Recent Advances in Quantitative Gait Analysis Using Wearable Sensors: A Review

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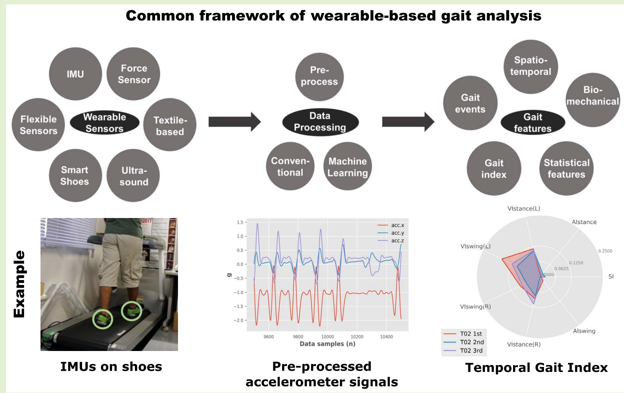

***Abstract*—The current gold standard for gait analysis involves performing the gait experiments in a laboratory environment with a constrained space. However, there is growing interest in using flexible, efficient, and inexpensive wearable sensors as tools to perform gait analysis. This review aimed to identify and summarize the current advances in wearable sensors for various aspects of gait analysis, such as the application of wearable gait analysis systems, sensor systems and their attachment locations, and the algorithms used for the analysis. The PRISMA guideline was adopted to find relevant studies from the period 2011 to 2020 from several scientific databases. A total of 76 articles were selected based on the inclusion and exclusion criteria. A wearable inertial measurement unit (IMU) attached to the lower limb region was found to be the most common approach for gait analysis. Temporal, spatial, and spatiotemporal features were the most common quantitative gait features extracted from the wearable sensors. The proposed frameworks showed varying performances, and an increased number of sensors did not necessarily improve the estimation performance metrics. A few studies have integrated various machine learning techniques for classification problems, correction algorithms, crosschecking functions, and scoring functions. Finally, this review paper discusses the challenges and future direction of the research on quantitative gait analysis.**

***Index Terms*—Gait analysis, wearable sensors, inertial measurement units, machine learning, walking, clinical applications.**

I. Introduction

GAIT is often interpreted as the manner of walking. Quantitative gait analysis is the in-depth analysis of the gait of a person based on various quantifiable parameters. Gait analysis has wide applications ranging from sports to clinical investigations. In sports, gait analysis is often utilized to assess the performance of athletes, prevent injuries, and provide a training guide [1], [2]. In clinical applications, gait analysis is performed to characterize certain gait pathologies, track rehabilitation progress, and evaluate the effectiveness of certain treatments [3]–[5]. In addition to these applications, gait analysis can be used to predict the risk of falling in elderly subjects [6], [7].

Several approaches can be used to perform the gait analysis. In most clinical settings, a combination of observation and qualitative assessment by clinicians and self-reported assessments by patients is employed [8], [9]. Observations collected by clinicians such as doctors or physical therapists may provide some quantitative gait features such as distance covered, total walking time, gait speed, and cadence. Nevertheless, these are subject to inter-observer variability and human error.

Presently, it is very common to perform quantitative gait analysis in a laboratory environment by using a gold standard measurement such as the combination of motion capture and force plate systems. Motion capture enables precise tracking of the spatial information of human motion in 3D, whereas the force plates provide dynamic features such as ground reaction forces and moments. However, the use of these specialized instruments is limited to only a few clinics or research facilities and have limited capture volume; thus, they may not necessarily capture the natural gait of the subject [10]. Another concern is the considerable time required for preparing for the experiment, such as placing markers and conducting anthropometric measurements, which may not be convenient for patients participating in the study.

Manuscript received July 22, 2021; revised September 21, 2021; accepted October 4, 2021. Date of publication October 13, 2021; date of current version November 30, 2021. This work was supported by the Japan Society for the Promotion of Science (JSPS) KAKENHI under Grant JP18H01399. The associate editor coordinating the review of this article and approving it for publication was Dr. Shanhong Xia. *(Corresponding author: Yonatan Hutabarat.)*

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Digital Object Identifier 10.1109/JSEN.2021.3119658

The recent vast developments in sensor systems and computational methods have made it possible to assess the gait outside the laboratory through wearable sensor systems. In addition to gait analysis, wearable sensors have been investigated to predict several clinical conditions based on the resting heart rate, temperature, and other features [11], [12]. In this review, we focus on the recent advancements in wearable-based gait analysis, which has recently been widely adopted in various applications. The number of sensors used may depend on the subject of interest. For example, sensors attached to both legs are preferred for a highly impaired gait [13]. Wearable inertial sensor-based gait analysis also serves as a supplementary assessment of the physical function of patients undergoing total hip arthroplasty [14] and in clinical analysis of idiopathic normal pressure hydrocephalus [19]. Several studies have discussed the long-term assessment of gait using wearable sensors [15]. In clinical applications, it has been reported that there is a strong correlation between accelerometer-based motor fluctuation measurement and the gait item in the Unified Parkinson's Disease Rating Scale-Part III [16], which suggests that the accelerometer may be a useful tool for monitoring Parkinson's disease (PD) patients. Wearable inertial sensors have also been used in biofeedback systems for gait and balance training of PD subjects [17], [18]. Gait quality metrics were found to be robust in assessing the gait of two matched groups of multiple sclerosis patients at two separate locations with different experimental protocols [20]. In assessing gait ataxia in people with spinocerebellar degeneration, the accelerometer-based assessment is more responsive than the standard clinical scale for the assessment and rating of ataxia [21]. Nevertheless, the performance accuracy and types of analysis are dependent on many factors such as the types of sensors, number of sensors, their positions on the body, and the methods and algorithms used. Therefore, this study aimed to address the recent advances in wearable-based gait analysis based on the above mentioned factors. The overall scientific contributions of this review paper are as follows:

- It presents an overview of the recent state of the art in quantitative gait analysis using wearable sensors, which have been validated against the gold standard measurement or other measurement systems.
- It provides key insights into the existing wearable-technology-based gait analysis in terms of the number and types of sensors, gait features, positioning of the sensors on the body, as well as the method and algorithms used in each study.
- It highlights the current applications of wearable technology based gait analysis for both general purposes such as sports and clinical purposes related to various pathological conditions.
- It discusses the issues, challenges, and future research direction for researchers and clinicians working in this field.

The remainder of this paper is organized as follows. Section II presents the methods for locating relevant papers on gait analysis, as well as the exclusion and inclusion criteria for the paper to be reviewed. Section III presents the results of the literature search, which are classified based on key topics such as type and number of sensors, application of wearable gait analysis, sensor positions on the body, and algorithms implemented to extract the gait features. Section IV discusses the findings, current challenges, and possible future research directions. Finally, Section V concludes the review.

II. Methods

The method used to find relevant references containing state-of-the-art techniques followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guideline [22], which is commonly used for reporting systematic reviews. The search was conducted on several databases including PubMed, IEEE Xplore, Scopus, and ISI Web of Science for the period from 2011 until 2020. The time constraint was added to ensure that only recent advances in this topic were considered for the review. Search keywords and combinations were formulated, as shown in Fig. 1. In the case of abbreviated search terms such as IMU and GRF, the search was repeated with their expanded forms, i.e., "inertial measurement unit" and "ground reaction force," respectively. We limited the search to only the titles of the articles along with the time constraint from 2011 to 2020. Gait was a necessary word in the document title, followed by any combination of keywords, as depicted in Fig. 1.

The database search was performed on February 8, 2021. A total of 1550 records from all the databases were included in the selection process. These results were then imported into the Mendeley® Desktop reference management software (version 1.19.4, Elsevier). Duplicate records were automatically removed by the software if an exact match was detected. In all, 860 duplicates were identified, resulting in 690 records that needed to be screened.

The screening stage excluded certain studies on the topics depicted in Fig. 1 based on the title and abstract. Assistive walking technologies were not included in this study, as most of these placed the sensors on the walking device, such as on a cane or a walker. Studies using non-wearable sensors, such as studies employing cameras or Kinect or any combination of these systems, were excluded. Smartphone-based studies were excluded because they are not a fully dedicated system and are mostly used for activity recognition or human authentication as opposed to the detailed gait analysis targeted in this review. Other unrelated studies such as those on sensor development, sensor-to-body alignment, underwater gait, and person/gender recognition were also detected and excluded in the screening stage. At the end of the screening stage, 344 records were excluded based on the set criteria, leaving 356 articles for the next stage.

