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Wearables for independent living in older adults: gait and falls

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Abstract

Solutions are needed to satisfy care demands of older adults to live independently. Wearable technology (wearables) are one approach to offer a viable means for ubiquitous, sustainable and scalable monitoring in habitual free-living environments. Gait has been presented as a relevant (bio) marker in ageing and pathological studies, with objective assessment achievable by inertial-based wearables. Commercial wearables have struggled to provide accurate analytics and have been limited by non-clinically oriented gait outcomes. Moreover, some research grade wearables also fail to provide transparent functionality due to limitations in proprietary software. Innovation within this field is often sporadic with large heterogeneity of wearable types and algorithms for gait outcomes leading to a lack of pragmatic use. This review provides a summary of recent wearable gait assessment literature, focusing on the need for an algorithm fusion approach to measurement cumulating in the ability to better detect and classify falls. A brief presentation of wearables in one pathological group is presented, identifying appropriate work for researchers in other cohorts to utilise. Opportunities for how this domain needs to progress are also summarised.

Highlights

- Wearables can meet older adults' needs for independent living.
- Gait assessment is a (bio)marker within ageing and different pathologies.
- Measuring gait with wearables has been innovative but fraught with inconsistencies.
- Wearables utilising multiple algorithms need to be considered during free-living.
- Opportunities exist for wearables to be informative and pragmatic clinical tools.

1.0 Introduction

A definition of successful ageing has evolved from merely adding 'life to the years' to a combination of avoiding disease, high cognitive and physical functioning and engagement with life [1]. As average age and life expectancy increases, solutions are needed to deal with the complex care demands to satisfy older adult needs to live independently. Wearable technologies (wearables) have particular utility to meet that demand [2].

Wearables encompass a broad range of devices from research prototypes or commercial products worn anywhere on the body over clothing to those placed directly on or beneath the skin [3]. Utilising wearables as research or clinical aids has gained notable momentum since the turn of the century due to ease of wear, facilitated by advances in electronic component miniaturisation [4]. Yet, despite the relative youth of wearables to gather data their helpfulness to monitor health and wellness for later life independence and aid rehabilitation is clear [2, 5]. Their potential is amplified by integration into communication infrastructures, for relaying adverse events (e.g. fall) and accumulating longitudinal data in the community (free-living) to determine social contact and physical activity (PA). The integrated use of wearables and digital technologies to help independent living is described as 'enabling ageing in place', a means to safely and comfortably maintain a high quality of life in one's own home (inc. community) and seen as a viable solution to aid assisted living for an ageing population [6].

1.1 Inertial sensor-based wearables

Wearables facilitate remote monitoring by offering healthcare professionals the ability to gather important free-living physiological signs of patients, such as gait characteristics during walking [7]. Recent work established gait as a (bio) marker to assess relevant processes associated with ageing due to its robust objective assessment with a wearable [8, 9]. Inertial sensors such as accelerometers (acceleration forces), gyroscopes (rotational motion) and magnetometer (magnetic fields) can be used collectively to create very informative wearables offering many gait outcomes. However, the techniques/algorithms required to translate inertial sensor signals to pragmatic data are complex [10]. (A non-technical and concise description of engineering approaches to wearable signal processing algorithms is provided elsewhere [11].) Besides, the practicality to longitudinally deploy an appropriate sized wearable incorporating those sensors during free-living is severely curtailed due to increased power consumption and memory storage requirements [12]. Yet, use of the most power efficient sensor (accelerometer) only, can still provide useful data.

Commercial wearables (e.g. FitBit®, Jawbone®) have utilised accelerometers to quantify basic gait related outcomes (e.g. step count) with tolerable accuracy levels at different speeds over short distances [13, 14]. However, limitations arise when wearables and their digital infrastructures (i.e. cloud-computing analytical platforms, e.g. Koneksa Health) are assessed during continuous and habitual free-living conditions [15]. In the referenced study the authors conclude that although commercial wearables have transformed physiology research by providing new data streams, fundamental limitations remain with black-box type functionality (unknown algorithms) with questions about validation and accuracy of step count and walking detection across a range of gait speeds during free-living.

Similar limitations have been encountered in research grade wearables [16] which accumulate data at much higher sampling rates, but access to raw data facilitates bespoke algorithm design [17]. High resolution data and utilisation of novel algorithms allows more clinically sensitive outcomes such as spatio-temporal characteristics of gait e.g. step time, step length, to be estimated. This has notable clinical impact with the provision of a range of gait outcomes central to informing independence in later life [18]. Additionally, correct quantification of safe and effective gait is crucial for those with movement disorders whose independence is further threatened by falls [19], a leading cause of injury and death [18].

