by a pendulum model, efficient human gait can be considered as optimized movement for conserving energy during walking. And the smoothness of the gait motion can reflect the efficiency of walking. In other words, a complex jerky movement means inefficiency in the gait. A phase portrait can visually reflect this jerkiness [see Fig. 6(e)], and provide a measure of gait efficiency [126], i.e., gait complexity.

To quantify this complexity, DiBerardino III *et al.* [126] described a quantitative method, computing the number of harmonics needed to fit the shape of the phase portrait. In [126], elliptical Fourier analysis (EFA) [127] was used to find the number of harmonics in two-dimensional (2-D) curves needed to fit a particular phase portrait. To determine how many harmonics are required to best describe a phase portrait, DiBerardino III *et al.* [126] adopted a pointwise sum of squared errors (SSE) metric – comparing the difference between the phase portrait to be tested and a fully fitted phase portrait with 500 harmonics (note that a zero harmonics fitted phase portrait is a standard ellipse). Once the SSE is below a predefined threshold, the algorithm stops searching and registers the current number of harmonics as the quantitative measure of complexity for the phase portrait. Fig. 6(e) demonstrates the advantage of the quantitative techniques, where the complexity of the left plot in (e) is 11 magnitudes smaller than that of the right plot in (e) which appears to be more jerky.

F. Kinetics and Muscle Activity

Kinetic information is another set of gait measures essential for gait analysis [15]. While inertial sensors can provide rich information about the movement patterns of various body segments represented by kinematics and its derivative products, they cannot provide information about the kinetics that govern the movement, which can shed light on the underlying gait mechanisms from the perspectives of force and power generation, muscle activities, and energy cost minimization. Such kinetic information usually includes GRFs, joint moments, muscle activities, and energy costs.

GRF: In gait analysis, this information has been captured using force plates in order to obtain joint moments and powers. Nowadays, wearable insole pressure sensors can be used to obtain the plantar pressure distribution of the foot (i.e., force per unit area) when it is in contact with the ground and derive GRFs. Veltink *et al.* [128], [129] successfully demonstrated that insole pressure sensors can obtain GRFs as force plates can do, using mapping techniques with minimal errors. This means that insole pressure sensors can be a suitable wearable platform to replace preinstalled force plates in gait laboratories.

GRF alone can also be used to study gait patterns. Fineberg *et al.* [130] used the vertical GRF to distinguish the ground force pattern during the stance phase for spinal cord injury patients with assistance and without assistance, and healthy controls. Muniz *et al.* [131] used GRF data to differentiate Parkinson's gait from normal gait. Alaqtash *et al.* [132] used GRF to classify pathological gaits, such as CP gait and MS gait. These research efforts have shown the importance of obtaining GRF as a gait measure distinct from kinematic information.

Joint moment and joint power: Joint moment (also known as joint torque or joint moment of force) is the moment that a joint requires for walking. Knowing joint moments, in-depth knowledge such as the power generation mechanism of various joints can be obtained. Joint moment cannot be directly measured by sensors. However, it can be deduced from the measured GRF and kinematic information using inverse dynamics [133], [134]. Then, joint power can be obtained by

$$P = \tau \times \omega \tag{5}$$

Muscle Activities and Muscle Force: These two types of information can be obtained from an EMG sensor. EMG measures the electrical activity (i.e., whether the muscle is at rest or firing at a certain time) of a contracting muscle via either surface electrodes or fine wire electrodes. The surface electrodes are attached to the skin, though such a setup is subject to noise from the nearby muscles. The more accurate and precise measurement approach is to insert fine wire electrodes into the muscle using a hypodermic needle, but it is highly invasive and can even be painful. Either approach can only give information about whether and when the muscle is firing, but not quantitative information such as muscle forces or the amplitude of the muscle activity. However, with mathematical modeling, muscle forces can also be extracted from EMG signals [135]. EMG measurements can be critical to clinical gait assessment. Gage *et al.* [136] used EMG data to guide surgery for children with cerebral palsy, during which a muscle tendon may be transferred to a different location in order to correct the action of the muscle. For such surgery, EMG must be used in advance so muscular contraction is corrected accordingly. EMG can also be used with neuroconduction studies to test peripheral neuropathy. During such tests, the EMG electrodes release an electric shock in order to stimulate the nerves of the subject, and the speed of the signals of the nerve response (i.e., nerve conduction speed) is measured. A significant delay and weakness in the response signals indicates peripheral neuropathy [137].

Energy costs: Metabolic energy cost during walking is another measure of interest among gait analysis researchers. It is

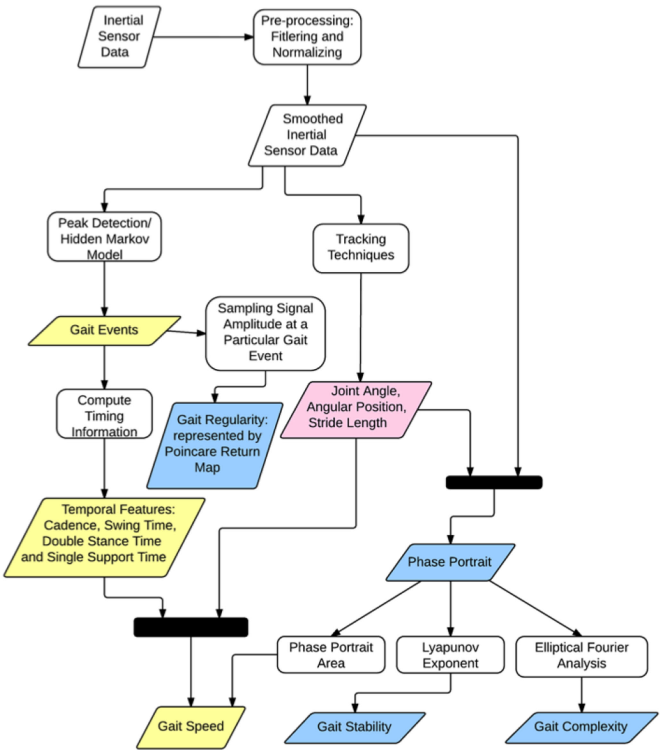

Fig. 7. Process of gait feature extraction from inertial sensors.