In the eligibility stage, the full-text articles were accessed to find relevant studies to review the state of the art. The inclusion criteria for full-text screening are shown in Fig. 1. We preferred studies that set a benchmark or compared their proposed framework/system with a gold standard system or other existing studies. Moreover, each of the studies addressed various gait features, as depicted in Fig. 1. Nevertheless, we found some studies that used sensors with cables tethered to a data processing unit such as a computer, and those studies were discarded. Another criterion was that the studies must

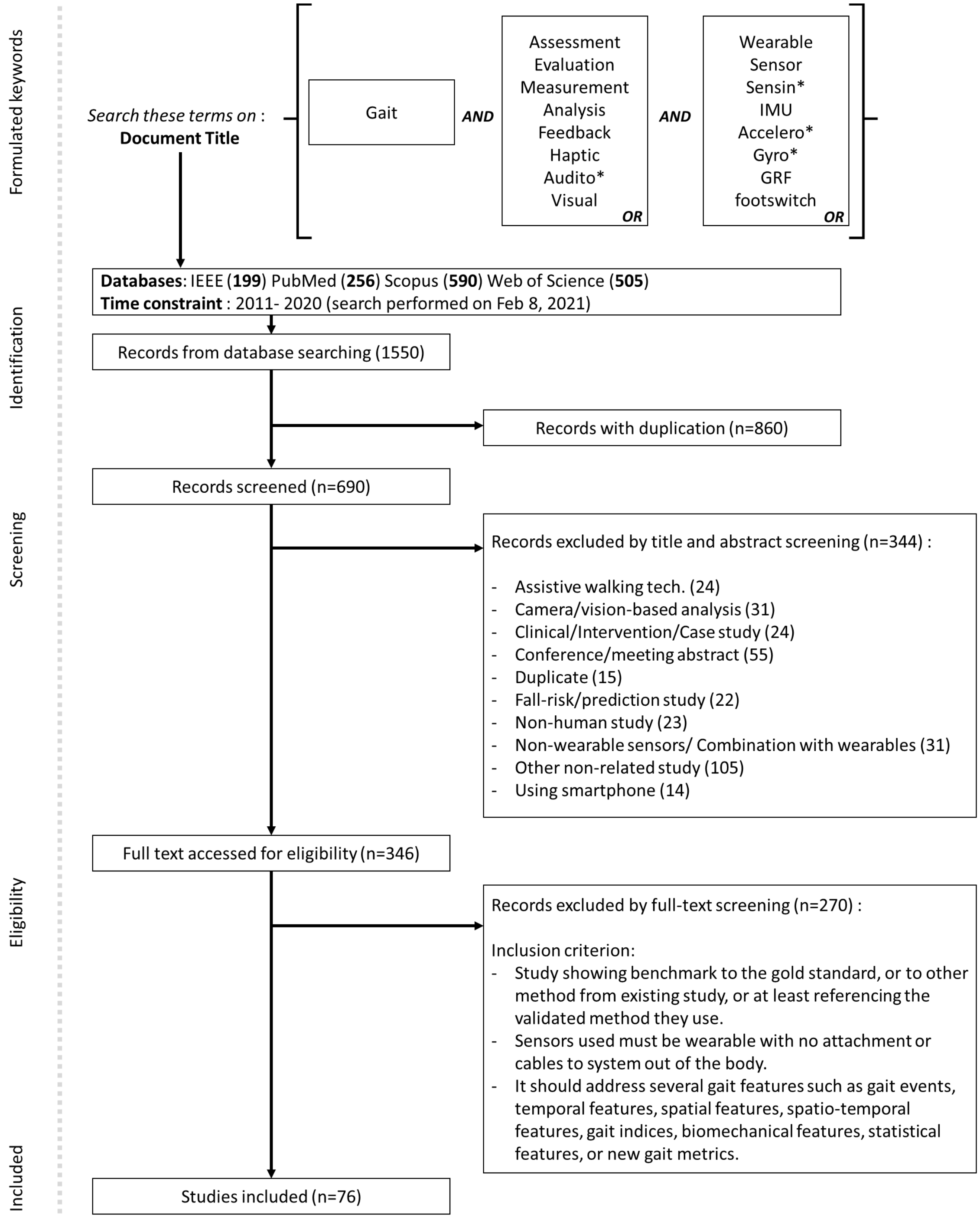
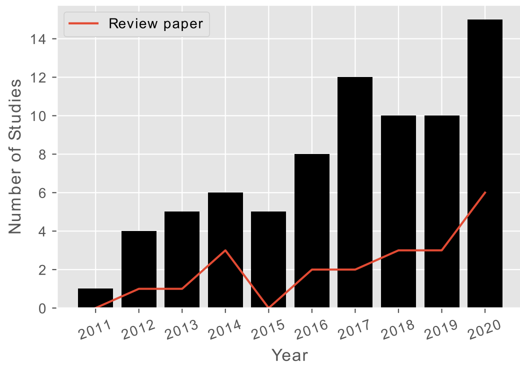


Fig. 1. Formulated search keywords on several scientific databases with the time constraint, followed by the PRISMA flowchart for inclusion process and exclusion criterion of the articles selected in this study. Asterisk (*) indicates wildcard for the search term.

address more than one gait feature. At the end of this stage, 76 articles were found eligible for a systematic review. The overall flowchart of the article selection process is depicted in Fig. 1, and the distribution of eligible articles is depicted in Fig. 2.

A. Existing Review

While doing this process, a total of 21 review papers were also identified regarding this topic. Among them, there are six review papers published in 2020, which are described briefly as the following. Kobsar *et al.* on [23] addressed a specific application of wearable inertial sensors for adults with osteoarthritis. Gondim *et al.* [24] discussed the use of the portable accelerometer to evaluate the gait of people with Parkinson's disease. Junior *et al.* [25] was focused on reviewing gait assessment in children. However, all of the above papers discussed a very specific subject and conditions. Díaz *et al.* [26] discussed a wider scope of gait that includes



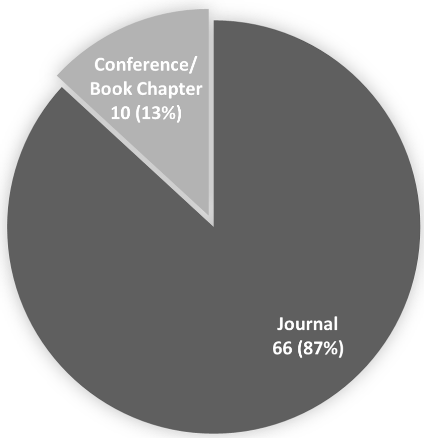


Fig. 2. Distribution of the eligible articles based on year (bar chart) and publication types (pie chart).

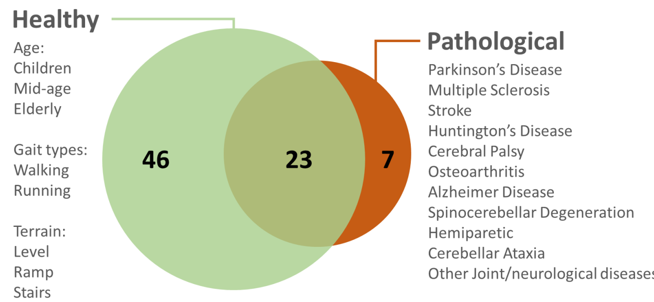


Fig. 3. Identified application of wearable-based gait analysis. Twenty-three studies discussed the application to both healthy control and patients with certain pathological conditions.

balance and range of motion analysis using wearable sensors. Dasgupta *et al.* [27] was focused on acceleration gait measure for motor skill assessment. Hence, it was specific to motor skills instead of gait. Saboor *et al.* [28] discussed the latest trend on gait analysis using wearable sensors combined with machine learning-based methods. However, the study selected was constrained from 2015 onwards with limitations only to machine learning methods. Other notable review papers are from Tao *et al.* [29] in 2012 that discussed basic human gait analysis and sensors system, Lopez-Nava and Munoz-Melendez [30] in 2017 that focused on wearable inertial sensors for motion analysis, and Caldas *et al.* [31] that specifically discussed inertial sensors and adaptive algorithms for gait analysis.

The differences between this review to the above works are this review aims to provide a comprehensive review of quantitative gait analysis using wearable sensors with no constraint on specific subject groups nor the method of analysis. Thus, it covers a wider range of gait analysis that includes various applications such in general walking gait, running gait, and different kinds of pathological gait. In addition to that, this review is intended to summarize the last decade's advancement of this topic, identify challenges in recent studies, and give future directions on research on this topic.

III. Synthesis of Results

We ensured that all the included papers validated their proposed techniques by comparison against the gold standard measurement such as motion capture and/or force plate systems or other widely accepted measurement methods, such as using an instrumented treadmill or the GAITRite® system. There were some exceptions to this criterion, such as studies that used force-based sensors [54], [94] on the foot to directly estimate the initial/terminal contact of the foot, analyzed only the statistical features from the raw data [55], employed a machine learning-based algorithm for classification [80], [111], or cited their previously validated framework [78], [88].

This section addresses several important points about wearable-based gait analysis, starting from the applications, sensors used and location attachment, gait features that can be extracted, data processing method, algorithms, as well as experiments and validation methods. Table I-IV summarize those important points from all of the eligible studies.

A. General Application of Wearable Gait Analysis

Based on the results of the literature search, we identified that 46 (61%) of the eligible studies tested their framework only on healthy control subjects, whereas 23 (30%) included both healthy control and patient groups. We did not discriminate the healthy subjects based on age; thus, children or the elderly were also considered as general applications. Analyses specific to the elderly [58], [62] or children [75], and comparisons between age groups such as normal middle-aged subjects and the elderly [49], [53], [61], [105] were examples of general application by age difference.

In terms of assessing different gait types, we identified a few studies that discussed both walking and running [38], [51], [91], [96]. The analysis of walking on different terrains such as ramp walkways, walking up- and downstairs, or outdoors was discussed in [68], [76], [96], [104], and [111]. Temporal, spatial, and spatiotemporal gait features were found to be the most commonly analyzed features within the studies. These features could be further derived into certain gait indices or gait metrics such as gait regularity and symmetry index [37], [102], which are mostly used in clinical applications. Estimation of lower limb joint angles [45], [51] and joint moments [50] were also conducted using wearable sensors.

B. Clinical Application of Wearable Gait Analysis

In addition to the general application of gait analysis, we identified several clinical applications such as

TABLE I
STATE OF THE ARTS OF QUANTITATIVE GAIT ASSESSMENT USING WEARABLE SENSORS

Ref.	Subjects (n)	Sensors (Location)	Experiments/ Benchmark	Algorithms/ Data Processing	Gait features [Performances metrics]
[36]	Healthy (3)	7 IMUs (lumbar, thighs, shanks, feet)	Overground indoor walk, variable-speed treadmill/ Motion capture	Non-ML/ Online (joint angles), Offline (stride length)	Stride length, joint angles (hip, knee, ankle) [RMSE $<$ 4 deg]
[37]	Healthy (5)	1 IMU (left heel)	20 m corridor walk with various speed/ Camera	Non-ML (threshold based, sliding window)/ Real-time	Stride count, cadence, gait speed, ratio of swing/stance, stride regularity, stride length [err. $<$ 3%], walking distance [err. $<$ 2%]
[38]	Healthy (5)	2 IMUs (shanks)	Treadmill walk at [2,4] kph and run [8,12] kph/ Motion capture	Non-ML (threshold based)/ Offline	Gait events (HS and TO [err. $<$ 1%], MSw) , stride time [err. $<$ 1.6%] , swing, stance time.
[39]	Healthy (22)	1 acc. (L4-L5)	Level walk, 10m, barefoot/ Motion capture	Non-ML (peak detection, integration)/ Offline	Step length, stride length [$p > 0.05$], {stride, step, stance, swing, DS, SS} time, gait speed [$p > 0.05$], cadence, foot symmetry
[40]	Healthy (10), OA(12)	4 IMUs (shanks and foot)	50 m corridor walk/ Motion capture	Non-ML/ Offline	Joint angles (multi-segment foot angles) [RMSE $<$ 2 deg, Mean RoM diff. $<$ 4 deg]
[41]	Healthy (10), pre-HD (10), HD (14)	1 acc (thorax level)	4.8 m level walk/ GAITRite®	Non-ML (Inverted pendulum)/ Offline	Gait speed [ICC(CI) 0.95(0.75,0.97)], cadence [ICC(CI) 0.95(0.75,0.97)], stride length [ICC(CI) 0.89(0.77,0.95)], step length, step time, step time asymmetry, step-stride regularity
[42]	Healthy (8)	Textile socks	2 min walk on treadmill at 4 kph/ F-scan	Non-ML (direct use of sensors data)/ Offline	Gait events (HS [0.08 $\pm$ 0.08 s], TO), stride time [err. $<$ 3.5%], stance time
[43]	Children (1), Children with CP (6)	7 IMUs (lumbar, thighs, shanks, feet)	10m walk preferred speed/ Motion capture	Non-ML ('Outwalk' protocol)/ Offline	Joint angles [RMSE $<$ 4 deg]
[44]	Older (10), PD (10)	2 IMUs (upper shoes)	2x20 m and 4x50 m walk with 180 deg turn/ Motion capture	Non-ML/ Offline	Gait speed [2.8 $\pm$ 2.4 cm/s], stride length [1.3 $\pm$ 3.0 cm], swing width, path length
[45]	Healthy (5)	7 IMUs (pelvis, thighs, shanks, feet)	5m indoor level walk/ Motion capture and force plates	Non-ML/ Offline	Joint angles [RMSE $<$ 10.14 deg] and 2D joint trajectories
[46]	Healthy (10)	Instrumented insoles	5m indoor level walk/ F-scan	Non-ML/ Real-time (Data streaming)	Step time, stance time, swing time
[47]	Healthy (10)	e-AR	Treadmill walk with variable speed and inclination/ Instrumented treadmill, High speed camera (250Hz)	Non-ML (recursive)/ Offline	Stride time [err. $<$ 1.47%], stance time [err. $<$ 4.84%], swing time [err. $<$ 8.03%]
[48]	Children (15), Children with CP (14)	2 IMUs (feet)	6 m straight walk and figure 8 walk for benchmark; 200 m walk in clinical setting with self selected speed for testing/ Motion capture	Non-ML/ Offline	Gait speed [4.3 $\pm$ 4.2 cm/s], stride length [3.4 $\pm$ 4.6 cm] , % {stance, swing, DS}, cadence, heel-toe clearance, strike [0.5 $\pm$ 2.9 deg] and lift off [3.9 $\pm$ 5.8 deg] angles
[49]	Healthy (12), Older (12)	1 IMUs (L5)	5x25 m route on preferred and fast speed/ GAITRite®, camera	Non-ML (continuous wavelet transform)/ Offline	Step time and count, stride time [ICC 0.994-0.999], step length [ICC 0.756-0.929], step velocity [ICC 0.853-0.942]
[50]	Healthy (4)	3 IMUs (thigh [right], shank, foot) and force sensors	3 m walking straight indoor/ Motion capture and force plates	Non-ML/ Offline	Joint moments [3.5 % $<$ NRMSE $<$ 21 %]
[51]	Healthy (3)	Soft sensing suit	Instrumented split-belt treadmill with 5 speeds (3 walk and 2 run)/ Motion capture	Non-ML/ Offline	Joint angles (hip, knee, ankle) [RMSE $<$ 15 deg]
[52][c]	Healthy (10)	2 acc. (L3-L4 and shank) and 1 gyro (shank)	Instrumented split-belt treadmill with 5 speeds (all walk)/ Motion capture	Non-ML/ Offline	Gait events (IC, TC), stride time [RMSE $<$ 1.6%], step time [RMSE $<$ 4.3%], DS time [RMSE $<$ 25.7%], stance and swing time
[53]	Young (9), Mid-age (5), Old (6)	2 IMUs (ankles)	Self-selected speed walking with variation on stride velocity and stride length/ Motion capture	Non-ML/ Offline	Heel [3.22 $\pm$ 1.50 cm] and toe [1.69 $\pm$ 0.70 cm] clearances, foot angle [2.49 $\pm$ 1.21 deg]

TABLE II
STATE OF THE ARTS OF QUANTITATIVE GAIT ASSESSMENT USING WEARABLE SENSORS

Ref.	Subjects (n)	Sensors (Location)	Experiments/ Benchmark	Algorithms/ Data Processing	Gait features [Performances metrics]
[54][f]	Healthy (10)	Sensorized insoles	Treadmill walk at 2 km/h/ Not needed	Non-ML/ Real-time	Gait phases
[55]	Healthy (25), SCD (25), PD (25)	2 IMUs (lower back, upper back)	6 min walking/ Not needed	Non-ML/ Offline	Statistical (Mean amplitude and Coefficient of Variation)
[56]	Older (19), PD (13)	3 IMUs (C7, L5, back of head)	2 min walking on 25 m circuit/ GAITRite®	Non-ML/ Offline	Statistical (Magnitude, attenuation, harmonic ratio)
[57]	Healthy (15), PD (5), Stroke (4)	2 IMUs (feet)	10 m straight walk normal speed/ FSR sensors	Non-ML/ Online	Gait events (HS [0.125 $\pm$ 0.01 s], TO [0.089 $\pm$ 0.015 s]), {stride, stance, swing, walking} time, stride count, stride length, gait speed, cadence
[58]	Older (82)	1 acc. (L3-L4)	2x40 m round walkway at comfortable walking speed/ GAITRite®	Non-ML/ Offline	(Cadence, gait speed, step length, step time) [ICC 0.91-0.96], variability and asymmetry indices
[59]	ACL (23), TKR (31)	e-AR	6 min walking on the corridor/ Pressure insoles	Non-ML/ Offline	Asymmetry($\|acc\|$) [MSE=0.044]
[60]	Healthy (10), OA (14)	Smart shoes	15 m walking straight/ Force plates	ML (SVM)/ Real-time	Gait phases (IC, FF, HO, TO, swing) [Accuracy 94.08 %]
[61]	Healthy (10), Older (21)	1 acc. (waist)	10 m walking/ Video camera	ML (K-means clustering)/ Offline	Gait event (IC), step detection [Sensitivity 99.33 %], frail classification
[62]	Older (24)	2 IMUs (shoes lateral)	5 min walking on treadmill with variable slope/ Instrumented treadmill	Non-ML/ Offline	Gait speed [RMSE $<$ 0.089 m/s], stride length [RMSE $<$ 0.336 m], stride time [RMSE $<$ 0.004 s], cadence [RMSE $<$ 0.098 steps/min]
[63][f]	PD (3)	Sensorized insoles, 6 IMUs (hips, shanks, feet)	18 m walking straight with variable pace/ Motion capture	Non-ML/ Offline	Gait phases (IC, FF, TC, swing), step length [Mean diff. 0.9 cm]
[64]	Healthy (10)	Smart shoes	Free walking and 4x5 m walk/ Motion capture	Non-ML/ Real-time (Data streaming)	Gait phases (HS, stance, HO, swing) [Error range between 0.036-0.110 s]
[65]	Healthy (16), Neurologic patients (6)	2 IMUs (feet)	Walking with preferred pace/ Kinect	Non-ML/ Real-time (Data streaming)	Stride length [RMSE 0.05 m], step length, cadence, gait speed, {stride, stance, swing [RMSE 0.02 s]} time, foot clearance, turning rate
[66]	Healthy (12), Obese (10)	7 IMUs (pelvis, thighs, shanks, feet)	14 m walk straight/ STEP32	Non-ML/ Offline	Cadence, % gait phases, ROM (ankle, knee, hip) [Range of ICC 0.43-0.72]
[67]	Healthy (16), PD with FoG (26) non FoG (16)	2 IMUs (shins)	TUG (3 m walk)/ Motion capture and video camera (for FoG)	Non-ML/ Offline	Step velocity, stride length, stride time, cadence, FoG detection [Accuracy 98.51 %]
[68]	Healthy (6)	1 IMU (foot)	Level ground walking, stairs climbing/ Motion capture	Non-ML/ Offline	Step count, walking distance [Err. ¡0.81 %], % gait phases, 3D trajectory [RMSE 0.28 m]
[69]	Healthy (7)	2 acc. (heels)	12 m walk/ Motion capture and video camera	Non-ML/ Offline	Gait events (HS [7.2 $\pm$ 22.1 ms], TS [0.7 $\pm$ 19.0 ms], HO [3.4 $\pm$ 27.4 ms], TO [2.2 $\pm$ 15.7 ms]), {stride, stance, swing} time [Range of ICC 0.87-0.98], heel clearance
[70]	Healthy (15), MS (45)	2 IMUs (shanks)	Various walking tasks/ Activity monitor, Inertial sensors	Non-ML/ Offline	Step count, {stride [6 $\pm$ 9 ms], step [6 $\pm$ 7 ms], swing [25 $\pm$ 19 ms]} time
[71]	Healthy (25)	4 IMUs (ankles, mid of superior iliac spine, C2)	15 m walk normal speed/ Motion capture, GAITRite®	Non-ML/ Offline	Cadence [SEM 5.24 steps/min], gait speed [SEM 0.14 m/s], stride length [SEM 0.21 m], {stride [SEM 0.04 s], stance [SEM 0.04 s], swing [SEM 0.02 s]} time, {strike [SEM 2.11 deg], lift-off [SEM 3.33 deg], pelvis, spine} angle
[72]	Stroke (25)	1 IMU (L5)	Laboratory and real-life longitudinal study/ GAITRite®, OPAL, video camera	Non-ML/ Offline	Step velocity [ICC 0.744 m/s], step length [ICC -0.411 m], {step [ICC 0.797 s], swing [ICC 0.431 s], stance [ICC 0.759 s]} time, step width, asymmetry and variability indices