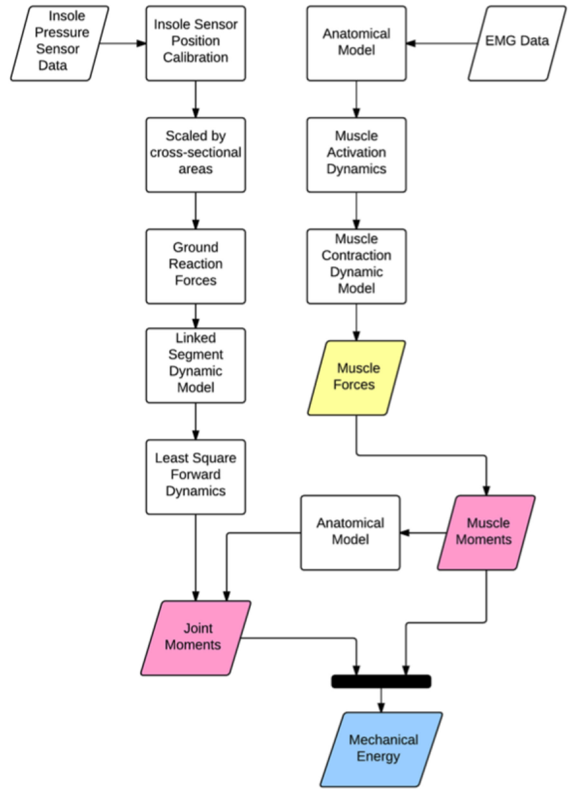

Fig. 8. Process of gait feature extraction from insole pressure sensors and EMG sensors.

believed that human gait is an optimized mechanism to achieve the least energy consumption and smooth movement in space. Waters and Mulroy [138] demonstrated that energy cost (measured by oxygen consumption) is directly related to the extent of a patient's gait disability. Once joint moments and EMG data are obtained, energy costs can be deduced from the combination of EMG and joint moments to further deduce the energy used for walking – and efficiency is an important sign of healthy gait.

G. Summary of Gait Feature Extraction From Wearable Sensors

The process of transforming wearable sensor data into relevant gait measures is summarized in Figs. 7 and 8. In both figures, the gait measures extractable from wearable sensors are highlighted. For inertial sensors, the raw inertial sensor data can be filtered and transformed into various kinematic products by tracking techniques. The critical temporal features of gait can also be extracted from inertial sensor data by event detection or the HMM. The events detected can also be used for gait regularity analysis. With both temporal features and kinematic information, gait speed can be estimated. With both the kinematic information and the sensor data, nonlinear analysis can be applied to extract more interesting measures, such as gait stability and gait complexity. For insole pressure sensor data, the insole position can first be calibrated with markers by optical motion capture systems and mapping techniques to extract general GRF. Then with a link segment model, the joint moment can be computed using generalized kinematics via optimized forward dynamics [139]. From EMG data, muscle force and muscle moment can be extracted using a combination of anatomical, muscle activation, and muscle contraction dynamic models [135]. Finally, with both joint moment and muscle moment known, mechanical energy of gait can also be obtained. All in all, wearable sensors can provide as rich, if not more, information on gait as their laboratory counterparts.

IV. Discussion

In this section, the metrics of accuracy, precision, and sensitivity of a measurement system are discussed with respect to the impact of wearable sensors on clinical practice for measuring gait. Since few papers in the field have adopted rigorous metrological terms to evaluate the gait measures extracted using various methods, it is difficult to provide a like-by-like comparison between the state-of-the-art methods. Therefore, in this section, we focus on establishing the metrological terminology for evaluation, and discuss how to assess the gait measures extracted from wearable sensors for clinical use. Practicality and the clinical interface are also considered.

A. Accuracy and Precision

Accuracy and precision imply different concepts, but are mostly misused. According to the International Vocabulary of Metrology [140], accuracy is the "closeness of agreement between a measured quantity value and the true quantity value of the measurand," whereas precision means "closeness of agreement between indications and measured quantity values obtained by replicated measurements on the same or similar objects under specified conditions," Accuracy is usually expressed as the relative error (or rather, its complement), while precision can be expressed numerically "by measures of imprecision, such as standard deviation, variance, or coefficient of variation under the specified conditions of measurement." Precision can be affected by repeatability and reproducibility. Repeatability evaluates whether, given the measuring instrument, the measurement can be repeated under the same conditions, including "the same measurement procedure, same operators, same operating conditions, and same location, and replicate measurements on the same or similar objects over a short period of time" [140]. Reproducibility evaluates whether the measurement can be replicated under the same set of conditions on the same or similar subjects, but with different locations, operators, and measuring systems [140].

Accuracy and precision are critical to both clinical diagnosis and treatment. Because the philosophy of diagnosis in medicine is rooted in comparing the statistical norm between the control group and the patient group, the quantitative assessment must be close to ground truth, so that both the control group and the patient group can be examined by the same reference. Thus, intricate calibration procedures are often required prior to data collection in order to ensure accuracy. Precision is essential to the quality of assessment as well. When the measurement uncertainty is higher (i.e., the precision of the system is lower) than the intersubject difference, the differences shown in the measurement results cannot be trusted to differentiate the patient group from the control group. Thus, "it is vitally important that variation due to imperfect analysis (the analytical uncertainty) is less than the measurement we are trying to discriminate" and "as a general principle, it has been widely suggested that the analytical goal for imprecision of a test method remain below half the intraindividual variation" [141].

B. Sensitivity and Resolution

Sensitivity and resolution can be used interchangeably, but the two concepts have subtle differences. Sensitivity is the "quotient of the change in an indication of a measuring system and the corresponding change in a value of a quantity being measured," while resolution is the "smallest change in a quantity being measured that causes a perceptible change in the corresponding indication"[140]. High sensitivity and resolution in a wearable sensor system mean that subtle gait changes escaping human observation can be picked up by the sensors. Note that sensitivity in clinical diagnosis is a different concept, which is used in binary classification – defined as the rate of correctly detecting the true positives.

The impact of the evaluation metrics on clinical practice is illustrated in Fig. 9. Fig. 9 gives the conservative requirements for data quality for clinical applications. The condition for the measurement result to serve for diagnosis is the strictest, as diagnosis requires both high precision and high accuracy from the measuring instrument. These key metrics can determine whether a wearable system is qualified to be a gait analysis tool for clinical applications.