TABLE III
STATE OF THE ARTS OF QUANTITATIVE GAIT ASSESSMENT USING WEARABLE SENSORS

Ref.	Subjects (n)	Sensors (Location)	Experiments/ Benchmark	Algorithms/ Data Processing	Gait features [Performances metrics]
[73]	Healthy (14), children (10), CP (22)	3 IMUs (L2-L3, thighs)	30 strides at various speed/ FSR sensors	Non-ML/ Offline	Statistical (Pearson's r, variance ratio, harmonic ratio), Gait segmentation [Sensitivity 83.34 % (CP), 96.67 % (Healthy)]
[74]	Older (23)	2 IMUs (feet)	Combination of normal and fast speed with added cognitive task/ GAITRite®	Non-ML/ Offline	Cadence, gait speed [ICC 0.34-0.96], step time [ICC 0.22-0.27], step length [ICC 0.45-0.84]
[75]	Children (10)	6 IMUs (sternum, wrists, L4-L5, shanks frontal)	7 m walk straight at self-selected and fast speeds/ Motion capture	Non-ML/ Offline	Stride length [RMSE 6.43 % of subject's height], gait speed [RMSE 7.80 % of subject's height], {stride [RMSE 0.014 s], stance [RMSE 0.026 s]} time
[76][c]	Healthy (20)	4 acc. (left wrist, waist, ankles)	Indoor, Outdoor, Treadmill walk and run/ FSRs sensors	Non-ML/ Offline	Gait events: (HS,TO) [F1 Scores (0.98,0.94) indoor, (0.82,0.53) outdoor]
[77][c]	Healthy (35)	5 IMUs (L5, shanks, dorsal shoes)	2 min walk at 10 m path back and forth/ Force plates	Non-ML/ Offline	Gait events (HS, TO), {step, stance} time
[78]	AD (16)	1 acc. (L5)	Lab-based and free-living/ Prev. paper [5]	Non-ML/ Offline	Step velocity, step length, {step, swing, stance} time, step width, asymmetry and variability indices
[79]	Knee arthoplasty patients (16)	2 IMUs (below knees)	6 m walk straight at self-selected/ Motion capture	Non-ML/ Offline	Gait events (IC, TO), {stride [RMSE 0.036 s], stance [RMSE 0.041 s], swing [RMSE 0.049 s]} time
[80][c]	Healthy (27), PD (27)	8 IMUs (chest, lumbar, thighs, shanks, feet)	15 m walk straight at self-selected and fast speeds/ Not needed	ML (SVM)/ Offline	Step length, gait speed, {step, stride} time, {hip, knee, ankle} ROM, Patient vs. control classification [Highest accuracy 79.96 %]
[81]	Healthy (30), Stroke (20), Joint disease (20)	7 IMUs (waist, thighs, shanks, feet)	Walk straight >15m on corridor/ Motion capture	Non-ML/ Offline	Stride length, gait speed, stride freq., {stride, stance, swing} time, foot clearance, knee ROM [Position err. <0.015 m]
[82]	Healthy (24)	7 IMUs (waist, thighs, shanks, feet)	6 min walk test/ Motion capture	Non-ML/ Real-time	Step [RMSE 0.04 m] and stride length, step and swing width [RMSE 0.03 m], cadence [RMSE 3.1 steps/min], {step, stride, stance, SS, DS, swing} time [RMSE 0.02 s], gait speed [RMSE 0.03 m/s]
[83]	Healthy (10)	1 IMU (CoM)	Walking at self-selected speed/ Motion capture	Non-ML/ Offline	Step length [Abs. Err. 5.6 %], gait speed [Abs. Err. 13.5 %], walking time [Abs. Err. 14.9 %], walking distance
[84]	MS (4), HSP (9)	IMUs, FSRs	10 m walk, may use walking aid/ GAITRite®	Non-ML/ Offline	Gait events (IC, TC), % DS [3.89 $\pm$ 2.61 %], DS time [0.064 $\pm$ 0.060 s]
[85]	Healthy (16)	Flexible sensors	6 m walk at preferred speed/ Motion capture	Non-ML/ Real-time (Data streaming)	Knee angle [RMSE 1.2 $\pm$ 0.4 deg]
[86][c]	Healthy (15)	1 IMU (foot)	50 strides walk/ Motion capture	Non-ML/ Real-time (Data streaming)	Walking distance [Accuracy 95.24 %], stride count [Accuracy 95.47 %], {stride, stance, swing} time
[87]	Older (20)	1 acc. (waist)	Real-world setting/ Video camera	Non-ML/ Offline	Step detection, gait speed [Mean diff. -0.206 m/s (for speed < 1 m/s), and -0.045 (for speed 1-1.5 m/s]
[88]	Healthy (20), Neurological (20)	2 IMUs (ankles)	10 m corridor walk at preferred speed/ Prev. paper	Non-ML/ Offline	Cadence, gait speed, stride length, stride time, % stance and swing, ankle ROM, gait symmetry and regularity [Position Error < 1%]
[89]	Healthy (20), Stroke (20), Joint disease (20)	6 IMUs (thighs, shanks, feet)	15 m obstacle-free corridor walk/ Motion capture	Non-ML/ Real-time (Data streaming)	Cadence, gait speed, stride length, stride time, % stance and swing, foot clearance, knee ROM and dorsiflexion-plantar angles [Err. < 3 deg]
[90]	Healthy (5)	2 IMUs (feet)	11 m walk indoor/ Motion capture	Non-ML/ Offline	Gait events (HS, TO), gait speed [Rel. Err. 6.3 $\pm$ 2.2 %], stride length [Rel. Err. 5.9 $\pm$ 3.3 %], % DS phase [Rel. Err. 4.3 $\pm$ 3.3 %]
[91]	Healthy (49)	2 IMUs (feet)	Treadmill run at comfortable speed/ High speed camera	Non-ML/ Real-time	Step length [ICC 0.968-0.975], step frequency, stance [ICC 0.813-0.896] and swing [ICC 0.807-0.857] time
[92][f]	Healthy (10)	4 IMUs (shanks, feet)	Treadmill walk with variable speeds/ Motion capture	Non-ML/ Real-time	Gait events (HS, TO), Gait phases (stance [Accuracy 97.9 %], swing [Accuracy 96.3 %]), ankle angle [RMSE 3.24 $\pm$ 0.67 deg]