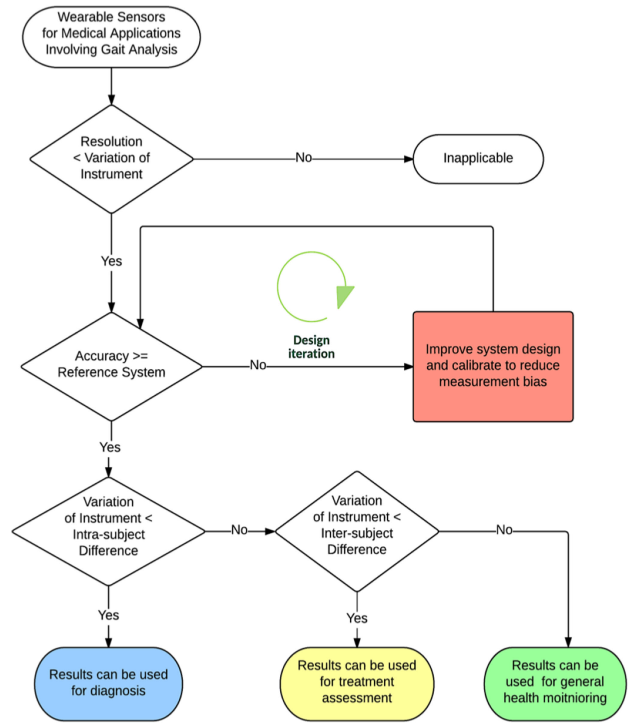

Fig. 9. Example of the impact of wearable sensor data quality on clinical applications.

C. Practicality and Clinical Interface

Gait analysis is underutilized in clinics and still considered to be research rather than a standard procedure. For wearable sensor-based gait analysis to become a commonplace in clinics, the field needs to consider the practical issues from the following perspectives.

Operating Cost: Wearable sensor systems can also greatly reduce the cost of clinical analysis. Currently, in a conventional gait laboratory, "a gait study can cost as much as $2000 USD, with an expected reimbursement of $500 or less" [142]. Moreover, "this is in addition to the extensive costs to set up a facility, reaching as high as $300 000 if no facility renovations are needed" [142]. Whereas even at the prototyping phase, a highly customized wearable sensor system would only cost about $3000 USD, and the cost of each gait study is almost negligible once the operating procedure is standardized.

Wearability: Designed for continuous monitoring, body sensors must be convenient and comfortable to wear for an extended period. Therefore, the size of the sensor system, the number of sensors, and the location of the sensors needs to be considered in experimental design. The choice of sensors is also likely to change with the rapid development of integrated circuit, microelectromechanical systems, and flexible printed circuit board technologies. For example, although the current form factor of inertial sensors (usually limited by battery sizes) does not allow them to be worn on lower limbs long term, it is possible that the sensors will become miniaturized enough for patients to patch them onto lower limbs such as adhesive bandages.

Test Procedure: Using wearable sensors, the process of gait analysis can be significantly reduced by avoiding marker labeling and detailed anthropometrical measurements. The test procedure, such as Unified Parkinson's Disease Rating Score [143] and Timed Up and Go (TUG) [113], can be predefined on a computer in advance, targeting different gait pathologies. The long hallways in clinics can be of great use for conducting the tests and all the test subjects have to do is to put on the sensors and walk a predefined distance. The sensor data can be wirelessly transmitted to a laptop and analyzed in real time with the gait analysis results reported on the spot.

Clinical Interface: Some commercial off-the-shelf products provide detailed gait analysis and a software interface to analyze the data collected from wearable sensors. The results from these systems are usually presented in lengthy reports with special gait measures. However, without the results being analyzed in the context of the gait pathology, it is challenging for clinicians to understand the gait features extracted [144]. The visualization effect provided by phase portraits as detailed in Section III-E is a good example of how impressive analysis results can help gait patterns to be better understood.

Information Integration: The abundant information that wearable sensors can provide also makes it difficult for clinical practitioners to pick out the relevant information quickly. This challenge can be conquered by targeting the gait analysis results to different diseases. For example, given different disease etiologies, hypotheses can be set up and relevant gait analysis results can be highlighted given the particular disease and presented to the clinical staff. A well-designed clinical interface should also integrate relevant diagnostic information given different gait analysis results. This would help gait analysis to be more widely adopted in clinical diagnosis and treatment procedures.

V. Conclusion

This paper explores the topic of pervasive gait analysis for medicine using wearable sensors. The review of many types of gait-manifested disorders demonstrates the importance of quantitative gait analysis in clinical diagnosis and treatment, whereas, currently, the expensive and cumbersome laboratory systems limit gait analysis to specialized centers. By reviewing the current methods of using wearable sensors for gait analysis, this paper demonstrates that wearable sensors can replace laboratory gait analysis systems, offering portable, objective, quantitative, continuous, and rich information for gait analysis without imposing constraints on the subjects – hence, providing seamless gait analysis from clinics to the free-living environment. Finally, the issues of applying wearable sensors to clinics are discussed by reviewing the practicality issues and metrics for evaluating measuring instruments, in order to propel wider adoption of wearable sensor-enabled gait analysis, particularly for routine clinical use.

References

[1] M. W. Whittle, "Clinical gait analysis: A review," *Human Movement Sci.*, vol. 15, no. 3, pp. 369–387, 1996.

[2] D. H. Sutherland, "Gait analysis in cerebral palsy," *Develop. Med. Child Neurol.*, vol. 20, no. 6, pp. 807–813, 1978.

[3] J. R. Gage, *Gait Analysis in Cerebral Palsy*. London, U.K.: Mac Keith Press, 1991.

[4] R. E. Cook, I. Schneider, M. E. Hazlewood, S. J. Hillman, and J. E. Robb, "Gait analysis alters decision-making in cerebral palsy," *J. Pediatric Orthopaedics*, vol. 23, no. 3, pp. 292–295, 2003.

[5] J. S. Rietman, K. Postema, and J. H. B. Geertzen, "Gait analysis in prosthetics: Opinions, ideas and conclusions," *Prosthetics Orthotics Int.*, vol. 26, no. 1, pp. 50–57, 2002.

[6] A. F. Polcyn, L. A. Lipsitz, D. C. Kerrigan, and J. J. Collins, "Age-related changes in the initiation of gait: Degradation of central mechanisms for momentum generation," *Arch. Physical Med. Rehabil.*, vol. 79, no. 12, pp. 1582–1589, 1998.

[7] A. Salarian *et al.*, "Gait assessment in Parkinson's disease: Toward an ambulatory system for long-term monitoring," *IEEE Trans. Biomed. Eng.*, vol. 51, no. 8, pp. 1434–1443, Aug. 2004.

[8] B. Noris, M. Nobile, L. Piccini, M. Molteni, F. Keller, and A. Billard, "Gait analysis of autistic children with echo-state networks," 2006.

[9] S. Chen *et al.*, "Aiding diagnosis of normal pressure hydrocephalus with enhanced gait feature separability," in *Proc. 3rd Conf. Wireless Health*, 2012, pp. 3-1–3-8.

[10] J. M. Hausdorff, D. A. Rios, and H. K. Edelberg, "Gait variability and fall risk in community-living older adults: a 1-year prospective study," *Arch. Physical Med. Rehabil.*, vol. 82, no. 8, pp. 1050–1056, 2001.

[11] J. Verghese, R. Holtzer, R. B. Lipton, and C. Wang, "Quantitative gait markers and incident fall risk in older adults," *J. Gerontology A, Biol. Sci. Med. Sci.*, vol. 64, no. 8, pp. 896–901, 2009.

[12] S. R. Simon, "Quantification of human motion: Gait analysis-benefits and limitations to its application to clinical problems," *J. Biomech.*, vol. 37, no. 12, pp. 1869–1880, 2004.

[13] S. Barker, R. Craik, W. Freedman, N. Herrmann, and H. Hillstrom, "Accuracy, reliability, and validity of a spatiotemporal gait analysis system," *Med. Eng. Phys.*, vol. 28, no. 5, pp. 460–467, 2006.

[14] M. Saleh and G. Murdoch, "In defence of gait analysis. observation and measurement in gait assessment," *J. Bone Joint Surg., Brit. Vol.*, vol. 67, no. 2, pp. 237–241, 1985.

[15] D. H. Sutherland, "The evolution of clinical gait analysis part III—Kinetics and energy assessment," *Gait Posture*, vol. 21, no. 4, pp. 447–461, 2005.

[16] A. Ali, K. Sundaraj, B. Ahmad, N. Ahamed, and A. Islam, "Gait disorder rehabilitation using vision and non-vision based sensors: A systematic review," *Bosnian J. Basic Med. Sci.*, vol. 12, no. 3, pp. 193–202, 2012.

[17] A. T. Barth *et al.*, "Longitudinal high-fidelity gait analysis with wireless inertial body sensors," in *Proc. 1st Conf. Wireless Health*, 2010, pp. 192–193.

[18] G.-Z. Yang and M. Yacoub, *Body Sensor Networks*. New York, NY, USA: Springer-Verlag, 2006.

[19] P. A. DeLuca, R. B. Davis Iii, S. Õunpuu, S. Rose, and R. Sirkin, "Alterations in surgical decision making in patients with cerebral palsy based on three-dimensional gait analysis," *J. Pediatric Orthopaedics*, vol. 17, no. 5, pp. 608–614, 1997.

[20] R. M. Kay, S. Dennis, S. Rethlefsen, R. A. K. Reynolds, D. L. Skaggs, and V. T. Tolo, "The effect of preoperative gait analysis on orthopaedic decision making," *Clin. Orthopaedics Related Res.*, vol. 372, pp. 217–222, 2000.

[21] M. K. Holden, K. M. Gill, M. R. Magliozzi, J. Nathan, and L. Piehl-Baker, "Clinical gait assessment in the neurologically impaired," *Physical Therapy*, vol. 64, no. 1, pp. 35–40, 1984.

[22] R. D. Sanders and P. M. Gillig, "Gait and its assessment in psychiatry," *Psychiatry*, vol. 7, no. 7, pp. 38–43, 2010.

[23] S. Studenski *et al.*, "Gait speed and survival in older adults," *JAMA*, vol. 305, no. 1, pp. 50–58, 2011.

[24] I. A. K. de Quervain, S. R. Simon, S. Leurgans, W. S. Pease, and D. McAllister, "Gait pattern in the early recovery period after stroke," *J. Bone Joint Surg.*, vol. 78, no. 10, pp. 1506–1514, 1996.

[25] P. Bulgheroni, M. V. Bulgheroni, L. Andrini, P. Guffanti, and A. Giughello, "Gait patterns after anterior cruciate ligament reconstruction," *Knee Surg., Sports Traumatol., Arthrosc.*, vol. 5, no. 1, pp. 14–21, 1997.

[26] J. A. McClelland, K. E. Webster, and J. A. Feller, "Gait analysis of patients following total knee replacement: A systematic review," *Knee*, vol. 14, no. 4, pp. 253–263, 2007.

[27] B. J. Fregly, J. A. Reinbolt, K. L. Rooney, K. H. Mitchell, and T. L. Chmielewski, "Design of patient-specific gait modifications for knee osteoarthritis rehabilitation," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 9, pp. 1687–1695, Sep. 2007.

[28] M. H. Granat, A. C. B. Ferguson, B. J. Andrews, and M. Delargy, "The role of functional electrical stimulation in the rehabilitation of patients with incomplete spinal cord injury-observed benefits during gait studies," *Spinal Cord*, vol. 31, no. 4, pp. 207–215, 1993.

[29] C. Heesen, J. Böhm, C. Reich, J. Kasper, M. Goebel, and S. M. Gold, "Patient perception of bodily functions in multiple sclerosis: gait and visual function are the most valuable," *Multiple Sclerosis*, vol. 14, pp. 988–991, 2008.

[30] W. C. Koller and J. Trimble, "The gait abnormality of Huntington's disease," *Neurology*, vol. 35, no. 10, pp. 1450–1450, 1985.

[31] A. J. Church, F. Cardoso, R. C. Dale, A. J. Lees, E. J. Thompson, and G. Giovannoni, "Anti-basal ganglia antibodies in acute and persistent Sydenham's chorea," *Neurology*, vol. 59, no. 2, pp. 227–231, 2002.

[32] M. Fernando *et al.*, "Biomechanical characteristics of peripheral diabetic neuropathy: A systematic review and meta-analysis of findings from the gait cycle, muscle activity and dynamic barefoot plantar pressure," *Clin. Biomech.*, vol. 28, no. 8, pp. 831–845, 2013.

[33] J. M. Hausdorff, A. Lertratanakul, M. E. Cudkowicz, A. L. Peterson, D. Kaliton, and A. L. Goldberger, "Dynamic markers of altered gait rhythm in amyotrophic lateral sclerosis," *J. Appl. Physiol.*, vol. 88, no. 6, pp. 2045–2053, 2000.

[34] P. L. Sheridan, J. Solomont, N. Kowall, and J. M. Hausdorff, "Influence of executive function on locomotor function: Divided attention increases gait variability in Alzheimer's disease," *J. Am. Geriatrics Soc.*, vol. 51, no. 11, pp. 1633–1637, 2003.

[35] M. A. Williams and D. Rigamonti, "Normal pressure hydrocephalus," *Current Therapy in Neurologic Disease*, vol. 1, pp. 335–336, 2006.

[36] S. Armand, M. Mercier, E. Watelain, K. Patte, J. Pelissier, and F. Rivier, "A comparison of gait in spinal muscular atrophy, type II and Duchenne muscular dystrophy," *Gait Posture*, vol. 21, no. 4, pp. 369–378, 2005.