TABLE IV
STATE OF THE ARTS OF QUANTITATIVE GAIT ASSESSMENT USING WEARABLE SENSORS

Ref.	Subjects (n)	Sensors (Location)	Experiments/ Benchmark	Algorithms/ Data Processing	Gait features [Performances metrics]
[93]	Stroke (25)	2 IMUs (feet)	Walking with total distance of 120 m/ Motion capture	Non-ML/ Offline	Stride time [Err. 0.003(0.020) s], stride length, cadence [Err. -0.341(0.467) steps/min], gait speed [Err. 0.002(0.003) m/s], % gait phases ; *Note*=[Err.=Non-paretic(Paretic)]
[94][f]	Healthy (17), hemiparetic (18)	Textile insoles	20 m corridor walk back and forth at self-selected/ Not needed	Non-ML/ Real-time (Data streaming)	Plantar pressure, stride time, stride count
[95]	Healthy (30)	1 IMU (L5)	6 m indoor walk at preferred speed/ GAITRite®	Non-ML/ Offline	Gait speed [ICC 0.92], cadence [ICC 0.96], stride length [ICC 0.88], stride time [ICC 0.93], % gait phases (SS, DS, Swing, Stance) [ICC 0.18, 0.12, 0.47, 0.47]
[96]	Healthy (3)	3 IMUs (waist, thigh, shank)	Walk and run on treadmill, up and down stairs walking/ Footswitch insoles	ML (Random Forest)/ Offline	Gait phases (SS, DS, swing) [Accuracy 98.94 % (walk), 98.45 % (run)]
[97]	Healthy (22), cerebellar ataxia (29)	3 IMUs (chest, ankles)	5 m walk back and forth/ Motion capture	ML (Random Forest)/ Offline	Gait speed, cadence, gait ataxia quantification. [RMSE 0.18]
[98]	Healthy (10)	3 IMUs (chest, wrist, thigh), 4 FSRs	7 min treadmill walk at various speed/ Instrumented treadmill	Non-ML/ Real-time (Data streaming)	Gait events (HS, TO), stride time [RMSE 5.027 ms], stride count [Accuracy 99.6 %]
[99]	Healthy (9), PD (6)	2 IMUs (feet)	Walk at self-preferred speed/ GAITRite®	Non-ML/ Offline	Step length [Mean Err. 4.50 $\pm$ 2.54 %] , step time [Mean Err. 2.97 $\pm$ 2.51 %]
[100]	Healthy (5)	4 Ultrasonics sensors	8.5 m walking back and forth at normal speed/ Video camera	Non-ML/ Offline	Gait events, ankle angle [Mean diff. 0.19 $\pm$ 1.19 deg], toe clearance [Mean diff. 0.02 $\pm$ 0.84 cm]
[101]	Healthy (30), stroke (30)	8 IMUs (waist [left and right], knees, ankles, feet)	More than 15 m level ground corridor walk/ Motion capture	Non-ML/ Offline	Stride length, cadence, gait speed, ankle ROM, gait symmetry, stance/swing ratio, foot clearance [Position Err. 0.02 m]
[102]	Healthy (6)	2 IMUs (shoes posterior)	4.5 m and 11 m indoor walk back and forth at self-preferred speed/ Motion capture, force plates	Non-ML/ Offline	Gait events (IC [4.22 $\pm$ 15.48 ms], TO [-8.31 $\pm$ 21.02 ms], % gait phases, gait speed, stride length [Accuracy 93.23 %], heel clearance [2.22 $\pm$ 5.28 cm], {stride, stance, swing} time, variability and asymmetry indices
[103]	Healthy (3)	E-textile socks	11 m indoor walk at various speeds/ Motion capture	Non-ML/ Real-time (Data streaming)	% Gait phases, cadence, stride length [Pearson's r = 0.283], gait speed
[104]	Healthy (11)	7 IMUs (CoM, thighs, shanks, feet)	Walking on various terrain (level ground, stairs, ramp)/ Inertial sensors	ML (Neural Network)/ Real-time	Joint angles [NRMSE $<$ 0.092 (knee joint)]
[105]	Healthy (20), older (20)	5 IMUs (chest, wrists, ankles)	Figure eight walk at normal speed on laboratory environment/ Motion capture	Non-ML/ Offline	Stide length [Abs. Err. 0.02 $\pm$ 0.03 m], gait speed [Abs. Err. -0.01 $\pm$ 0.02 m/s], step width, % gait phases, cadence, stride time, foot clearance, arm-related metrics
[106]	Healthy (5)	2 IMUs (top of shoes)	60 m total walking distance with variable stride length/ Optogait system	Non-ML/ Offline	Stride count, stride length [RMSE 5.0 cm], stride time [RMSE 0.04 s]
[107]	Healthy (8)	6 IMUs (thighs, shanks, feet)	4.5 m straight walk with variable speeds and tasks/ Motion capture	ML (kNN)/ Real-time	Stride time, stride length [RMSE 3.33 cm]
[108]	Healthy (9)	2 IMUs (lateral shoes)	20 m straight walk at preferred speed/ Motion capture	ML (Neural Network)/ Offline	Gait phases classification [Accuracy 92.63 %]
[109]	Healthy (40), PD (24)	1 IMU (L5)	10 m indoor straight walk at preferred speed/ GAITRite®	Non-ML/ Offline	Cadence [MSE Healthy(PD) 4.78(15.28) steps/min], gait speed [MSE Healthy(PD) 0.02($<$0.01) m/s], stride time, stride length, % gait phases [MSE 17.40 % (for double support on PD)
[110]	Healthy (40)	Pressure insoles	10 m indoor walk with various speeds/ GAITRite®	Non-ML/ Offline	Cadence [ICC 0.99], {stride, step, swing, stance, SS [ICC 0.65-0.96], DS [ICC 0.55-0.79]} time
[111]	Healthy (20)	1 IMU (ankle)	Walking on various terrain/ Not needed	ML (Random Forest)/ Offline	Gait activity classification [Accuracy 98.2 %]

Parkinson's Disease (PD), Huntington's Disease (HD), Cerebral Palsy (CP), Multiple Sclerosis (MS), Osteoarthritis (OA), post-stroke patients among much more clinical application within the literature. We found that most of the studies discussed the comparison from one disease group to the healthy control group or other disease groups. Other investigations on each of the mentioned disease groups are discussed below.

1) Parkinson's Disease: PD is a brain disorder that causes difficulties in walking, balance, coordination, and talking. Gait analysis performed in PD patients can provide several insights, such as the difference between the OFF and ON states of medication [44] and detection of freezing of gait (FoG) [67]. Quantitative gait analysis can provide clear quantifiable features that can track the progress of patients.

We found nine studies [44], [55]–[57], [63], [67], [80], [99], [109] that implemented a wearable sensor approach for gait analysis in PD patients. All of these studies used IMU sensors with a combination of two to eight IMU units. One study [63] proposed a combination of sensorized insoles and six IMUs to estimate the gait phases and step length while also providing rhythmic auditory feedback to the user.

The PD group has also been used as a disease control group to identify other neurological conditions such as spinocerebellar degeneration [55]. Other applications such as analysis of the upper body and postural control were discussed in [56], whereas the comparison of several machine learning-based classifications of PD patients was extensively discussed in [80].

2) Stroke: Stroke is caused by an interruption of blood supply to the brain, usually in the form of a blood clot. In the case of stroke or post-stroke patients, gait analysis is usually performed to track the rehabilitation progress. Six studies discussed the application of wearable gait analysis for stroke patients [57], [72], [81], [89], [93], [101]. A study used six IMUs on the lower limb [89] to provide a solution for tracking the rehabilitation progress of different groups of patients, including stroke patients, by estimating their pre- and post-treatment knee ROM.

All studies used various combinations of one to eight IMUs. A study, which used two IMUs on the feet [57], showed significant differences in several spatiotemporal features between stroke patients and healthy control groups. Another study [81], [101] also reported clear differences in gait features between the compared subject groups.

An extensive reliability and validation study of a single trunk-attached (L5) IMU [72] showed moderate to good agreement with the GAITRite® system in estimating the stance time and several step-based features. Another validation study using a foot-worn IMU [93] showed good to excellent agreement on various spatiotemporal gait features for both the paretic and non-paretic sides, and moderate agreement for the stance and swing phases.

3) Huntington's Disease: HD is a neurodegenerative condition characterized by progressive movement disorders. In [41], an accelerometer was used at the thorax level to extract various spatiotemporal features based on an inverted pendulum model [32]. A comparison between three distinct groups of healthy controls, pre-manifest HD, and manifest HD was presented. The results showed that there was a strong agreement between the sensor and the GAITRite® system, and the gait features extracted from the accelerometer proved effective in differentiating between the groups, especially the pre-manifest and manifest HD groups.

4) Cerebral Palsy: CP is the most common motor disability among children. CP is classified into three types: ataxia (poor balance and coordination), dyskinesia (uncontrollable movement), and spasticity (stiff muscles). Three studies [43], [48], [73] discussed the application of wearable sensors for gait analysis of CP patients.

In [43], a specific protocol was developed for children with CP, called the "Outwalk" protocol, to estimate the joint angles using seven IMUs. In [48], the authors pointed out significant differences between children with CP and typically developing children, as indicated by various spatiotemporal and kinematic features. Another study [73] showed that the three subclasses of CP subjects could be distinguished based on their motor function by analyzing their unique statistical features.

5) Multiple Sclerosis: MS is a disease that affects the central nervous system (brain and spinal cord) and causes communication problems between the brain and other body functions. Two studies [70], [84] employed wearable sensors for gait analysis in MS, as discussed below. Both studies employed IMU sensors; in [70], two units were used on the shanks, and in [84], an IMU was combined with three force sensing resistor (FSR) sensors inside the insole to form a wearable system.

In [70], various walking protocols were designed with variable walking speeds to assess the MS group. The gait event detection algorithm was adapted from [33] and the gait parameters were further categorized into temporal features. Their proposed framework was validated against an activity monitoring system (GT3X) and a commercially available inertial sensor (MTx). The results showed that there were 2 ± 2, 6 ± 9 ms, and 25 ± 19 ms errors in the step count, stride time, and swing time, respectively. By comparing the MS group with the healthy control group, it was found that the proposed system could detect significant ($p < 0.01$) and distinct gait characteristics between the two groups. The authors of [84] proposed the use of sensorized insoles consisting of three FSR sensors and an IMU to extract the temporal gait features of patients with gait disorders such as MS and hereditary spastic paraplegia. Initial contact (IC) and terminal contact (TC) events were labeled manually based on the heel FSR and lateral FSR, respectively. The results showed that there was a mean error of 64 ± 60 ms in the double support (DS) time, expressed as $3.89 \pm 2.61\%$ of the DS phase by analyzing 1321 strides of all participants.