[37] T. G. Hampton, M. R. Stasko, A. Kale, I. Amende, and A. Costa, "Gait dynamics in trisomic mice: Quantitative neurological traits of down syndrome," *Physiol. Behavior*, vol. 82, no. 2, pp. 381–389, 2004.

[38] Y. Leitner *et al.*, "Gait in attention deficit hyperactivity disorder," *J. Neurol.*, vol. 254, no. 10, pp. 1330–1338, 2007.

[39] S. Chen, C. L. Cunningham, B. C. Bennett, and J. Lach, "Enabling longitudinal assessment of ankle-foot orthosis efficacy for children with cerebral palsy," in *Proc. 2nd Conf. Wireless Health*, 2011, pp. 4-1–4-10.

[40] B. Lofterød, T. Terjesen, I. Skaaret, A.-B. Huse, and R. Jahnsen, "Preoperative gait analysis has a substantial effect on orthopedic decision making in children with cerebral palsy: Comparison between clinical evaluation and gait analysis in 60 patients," *Acta Orthopaedica*, vol. 78, no. 1, pp. 74–80, 2007.

[41] D. Hocking, N. Rinehart, J. McGinley, and J. Bradshaw, "Gait function in adults with Williams syndrome," *Exp. Brain Res.*, vol. 192, no. 4, pp. 695–702, 2009.

[42] M. J. Weiss, M. F. Moran, M. E. Parker, and J. T. Foley, "Gait analysis of teenagers and young adults diagnosed with autism and severe verbal communication disorders," *Front. Integr. Neurosci.*, vol. 7, pp. 33-1–33-10, 2013.

[43] N. J. Rinehart, B. J. Tonge, J. L. Bradshaw, R. Iansek, P. G. Enticott, and J. McGinley, "Gait function in high-functioning autism and Asperger's disorder," *Eur. Child Adolescent Psychiatry*, vol. 15, no. 5, pp. 256–264, 2006.

[44] N. J. Rinehart *et al.*, "Gait function in newly diagnosed children with autism: Cerebellar and basal ganglia related motor disorder," *Develop. Med. Child Neurol.*, vol. 48, no. 10, pp. 819–824, 2006.

[45] A. Putzhammer, B. Heindl, K. Broll, L. Pfeiff, M. Perfahl, and G. Hajak, "Spatial and temporal parameters of gait disturbances in schizophrenic patients," *Schizophrenia Res.*, vol. 69, no. 2, pp. 159–166, 2004.

[46] T. Lempert, T. Brandt, M. Dieterich, and D. Huppert, "How to identify psychogenic disorders of stance and gait," *J. Neurol.*, vol. 238, no. 3, pp. 140–146, 1991.

[47] K. P. Granata and T. E. Lockhart, "Dynamic stability differences in fall-prone and healthy adults," *J. Electromyography Kinesiol.*, vol. 18, no. 2, pp. 172–178, 2008.

[48] J. Verghese, R. B. Lipton, C. B. Hall, G. Kuslansky, M. J. Katz, and H. Buschke, "Abnormality of gait as a predictor of non-Alzheimer's dementia," *New England J. Med.*, vol. 347, no. 22, pp. 1761–1768, 2002.

[49] F. Li, K. J. Fisher, P. Harmer, E. McAuley, and N. L. Wilson, "Fear of falling in elderly persons: Association with falls, functional ability, and quality of life," *J. Gerontol. B, Psychological Sci. Soc. Sci.*, vol. 58, no. 5, pp. P283–P290, 2003.

[50] J. Verghese, A. F. Ambrose, R. B. Lipton, and C. Wang, "Neurological gait abnormalities and risk of falls in older adults," *J. Neurol.*, vol. 257, no. 3, pp. 392–398, 2010.

[51] F. W. Van Hook, D. Demonbreun, and B. D. Weiss, "Ambulatory devices for chronic gait disorders in the elderly," *Am. Family Physician*, vol. 67, no. 8, pp. 1717–1724, 2003.

[52] A. Elbaz *et al.*, "Lower extremity kinematic profile of gait of patients after ankle fracture: A case-control study," *J. Foot Ankle Surg.*, vol. 55, pp. 918–921, 2016.

[53] E. A. Ihlen, A. Weiss, Y. Beck, J. L. Helbostad, and J. M. Hausdorff, "A comparison study of local dynamic stability measures of daily life walking in older adult community-dwelling fallers and non-fallers," *J. Biomech.*, vol. 49, no. 9, pp. 1498–1503, 2016.

[54] S. Tadano, R. Takeda, K. Sasaki, T. Fujisawa, and H. Tohyama, "Gait characterization for osteoarthritis patients using wearable gait sensors (h-gait systems)," *J. Biomech.*, vol. 49, no. 5, pp. 684–690, 2016.

[55] G. Chini *et al.*, "Local stability of the trunk in patients with degenerative cerebellar ataxia during walking," *Cerebellum*, pp. 1–8, 2016.

[56] B. R. Greene *et al.*, "Assessment and classification of early-stage multiple sclerosis with inertial sensors: Comparison against clinical measures of disease state," *IEEE J. Biomed. Health Informat.*, vol. 19, no. 4, pp. 1356–1361, Jul. 2015.

[57] C. F. Pasluosta, J. Barth, H. Gassner, J. Klucken, and B. M. Eskofier, "Pull test estimation in Parkinson's disease patients using wearable sensor technology," in *Proc. 2015 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2015, pp. 3109–3112.

[58] W. Rapp, T. Brauner, L. Weber, S. Grau, A. Mündermann, and T. Horstmann, "Improvement of walking speed and gait symmetry in older patients after hip arthroplasty: A prospective cohort study," *BMC Musculoskeletal Disorders*, vol. 16, no. 1, pp. 291–298, 2015.

[59] J. Gong, J. Lach, Y. Qi, and M. D. Goldman, "Causal analysis of inertial body sensors for enhancing gait assessment separability towards multiple sclerosis diagnosis," in *Proc. 2015 IEEE 12th Int. Conf. Wearable Implantable Body Sensor Netw.*, 2015, pp. 1–6.

[60] A. Rampp, J. Barth, S. Schülein, K.-G. Gaßmann, J. Klucken, and B. M. Eskofier, "Inertial sensor-based stride parameter calculation from gait sequences in geriatric patients," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 4, pp. 1089–1097, Apr. 2015.

[61] R. M. Kwasnicki *et al.*, "Assessing functional mobility after lower limb reconstruction: A psychometric evaluation of a sensor-based mobility score," *Ann. Surg.*, vol. 261, no. 4, pp. 800–806, 2015.

[62] B. Mariani, M. C. Jiménez, F. J. Vingerhoets, and K. Aminian, "On-shoe wearable sensors for gait and turning assessment of patients with Parkinson's disease," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 1, pp. 155–158, Jan. 2013.

[63] D. Jarchi *et al.*, "Assessment of the e-AR sensor for gait analysis of Parkinson's disease patients," in *Proc. 2015 IEEE 12th Int. Conf. Wearable Implantable Body Sensor Netw.*, 2015, pp. 1–6.

[64] J. Barth *et al.*, "Combined analysis of sensor data from hand and gait motor function improves automatic recognition of Parkinson's disease," in *Proc. 2012 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2012, pp. 5122–5125.

[65] F. Bagala, J. Klenk, A. Cappello, L. Chiari, C. Becker, and U. Lindemann, "Quantitative description of the lie-to-sit-to-stand-to-walk transfer by a single body-fixed sensor," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 21, no. 4, pp. 624–633, Jul. 2013.

[66] S. Bolink, S. van Laarhoven, M. Lipperts, I. Heyligers, and B. Grimm, "Inertial sensor motion analysis of gait, sit–stand transfers and step-up transfers: Differentiating knee patients from healthy controls," *Physiol. Meas.*, vol. 33, no. 11, pp. 1947–1958, 2012.

[67] M. El-Gohary *et al.*, "Continuous monitoring of turning in patients with movement disability," *Sensors*, vol. 14, no. 1, pp. 356–369, 2013.

[68] M. Mancini, P. Carlson-Kuhta, C. Zampieri, J. G. Nutt, L. Chiari, and F. B. Horak, "Postural sway as a marker of progression in Parkinson's disease: A pilot longitudinal study," *Gait Posture*, vol. 36, no. 3, pp. 471–476, 2012.

[69] D. Jovicic, N. S. Jovicic, S. M. Radovanovic, I. D. Stankovic, M. Popovic, and V. S. Kostic, "Automatic identification and classification of freezing of gait episodes in Parkinson's disease patients," vol. 22, no. 3, pp. 685–694, May 2014.

[70] C. Azevedo Coste, B. Sijobert, R. Pissard-Gibollet, M. Pasquier, B. Espiau, and C. Geny, "Detection of freezing of gait in Parkinson disease: Preliminary results," *Sensors*, vol. 14, no. 4, pp. 6819–6827, 2014.

[71] E. Grimpampi, V. Bonnet, A. Taviani, and C. Mazzà, "Estimate of lower trunk angles in pathological gaits using gyroscope data," *Gait Posture*, vol. 38, no. 3, pp. 523–527, 2013.

[72] P.-C. Chung, Y.-L. Hsu, C.-Y. Wang, C.-W. Lin, J.-S. Wang, and M.-C. Pai, "Gait analysis for patients with Alzheimer's disease using a triaxial accelerometer," in *Proc. 2012 IEEE Int. Symp. Circuits Syst.*, 2012, pp. 1323–1326.

[73] J. Barth *et al.*, "Biometric and mobile gait analysis for early diagnosis and therapy monitoring in Parkinson's disease," in *Proc. 2011 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2011, pp. 868–871.

[74] Y. Wang, J. Xu, X. Xu, X. Wu, G. Pottie, and W. Kasier, "Inertial sensor based motion trajectory visualization and quantitative quality assessment of hemiparetic gait," in *Proc. 8th Int. Conf. Body Area Netw.*, 2013, pp. 169–172.

[75] M. G. Benedetti *et al.*, "Gait measures in patients with and without AFO for equinus varus/drop foot," in *Proc. 2011 IEEE Int. Workshop Med. Meas. Appl.*, 2011, pp. 591–592.

[76] Y. Hsu *et al.*, "Gait and balance analysis for patients with Alzheimer's disease using an inertial-sensor-based wearable instrument," *IEEE J. Biomed. Health Informat.*, vol. 18, no. 6, pp. 1822–1830, Nov. 2014.

[77] D. G. M. Zwartjes, T. Heida, J. P. P. van Vugt, J. A. G. Geelen, and P. H. Veltink, "Ambulatory monitoring of activities and motor symptoms in Parkinson's disease," *IEEE Trans. Biomed. Eng.*, vol. 57, no. 11, pp. 2778–2786, Nov. 2010.

[78] A. Sant'Anna, A. Salarian, and N. Wickstrom, "A new measure of movement symmetry in early Parkinson's disease patients using symbolic processing of inertial sensor data," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 7, pp. 2127–2135, Jul. 2011.

[79] X. Meng, H. Yu, and M. P. Tham, "Gait phase detection in able-bodied subjects and dementia patients," in *Proc. 2013 35th Annu. Int. Conf. Eng. Med. Biol. Soc.*, 2013, pp. 4907–4910.

[80] S. Chen, "Gait feature extraction from inertial body sensor networks for medical applications," Ph.D. dissertation, Dept. Elect. Eng., The University of Virginia, Charlottesville, VA, USA, 2013.

[81] Y. Guo, G. Zhao, Q. Liu, Z. Mei, K. Ivanov, and L. Wang, "Balance and knee extensibility evaluation of hemiplegic gait using an inertial body sensor network," *Biomed. Eng. Online*, vol. 12, no. 1, pp. 83–89, 2013.

[82] J. S. Paton, E. A. Stenhouse, G. Bruce, D. Zahra, and R. B. Jones, "A comparison of customised and prefabricated insoles to reduce risk factors for neuropathic diabetic foot ulceration: A participant-blinded randomised controlled trial," *J. Foot Ankle Res.*, vol. 5, no. 1, pp. 31–41, 2012.

[83] C. Strohrmann *et al.*, "Automated assessment of gait deviations in children with cerebral palsy using a sensorized shoe and active shape models," in *Proc. 2013 IEEE Int. Conf. Body Sensor Netw.*, 2013, pp. 1–6.

[84] M. L. Zequera and S. Solomonidis, "Performance of insole in reducing plantar pressure on diabetic patients in the early stages of the disease," in *Proc. 2010 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2010, pp. 2982–2985.

[85] D. H. Sutherland, "The evolution of clinical gait analysis: Part II kinematics," vol. 16, pp. 159–179, 2002.

[86] C. Wong, Z. Zhang, B. Lo, and G.-Z. Yang, "Markerless motion capture using appearance and inertial data," in *Proc. 2014 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2014, pp. 6907–6910.

[87] K. Tong and M. H. Granat, "A practical gait analysis system using gyroscopes," *Med. Eng. Phys.*, vol. 21, no. 2, pp. 87–94, 1999.

[88] A. D. Young, "Wireless realtime motion tracking system using localised orientation estimation," Ph.D. dissertation, Sch. Informat., Univ. Edinburgh, Edinburgh, U.K., 2010.