From both studies, we found that temporal features were the main gait features used to characterize MS patients. Several temporal features, such as stride time and step time, were found to be effective in differentiating between healthy and MS subject groups. Moreover, it was demonstrated that temporal features could also distinguish MS subjects based on the disease severity level [70].

6) Joint Diseases: Articles on various joint-related diseases such as osteoarthritis (OA) were found in the search pool.

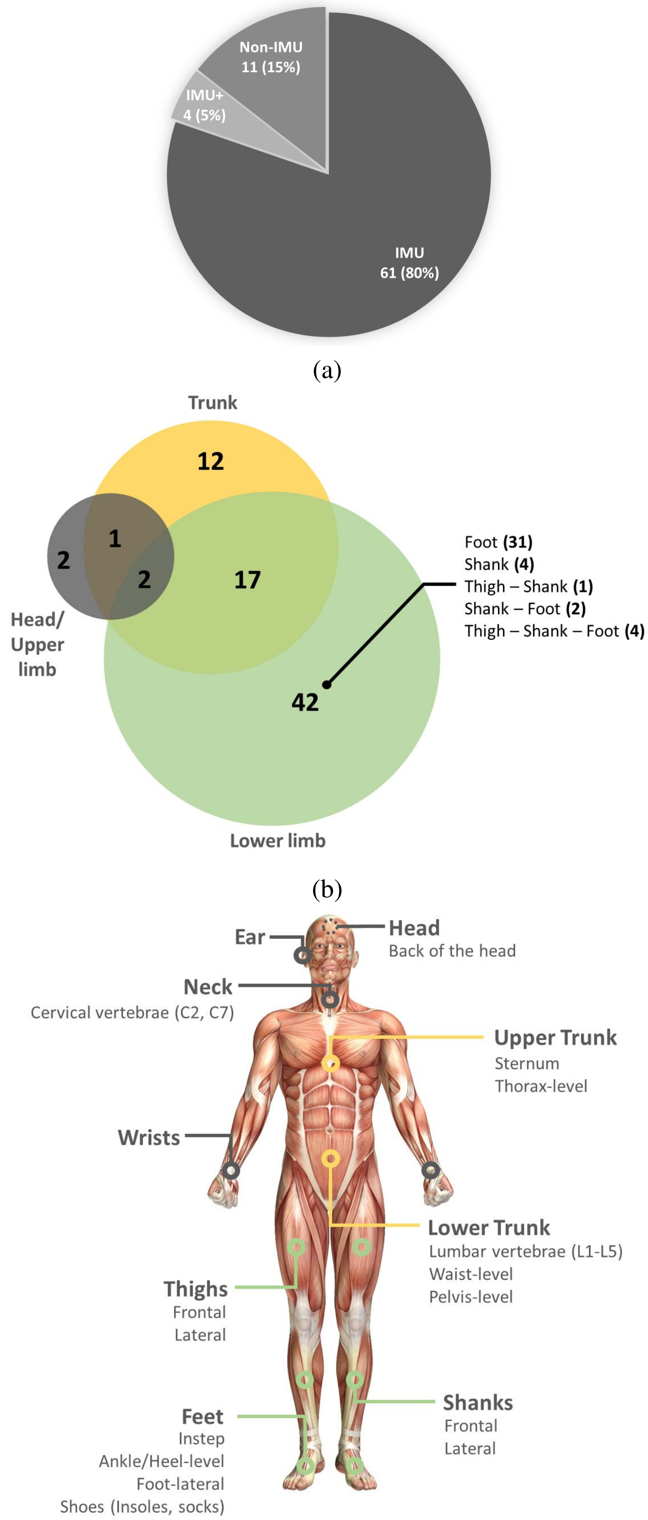
OA is a degenerative joint disease, which occurs when the protective cartilage at the ends of bones is worn down. In this case, gait analysis was performed to assess the effectiveness of the treatment plan. Six studies have discussed various joint-related diseases, such as OA [40], [60], anterior cruciate ligament (ACL) reconstruction [59], knee arthroplasty [79], and other joint diseases [81], [89].

The estimation of kinematic features such as foot angles was found to be effective in differentiating between healthy control and ankle OA groups [40]. A study using an ear-worn accelerometer [59] provided various asymmetry metrics to monitor the recovery gait of patients who underwent ACL reconstruction or total knee replacement. Integrated FSRs and IMU sensors on smart shoes were used to extract the gait phases of OA patients by using the SVM algorithm in real time with 94 % accuracy [60]. Two IMUs placed below the knees were used to extract the temporal features in [79] for the analysis of knee arthroplasty patients after knee replacement surgery. The studies [81] and [89] used seven and six IMUs, respectively, and extracted the gait features, which mainly comprised the temporal, spatial, spatiotemporal, and kinematic features. Knee ROM was chosen as one of the primary features to track the prior and post-treatment gaits of the patients.

C. Sensors and Their Locations

In this review, we simplify the sensor categorization to IMU-based, non-IMU, and a combination of IMU and other sensors (IMU+). IMU-based sensors were found to be the most common wearable sensors used in this study. An IMU generally consists of an accelerometer, a gyroscope, and a magnetometer. Using all three components can provide the orientation and relative position information by means of the sensor fusion method. Nevertheless, in this review, we found that these three components are not always used together. Some studies used only the accelerometer [39], [55], [56], whereas others used only the gyroscope unit [38]. In addition, we found unique sensor systems such as textile-based [42], [103], ultrasonic-based [103], and flexible [85] sensors.

In terms of sensor location, we found that 42, 17, and 12 studies proposed the attachment of the sensor on the lower limb, both the trunk and lower limb, and only the trunk, respectively. From the 42 studies that proposed lower-limb attachment, we found that 31 of those studies proposed the foot-based sensors which accounts for either ankle, instep, heel-level, or lateral foot sensor attachment, or could also be in the compact form of either socks, insoles, or smart shoes. Only two papers proposed a head-attached sensor, both of which were from the same authors who proposed an ear-attached sensor [47], [59]. Interestingly, two papers proposed the attachment of the sensors on the upper limb, trunk, and lower limb; reference [75] focused on the gait assessment in children, whereas [76] compared several algorithms and tested them on various terrains/environments. One study proposed a combination of sensors attached on the trunk and head [56] for the assessment of gait in elderly and PD patients. The distribution of the sensors and their locations are depicted in Fig. 4.



(a) (b) (c)

Fig. 4. (a) Distribution of wearable sensors used, where IMU-based sensors account for 80%, and IMU+ which is combination of IMU and other sensors account for 5% of the total eligible studies. (b) Location of sensor attachment to the body, where the most was found at lower limbs (42 studies) followed by lower limbs and trunk attachment (17 studies). Overall, foot-based sensor attachment (31 studies) was favored over the last ten years. (c) The detailed view of attachment of sensors in different region of human body as summarized from the eligible papers.

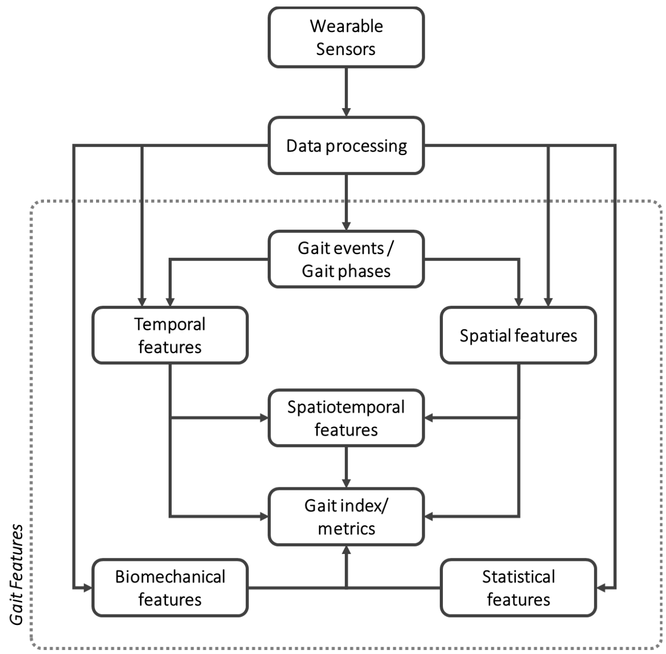


Fig. 5. Classification of gait features that are extracted from wearable sensors, which comprised of gait event/gait phases, spatial, temporal, spatiotemporal, gait index/metrics, biomechanical features, statistical features. In this review, biomechanical features are any kinematic or kinetic-based gait features such as joint angles and joint moment.