[89] A. M. Sabatini, "Quaternion-based extended Kalman filter for determining orientation by inertial and magnetic sensing," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 7, pp. 1346–1356, Jul. 2006.

[90] J. L. Marins, X. Yun, E. R. Bachmann, R. B. McGhee, and M. J. Zyda, "An extended Kalman filter for quaternion-based orientation estimation using MARG sensors," in *Proc. 2001 IEEE/RSJ Int. Conf. Intell. Robots Syst.*, 2001, vol. 4, pp. 2003–2011.

[91] D. Roetenberg, P. J. Slycke, and P. H. Veltink, "Ambulatory position and orientation tracking fusing magnetic and inertial sensing," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 5, pp. 883–890, May 2007.

[92] C. Kirtley, *Clinical Gait Analysis: Theory and Practice*. Amsterdam, The Netherlands: Elsevier Health Sciences, 2006.

[93] M. W. Whittle, *Gait Analysis: An Introduction*. London, U.K.: Butterworth-Heinemann, 2003.

[94] R. Craik and C. A. Oatis, *Gait Analysis: Theory and Application*. St. Louis, MO, USA: Mosby, 1994.

[95] I. W. Griffiths, "Principles of biomechanics and motion analysis," *Int. J. Sports Sci. Coaching*, vol. 1, no. 4, pp. 421–423, 2006.

[96] D. A. Winter, *Biomechanics and Motor Control of Human Movement*. Hoboken, NJ, USA: Wiley, 2009.

[97] G. Robertson, G. Caldwell, J. Hamill, G. Kamen, and S. Whittlesey, *Research Methods in Biomechanics*, 2 ed. Champaign, IL, USA: Human Kinetics, 2013.

[98] S. Chen, C. L. Cunningham, J. Lach, and B. C. Bennett, "Extracting spatio-temporal information from inertial body sensor networks for gait speed estimation," in *Proc. 2011 Int. Conf. Body Sensor Netw*, 2011, pp. 71–76.

[99] A. Mannini and A. M. Sabatini, "A hidden Markov model-based technique for gait segmentation using a foot-mounted gyroscope," in *Proc. 2011 Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, 2011, pp. 4369–4373.

[100] S. Miyazaki, "Long-term unrestrained measurement of stride length and walking velocity utilizing a piezoelectric gyroscope," *IEEE Trans. Biomed. Eng.*, vol. 44, no. 8, pp. 753–759, Aug. 1997.

[101] S. Chen and J. Lach, "Nonlinear feature for gait speed estimation using inertial sensors," in *Proc. 8th Int. Conf. Body Area Netw.*, 2013, pp. 185–188.

[102] A. M. Sabatini, C. Martelloni, S. Scapellato, and F. Cavallo, "Assessment of walking features from foot inertial sensing," *IEEE Trans. Biomed. Eng.*, vol. 52, no. 3, pp. 486–494, Mar. 2005.

[103] S. Yang and Q. Li, "Inertial sensor-based methods in walking speed estimation: A systematic review," *Sensors*, vol. 12, no. 5, pp. 6102–6116, 2012.

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

[105] H. Vathsangam, B. A. Emken, D. Spruijt-Metz, and G. S. Sukhatme, "Toward free-living walking speed estimation using Gaussian process-based regression with on-body accelerometers and gyroscopes," in *Proc. 2010 4th Int. Conf. Pervasive Comput. Technol. Healthcare*, 2010, pp. 1–8.

[106] K. Nagarajan, N. Gans, and R. Jafari, "Modeling human gait using a Kalman filter to measure walking distance," in *Proc. 2nd Conf. Wireless Health*, 2011, pp. 34-1–34-2.

[107] E. Martin, "Novel method for stride length estimation with body area network accelerometers," in *Proc. 2011 IEEE Topical Conf. Biomed. Wireless Technol., Netw. Sensing Syst..*, 2011, pp. 79–82.

[108] A. Salarian, P. R. Burkhard, F. J. Vingerhoets, B. M. Jolles, and K. Aminian, "A novel approach to reducing number of sensing units for wearable gait analysis systems," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 1, pp. 72–77, Jan. 2013.

[109] Z. Zhang, C. Wong, B. Lo, and G.-Z. Yang, "A simple and robust stride length estimation method using foot-mounted micro gyroscopes," in *Proc. 2015 Int. Conf. Poster Presentation Body Sensor Netw.*, 2014.

[110] E. Martin, V. Shia, and R. Bajcsy, "Determination of a patient's speed and stride length minimizing hardware requirements," in *Proc. 2011 Int. Conf. Body Sensor Netw.*, 2011, pp. 144–149.

[111] A. Panagiota, S. Layal, and H. Stefan, "Assessment of human gait speed and energy expenditure using a single triaxial accelerometer," in *Proc. 2012 9th Int. Conf. Wearable Implantable Body Sensor Netw.*, 2012, pp. 184–188.

[112] Q. Li, M. Young, V. Naing, and J. M. Donelan, "Walking speed and slope estimation using shank-mounted inertial measurement units," in *Proc. IEEE Int. Conf. Rehabil. Robot.*, 2009, pp. 839–844.

[113] A. Salarian, F. B. Horak, C. Zampieri, P. Carlson-Kuhta, J. G. Nutt, and K. Aminian, "iTUG, a sensitive and reliable measure of mobility," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 3, pp. 303–310, Jun. 2010.

[114] X. Xu, M. A. Batalin, W. J. Kaiser, and B. Dobkin, "Robust hierarchical system for classification of complex human mobility characteristics in the presence of neurological disorders," in *Proc. 2011 Int. Conf. Body Sensor Netw.*, 2011, pp. 65–70.

[115] J. B. Dingwell and J. P. Cusumano, "Nonlinear time series analysis of normal and pathological human walking," *Chaos: An Interdisciplinary J. Nonlinear Sci.*, vol. 10, no. 4, pp. 848–863, 2000.

[116] J. V. José and E. J. Saletan, *Classical Dynamics: A Contemporary Approach*. Cambridge, U.K.: Cambridge Univ. Press, 1998.

[117] N. Stergiou, *Innovative Analyses of Human Movement*. Champaign, IL, USA: Human Kinetics, 2004.

[118] Y. Hurmuzlu, C. Basdogan, and J. J. Carollo, "Presenting joint kinematics of human locomotion using phase plane portraits and Poincare maps," *J. Biomech.*, vol. 27, no. 12, pp. 1495–1499, 1994.