D. Gait Features

In this review, gait features are quantifiable parameters or characteristics of gait that are measured directly from wearable sensors or estimated through sets of algorithms. We classified the gait features into seven categories, as depicted in Fig. 5. The first category is the gait event or gait phase. Gait events are instantaneous events that occur based on the set detection algorithm, whereas the gait phase marks the time period between the initiation and termination of that phase. The most important gait events are IC and TC, which represent the instants when the stance phase and swing phase are about to commence, respectively. In some of the identified studies, IC and TC may also be called heel-strike (HS) and toe-off (TO), respectively. Other important gait events identified throughout the review are midswing (MSw), toe-strike (TS), and heel off (HO). These events were used as markers to identify gait phases, which under the new terms of gait classification are classified into eight distinct phases: IC, loading response, mid-stance, terminal stance, pre-swing, initial swing, MSw, and terminal swing. In addition to those phases, we also identified single support (SS), double support (DS), and foot flat (FF), in the eligible studies.

The second category encompasses the temporal features, which contain time-based information. Stride time, step time, stance time, swing time, SS time, DS time, and cadence are the widely known temporal gait features. Usually, these features are computed using information from gait event detection. For example, stride time, which is defined as the time taken to complete a gait cycle, can be estimated from the results of the HS or TO event. The stance time is estimated from the point of IC or HS to the point of TC or TO. The SS and DS times are estimated from the information corresponding to both sides of the foot, where the SS time is equivalent to the time elapsed when only one foot is in contact with the ground. The DS time is the time elapsed when both feet are in contact with the ground. Cadence is the number of steps walked per minute. Other than these features, some studies also computed the total walking time, which is the sum of the stride times per walking trial.

The third category encompasses the spatial features that contain the length-based information, such as stride length and step length. In addition, we also identified several spatial features such as swing width, path length, walking distance, traveled arm distance, and foot clearance (heel and toe).

The fourth category encompasses the spatiotemporal features, which are derived based on both spatial and temporal features. In this case, the gait speed and step velocity were defined as the spatiotemporal gait features.

The fifth category encompasses the biomechanical features, which consist of kinematic and kinetic features. The joint angles such as the hip, knee, and ankle angles are the most commonly analyzed kinematic gait features. In addition, we also identified the strike and lift-off angles, which are the angles at which the foot is about to contact the ground and is lifted from the ground, respectively. We found a clinical gait analysis study, which extracted and used the pelvis and spine angles of all axes [71] for their analysis. In another study, we noticed the use of the turning rate feature to assess the turning movement performed by the subject. Regarding dynamic features, we identified some studies that estimated the joint moments and extracted the plantar pressures from pressure-based insoles.

The sixth category encompasses the statistical features derived from the raw sensor data. We observed that the magnitude, RMS value, harmonic ratio, mean amplitude, coefficient of variation, Pearson coefficient, and variance ratio were extracted and classified as the statistical features within the reviewed studies.

The seventh category encompasses the gait index or gait metrics, which are unique features derived from any of the major gait features mentioned previously. For example, the variability, symmetry, and asymmetry indices were identified based on the step length, stance time, and swing time. Another commonly reported gait metric is the stride or step count, which is the total number of strides or steps in a particular walking trial. Stride and step regularity, ratio of swing and stance, joint trajectory, and stride frequency were also used in the eligible studies. Regarding clinical gait metrics, we found a few studies that discussed frailty classification in the elderly [61] and the FoG metric in PD patients [67].

E. Data Processing

Raw data from sensors can be processed in an offline, online, or real-time manner. We found that most of the studies in this review adopted offline data processing. This may have been due to the need for proper experimental procedures designed carefully to validate the proposed framework against the gold standard system such as motion capture and force plates. Online data processing was presented in two studies [36], [57]. The first study [36] used seven IMUs attached to the lumbar, thighs, shanks, and feet to estimate the joint angles in an online manner. The integral differences in the angular velocity between the two sensor locations, coupled with the Kalman filter (KF), was proposed to estimate the joint angles. The results showed that the root mean squared error (RMSE) of the joint angle estimation varied depending on the walking speed, where the slowest walking speed resulted in the lowest RMSE. The second study [57] used a threshold-based algorithm to estimate the HS and TO events from a foot-mounted IMU. Several spatiotemporal features were derived and compared between the subject groups by conducting a 10 m walking experiment followed by online data processing. Their method was validated against the results of FSR sensors and by comparison with the results of some existing studies. The proposed method showed good agreement with the FSR sensor-based method and was comparable to the existing method. Moreover, some of the extracted spatiotemporal features showed a significant difference ($p < 0.05$) between the stroke patients and healthy controls, and PD patients and healthy controls.

Real-time data streaming has become more common in recent years [46], [64], [65], [85], [86], [89], [94], [98], [103] and has contributed to improved processing time efficiency. Real-time data processing was implemented in [37], [54], [60], [82], [91], [92], [104], [107]; in [104], up to seven IMU units were used for lower limb joint angle estimation. We briefly discuss the studies that have implemented real-time data processing. In [37], one IMU was attached to the left heel to extract the spatiotemporal gait features such as cadence, velocity, stride length, and walking distance. Threshold-based algorithms and sliding window techniques enabled real-time implementation. Real-time data processing was employed to estimate the gait phases from an insole equipped with 64 pressure-sensitive elements, which simultaneously recorded the GRF and center of pressure [54].

Smart shoes equipped with seven FSRs and one accelerometer on each shoe were proposed to estimate the gait phases in real time using a machine-learning-based algorithm [60]. An investigation of the validity and test-retest reliability of real-time event detection and further spatiotemporal gait feature estimation using seven IMUs were presented in [82]. The validity of two commercial wearables, Stryd and RunScribe, for performing gait analysis was presented in [91], which were benchmarked against a high-speed video analysis recorded at 1000 Hz. The use of four IMUs attached to the shank and foot of both legs for gait phase recognition and ankle angle estimation in real time was studied in [92]. Another study [104] used seven IMUs placed near the center of mass, both thighs, shanks, and feet to estimate the joint angles in real time. Finally, an open-source application on Python for gait analysis using six IMUs attached to the thighs, shanks, and feet was proposed in [107]. kNN followed by correction using foot acceleration was used as a gait segmentation algorithm to estimate the TO events. A GUI was developed for the commands and visualization tools.

F. Algorithms

Treatment of raw data, or data pre-processing, usually involves applying filtering techniques to remove unnecessary data or noise from the raw data. For example, Butterworth low-pass filters with various orders and cut-off frequencies were commonly applied in these studies. The sliding window technique was implemented in studies proposing a real-time processing approach [37] or in data preparation for threshold-based algorithms [76], [108].

We identified various sets of algorithms for processing the raw data from wearable sensors to perform quantitative gait analysis. To simplify, we classified the main algorithm into two classes: ML-based algorithm and non-ML-based (conventional) algorithm. Most eligible studies employed the conventional algorithm to extract the gait features. Regarding gait event/gait phase detection, we identified several algorithms such as peak detection algorithm, threshold-based algorithms, state machines, heuristic rule-based algorithm, and finding of local minima/local maxima, which have nearly the same principles. A fast Fourier transform (was implemented to extract the gait frequency and cadence in a few studies [57], [97]. Other methods such as continuous wavelet transform have been implemented to extract the gait events [49], [72], [78] and perform stride segmentation [69].

Because the majority of the eligible papers used IMU-based sensors, several sensor fusion algorithms were applied to estimate the orientation of the sensor position. The KF and complementary filter are the two most adopted orientation estimation methods. This orientation position combined with the knowledge of gait events or gait phases can provide spatial features such as the stride length and step length, listed in section III-D. Double-integration combined with the zero-velocity update method was implemented in several studies to estimate the stride length. A model-based approach such as an inverted pendulum [41], [49], [72], [78], [83], [103] was also used in a few studies to estimate the gait features such as stride length.

Several studies have implemented ML-based algorithms such as SVM [60], [80], [104], RF [96], [97], [111], NN [96], [104], [108], kNN [80], [107], k-means clustering [61], decision tree [80], [104], logistic regression [96], naïve Bayes, and LDA [80] in their proposed framework for quantitative gait analysis using wearable sensors. Most of the studies used ML-based algorithms for classification problems such as gait event/gait phase classification [60], [80], [96], [108], and classification of gait on different terrains [111]. Further, we identified four studies that employed an ML-based algorithm as a supporting algorithm for performing operations such as crosschecking [61], correction [104], and false phase detection [107]. Lastly, only one study has proposed a scoring function for gait ataxia [97].

G. Experiments and Validation

Experiments to capture the gait can be performed in various ways. The experimental protocols were mostly designed to suit the objective of gait analysis. Therefore, no experimental protocol can be deemed better than the rest. In this review, we present various experimental protocols developed in the identified studies, as summarized in Table I-IV. Indoor-level ground walking was the most commonly adopted protocol. Other experiments such as running on a treadmill operated at various speeds, outdoor walking, figure-eight walk, timed up and go, walking on a ramp, and walking on stairs with different distances covered or different number of repetitions were also identified. We found that the design of the experimental protocols was highly dependent on the environmental constraints, subjects in the study, and types of wearable sensors.

We noticed several validation systems that are considered the gold standard for assessing gait, such as the motion capture system, GAITRite®, instrumented treadmill, and force plates. Besides these systems, some studies have validated their proposed wearable gait analysis framework against camera-based systems, pressure-sensor systems, and other inertial sensor-based systems. Each of the studies has its own method of reporting the benchmark or validation results. The summary of performance metrics from each of the studies are presented in Table I-IV. We identified several validation metrics such as the absolute error, relative error, accuracy and precision, RMSE, mean differences, student's t-test (p-values), intra-class correlation (ICC), confidence interval, limit of agreement, Bland–Altman plot, sensitivity and specificity, F1 score, false-positive rate, and standard error of mean. The broad range of validation metrics has made reporting a meta-analysis of the benchmark studies impractical.