[119] D. Hamacher, N. B. Singh, J. H. Van Dieën, M. O. Heller, and W. R. Taylor, "Kinematic measures for assessing gait stability in elderly individuals: A systematic review," *J. Roy. Soc. Interface*, vol. 8, no. 65, pp. 1682–1698, 2011.

[120] B. H. Wood, J. A. Bilclough, A. Bowron, and R. W. Walker, "Incidence and prediction of falls in Parkinson's disease: A prospective multidisciplinary study," *J. Neurol., Neurosurg. Psychiatry*, vol. 72, no. 6, pp. 721–725, 2002.

[121] J. B. Dingwell and H. G. Kang, "Differences between local and orbital dynamic stability during human walking," *J. Biomech. Eng.*, vol. 129, no. 4, pp. 586–593, 2007.

[122] H. R. F. Yakhdani *et al.*, "Stability and variability of knee kinematics during gait in knee osteoarthritis before and after replacement surgery," *Clin. Biomech.*, vol. 25, no. 3, pp. 230–236, 2010.

[123] A. Wolf, J. B. Swift, H. L. Swinney, and J. A. Vastano, "Determining Lyapunov exponents from a time series," *Physica D, Nonlinear Phenomena*, vol. 16, no. 3, pp. 285–317, 1985.

[124] M. T. Rosenstein, J. J. Collins, and C. J. De Luca, "A practical method for calculating largest Lyapunov exponents from small data sets," *Physica D, Nonlinear Phenomena*, vol. 65, no. 1, pp. 117–134, 1993.

[125] F. Cignetti, L. M. Decker, and N. Stergiou, "Sensitivity of the Wolf's and Rosenstein's algorithms to evaluate local dynamic stability from small gait data sets," *Ann. Biomed. Eng.*, vol. 40, no. 5, pp. 1122–1130, 2012.

[126] L. A. DiBerardino, III, J. D. Polk, K. S. Rosengren, J. B. Spencer-Smith, and E. T. Hsiao-Wecksler, "Quantifying complexity and variability in phase portraits of gait," *Clin. Biomech.*, vol. 25, no. 6, pp. 552–556, 2010.

[127] F. P. Kuhl and C. R. Giardina, "Elliptic Fourier features of a closed contour," *Comput. Graph. Image Process.*, vol. 18, no. 3, pp. 236–258, 1982.

[128] P. H. Veltink, C. Liedtke, E. Droog, and H. van der Kooij, "Ambulatory measurement of ground reaction forces," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 3, pp. 423–427, Sep. 2005.

[129] A. M. Howell, T. Kobayashi, H. A. Hayes, K. B. Foreman, and S. J. M. Bamberg, "Kinetic gait analysis using a low-cost insole," *IEEE Trans. Biomed. Eng.*, vol. 60, no. 12, pp. 3284–3290, Dec. 2013.

[130] D. B. Fineberg *et al.*, "Vertical ground reaction force-based analysis of powered exoskeleton-assisted walking in persons with motor-complete paraplegia," *J. Spinal Cord Med.*, vol. 36, no. 4, pp. 313–321, 2013.

[131] A. M. S. Muniz *et al.*, "Comparison among probabilistic neural network, support vector machine and logistic regression for evaluating the effect of subthalamic stimulation in Parkinson disease on ground reaction force during gait," *J. Biomech.*, vol. 43, no. 4, pp. 720–726, 2010.

[132] M. Alaqtash, T. Sarkodie-Gyan, H. Yu, O. Fuentes, R. Brower, and A. Abdelgawad, "Automatic classification of pathological gait patterns using ground reaction forces and machine learning algorithms," in *Proc. 2011 Annu. Int. Conf. Eng. Med. Biol. Soc.*, 2011, pp. 453–457.

[133] B. Koopman, H. J. Grootenboer, and H. J. de Jongh, "An inverse dynamics model for the analysis, reconstruction and prediction of bipedal walking," *J. Biomech.*, vol. 28, no. 11, pp. 1369–1376, 1995.

[134] A. Forner-Cordero, H. J. F. M. Koopman, and F. C. T. van der Helm, "Inverse dynamics calculations during gait with restricted ground reaction force information from pressure insoles," *Gait Posture*, vol. 23, no. 2, pp. 189–199, 2006.

[135] Q. Shao, D. N. Bassett, K. Manal, and T. S. Buchanan, "An EMG-driven model to estimate muscle forces and joint moments in stroke patients," *Comput. Biol. Med.*, vol. 39, no. 12, pp. 1083–1088, 2009.

[136] J. R. Gage, J. Perry, R. R. Hicks, S. Koop, and J. R. Werntz, "Rectus femoris transfer to improve knee function of children with cerebral palsy," *Develop. Med. Child Neurol.*, vol. 29, no. 2, pp. 159–166, 1987.

[137] A. Moghtaderi, A. Bakhshipour, and H. Rashidi, "Validation of Michigan neuropathy screening instrument for diabetic peripheral neuropathy," *Clin. Neurol. Neurosurg.*, vol. 108, no. 5, pp. 477–481, 2006.

[138] R. L. Waters and S. Mulroy, "The energy expenditure of normal and pathologic gait," *Gait Posture*, vol. 9, no. 3, pp. 207–231, 1999.

[139] E. S. Chumanov, C. D. Remy, and D. G. Thelen, "Computational techniques for using insole pressure sensors to analyse three-dimensional joint kinetics," *Comput. Methods Biomech. Biomed. Eng.*, vol. 13, no. 5, pp. 505–514, 2010.

[140] I. S. O. Vim, "International vocabulary of basic and general terms in metrology (VIM)," *Int. Org.*, vol. 2004, pp. 9–14, 2004.

[141] G. H. White and I. Farrance, "Uncertainty of measurement in quantitative medical testing: A laboratory implementation guide," *Clin. Biochemist Rev.*, vol. 25, no. 4, pp. S1–S24, 2004.

[142] K. A. Edginton, H. C. Güler, J. J. Ober, and N. Berme, "Instrumented treadmills: Reducing the need for gait labs," Bertec Corporation, Columbus, OH, USA. [Online]. Available: http://bertec. com/uploads/pdfs/papers

[143] C. G. Goetz *et al.*, "Movement disorder society-sponsored revision of the unified Parkinson's disease rating scale (MDS-UPDRS): Scale presentation and clinimetric testing results," *Movement Disorders*, vol. 23, no. 15, pp. 2129–2170, 2008.

[144] M. Benedetti, F. Catani, A. Leardini, E. Pignotti, and S. Giannini, "Data management in gait analysis for clinical applications," *Clin. Biomech.*, vol. 13, no. 3, pp. 204–215, 1998.

Authors', photographs and biographies not available at the time of publication.