IV. Discussion

A. Inferences Drawn From Wearable-Based Gait Analysis for General Application

As discussed in Section III, 91 % of the eligible papers implemented their proposed approach on a healthy group or demonstrated a general application. We found that the healthy group mostly served as the control variable for comparison with other pathological groups. Temporal, spatial, and spatiotemporal gait features were found to be the most common assessments for general application. These features were not only reported as obtained, but could also be utilized to determine gait index features such as gait regularity or gait symmetry [88]. A few papers have discussed the difference between age groups, that is, healthy adult subjects and elderly subjects [49], [61], [105]. Regarding sports applications, running-based studies were discussed in [38], [51], [91], and [96]. Gyroscope-based temporal gait analysis with a peak running speed of 12 km/h was validated in [38]. Commercial wearables such as RunScribe and Stryd were evaluated to be effective wearables for measuring the spatiotemporal gait features while running at a comfortable speed [91]. In another study, the spatiotemporal features such as gait speed were associated with survival in older adults [115]. The importance of foot clearance assessment among elderly subjects was explained in [112].

B. Most Influential Features and Challenges in Wearable-Based Gait Analysis for Clinical Application

No particular gait feature can be considered superior to the rest for explaining certain gait conditions of a subject. Each gait condition has its own unique features or markers that are distinguishable from the other conditions. In certain cases, a visual inspection can be sufficient to assess certain pathological markers such as hemiparesis, where one side of the body is weakened. However, a quantifiable parameter is required to report the factual condition of the subject. Temporal gait features such as stride time or step time were found to be effective in differentiating between three types of MS patients based on the severity level of the disease [70]. Detection of FoG, as discussed in [67], was found to be helpful in the assessment of PD patients. Statistical features, as described in [73], were found to be successful in detecting gait impairment in CP subjects. Other studies have shown that the knee ROM feature can be used to track the rehabilitation progress of arthropathy and stroke patients [89]. Furthermore, combining gait and other motions may provide a more comprehensive assessment of the motor performance [117].

We identified various clinical applications such as PD, MS, and post-stroke pathology, as depicted in Fig. 3. The performance, validity, and reliability of each proposed wearable approach have been extensively investigated. Because each clinical condition may produce a unique gait pattern disorder, we presume that it will affect the performance of any of the wearable-based approaches considered in this review. This issue highlights the importance of benchmark experiments before applying the proposed approach to new applications.

C. Challenges in Wearable Sensors Application and the Importance of Sensor Placement

We found that gyro drift is a major concern when using IMU-based sensors. There are several methods for reducing or removing the drift, such as using the KF [36], [65], [68], [104] and applying zero velocity update [65], [81], [90], [101], which are widely implemented in the studies examined in this review. Environmental interference, which affects the magnetometer, is also a problems observed in this review. A simple calibration procedure, which is easy to implement, was proposed in [81] to compensate the interference. Concerns relating to the secure attachment of the device to the body have also been raised in several studies. Soft-tissue artifacts have been found to be a source of noise in data processing [43], [66]. Some studies that used multiple IMUs were required to perform sensor-to-segment alignment and calibration [45], [92] to achieve better performance. This may increase the preparation time but is comparatively faster than using marker-based systems.

Regarding placement of the sensor, most studies placed the sensors on the lower limbs, followed by the lower trunk in the lumbar vertebrae region. To emphasize more on the lower-limb region attachment, we observed a trend of foot-based sensor attachment for wearable-based gait analysis over the past ten years, which account for 31 studies in this review. These positions were found to be well suited for wearable-based gait analysis in terms of the number of features that can be extracted as well as the accuracy of gait feature estimation, where attaching the sensor to the foot yielded better results of gait event detection than attaching to the shank or trunk [77]. The number and location of sensors were found to be more influential factors than the algorithm used for discriminating the severity stages of PD patients [80]. The search for the optimal location of foot-based sensors was investigated in [86], where the medial aspect of the foot, followed by the posterior side of the foot, were identified as the optimal locations for stride-related feature extraction.

D. Contribution of Machine Learning Algorithms in Wearable Sensor Gait Analysis and Current Challenges

Machine learning algorithms have been employed in several studies, where they have been mostly used for classification problems such as gait events or gait phase classification [60], [80], [96], [108] and gait activity/terrain classification [111]. We also identified a few other applications such as verification of frailty discrimination [61], joint angle correction [104], false swing phase detection [107], and scoring algorithms in gait ataxia [97]. With our search strategy, we did not find any paper on machine-learning algorithms for extracting gait features. However, we found a recent study [116] outside our search criteria, which implemented a deep learning approach to estimate the spatiotemporal gait features. The dataset for deep learning and the ground truth were collected from seven IMUs and motion capture combined with force plate systems, respectively, with multiple 5 m walk protocols at various speeds. Another challenge related to machine learning is the availability of datasets for various sensor positions and the validated ground truth.

E. Online and Real-Time Data Processing for Wearable-Based Quantitative Gait Analysis

We found several studies that implemented online or real-time data processing, as discussed in Section III-E. The vast development in computing power has enabled easier implementation of online and real-time data processing. This provides several advantages for both general users of wearable devices and for patients and clinicians in clinical settings. For example, in sports applications, real-time data processing enables the user to directly reflect and possibly correct their actions in real time for motion improvement based on the received real-time insights. In the clinical setting, real-time visualization is favored as real-time insight for both patients and clinicians. Real-time data processing also enables real-time feedback to the user, which may act as an intervention in the case of FoG in PD patients. Nevertheless, the implementation of online or real-time data processing may face problems such as data package loss while transmitting the data to the processing unit; therefore, such methods must be validated first to ensure the accuracy of the extracted gait features.

F. Slow Walking Speed and Its Effect to the Performance of Algorithms

Slow walking speed is often observed in elderly subject and pathological groups. In some of the studies, we observed that the stride detection performance was decreased at a slow walking speed. For example, a study reported a 97.8 % mean accuracy on 1.0 km/h speed, while 99.9 % detection accuracy was observed from speed 1.5 - 4.0 km/h [98]. Another example relates to the ICC metric, where slow walking speed produced the lowest ICC value when compared with the comfortable and maximum walking speeds [110]. The algorithm design and evaluation process should be improved to accommodate slower walking speeds for gait analysis in the elderly group.

G. Issues Related to Experiment Protocols and Validation Metrics

Each of the reviewed studies proposed various experimental protocols. Most of it can be simplified and referred to as "level ground walking," performed in a laboratory, long corridor, or outdoor setting. Pragmatically, a longer walkway is more suitable for capturing the natural gait of a subject, as it provides adequate time and distance for the subjects to adjust their walking as desired. This study [119] concluded that a minimum of 25 and 33 strides are required to properly compute the step symmetry and stride regularity, respectively, in healthy control subjects. Regarding the experimental protocol, a study [120] suggested that curved walking instead of straight walking is more appropriate for assessing people with gait disorders. However, a treadmill-based experiment may affect the natural gait of the subject. Further, the authors of [121] and [122] suggested that self-paced instead of fixed speed walking allows more natural stride variability.

We found that each of the studies adopted various validation metrics. This made it difficult to quantitatively compare the performances of the proposed frameworks. For example, the gait event detection was validated based on the absolute error, relative error, accuracy, and precision, as well as the ICC metric. Therefore, researchers working in this area may need to report their benchmark and validation studies in terms of various metrics to allow comparison with the existing state-of-the-art methods.

H. Integration of Wearable Sensor Gait Analysis and Feedback System

In this review, several studies were found to analyze the data from wearable sensors and provide them as feedback to the user through various modalities such as audio, visual, and haptic feedback [54], [63], [92], [94]. Feedback strategies are needed for gait retraining or real-time assessment to correct certain parameters in rehabilitation or sports applications. Notwithstanding the studies considered in this review, several studies have demonstrated immense progress made in the wearable-based gait feedback system. The auditory feedback investigated in [118] was found to be effective in the short-term rehabilitation of stroke patients with hemiparesis. A biofeedback system for gait and balance training in PD subjects was proposed in [17] and [18]. In another study [113], a sensing sock device with smartphone-based feedback based on various modalities, including combining several feedback strategies such as auditory, visual, and haptic feedback, was proposed. By comparing different feedback modalities, a study concluded that real-time haptic feedback was effective and less expensive than visual feedback [114] for gait retraining of runners with high tibial load. Nevertheless, the effectiveness and correctness of the feedback strategies need to be investigated further.

V. Conclusion

This review investigated the use of wearable sensors for quantitative gait analysis. The proposed frameworks for wearable gait analysis, identified in this review, must be validated against gold standard measurements or other established sensor systems to ensure the accuracy of the acquired measurements. The correlation between the number and types of sensors along with the location of attachment to the body, proposed method and algorithms used, and number and types of quantitative gait features that can be extracted were discussed comprehensively in this review. Future research should explore the integration between wearable-based gait assessment and feedback systems to provide real-time feedback to users and patients. Another area is to investigate the performance and validity of wearable-based gait analysis in other clinical applications. The use of machine learning algorithms to quantify the gait features and achieve certain performance scores for clinical application is also a challenge but necessary for researchers pursuing this research field.

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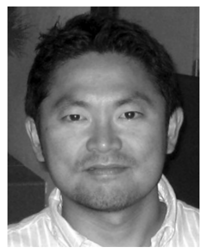

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