For the purposes of this review, gait and recent developments on its direct measurement with inertial sensor-based wearables will be explored. This narrative review highlights the most recent literature including fall detection. Some opportunities for wearable developments are presented, in particular the need for a system and algorithm integration/fusion approach.

2.0 Discussion

Gait has been defined on two levels: (i) macro gait; time spent walking or periods of ambulatory behaviour and (ii) micro gait; spatio-temporal characteristics [19]. The role of technology in free-living assessment has led to miniaturised networks that can be integrated into the living environment or worn without impacting on a person's gait [20]. However, retrofitting technologies (e.g. cameras) within a living environment [21] has obvious barriers to installation (e.g. cost, disruption), leaving wearables as the preferred solution for now. Yet, distribution of wearables for robust macro and micro gait assessment is still fraught with pragmatic complications: routine charging, periodic calibration and difficulties arising from remembering to don wearables in certain cohorts suffering from cognitive impairment [22]. Alternatively, those who have capacity to correctly utilise wearables must overcome comfort and general acceptance of the technology.

2.1 User needs

Wearables are usually attached directly to the person with straps or adhesives [23] as current gait and falls algorithms require rigid attachment to the body (e.g. leg, waist) for correct functionality. While most are location dependant, a recent algorithm aims to recognise macro gait from wearables worn on either the ankle, thigh, hip, arm or waist with 97.4% accuracy [24]. Other work has quantified macro gait via generic placement/orientation in a pocket or bag to facilitate comfort and ease of use [25]. Problems arise when: (i) those who are meant to don the wearable do not; (ii) similar wearables become accidently switched leading to incorrect user/wearer data collection; and (iii) inconsistent reattachment location/orientation could impact data extraction. However, recent work aims to overcome such problems by accurately identifying (85%) the true wearer [26] and classifying an individual's gait during different conditions (e.g. stairs, up/down slope) [27]. Approaches such as these can lead to more robust data collection during free-living as well as reduce burden on the wearer to don or carry the wearable where most comfortable.

Lack of adherence to using wearables is a complex topic of human behaviour which goes beyond the scope of this paper. However, it is worth briefly discussing within the remit of wearables as facilitators, not drivers of health [28]. To date, research grade wearables (created or adopted during studies) have regularly been research driven, providing necessary (gait) outcomes sensitive to the study hypothesis with little consideration given for user requirements. This expedited research but as the field matures, strategies must engage the wearer rather than rely on features of technology [28]. The selection of a wearable based on user needs should examine a range of variables (e.g. wearable weight, training on use of device) to facilitate user needs rather than ad-hoc selection of technology [29]. Creation of fall and activity recognition systems have shown that older adult involvement is an important process to ensure wearable longevity, where there is a requirement for a 'needs-driven' rather than a 'technology-driven' approach [30-32]. Shortcomings within a needs-driven approach is one reason attributed to the disappointing findings from the European Union's Ambient and Assisted Living Joint Programme: €600m across 152 projects led to 2 marketable products and no evidence indicating greater health in older adults [33].

2.2 Research grade wearables

Recent reviews have examined wearable type, placement/location, algorithms and gait outcomes across a range of cohorts [23, 34-36]. In general author's remark on the heterogeneity of wearables, algorithms and gait outcomes due to a general lack of standardisation which make it difficult to compare and contrast across studies. (The complexity of wearables and algorithms also extends to PA measurement [37].) From a positive perspective this highlights innovation and technical achievement. Alternatively it suggests greater efforts should be made toward a consensus on wearable gait assessment, facilitating uniform deployment and better acceptance within clinical practice.

2.2.1 Activity recognition: Macro and micro gait

A challenge for wearable algorithms typically involve the segmentation/extraction of macro and micro gait from a continuous stream of inertial sensor data. Wearables utilising additional features of a camera, video recorder or global positioning system allow for absolute detection and/or contextual recognition when gait is performed, e.g. indoor within a cluttered environment or outdoors on uneven terrain. Integration of those sensing technologies would provide additional insight (gold standard reference) when trying to tease out pathological issues relating to free-living gait assessment [38, 39]. A recent study utilised a smartphone-based camera as a wearable placed on the front waist to quantify gait characteristics, a holistic approach to gait and contextual data recognition [40]. However, that requires additional markers on the feet. Nevertheless, where camera-based technologies aren't available, inertial sensor-based segmentation/extraction algorithms must be used. Table 1 provides an example of some recent algorithms to segment macro gait. (A more comprehensive presentation of gait recognition algorithms can be found elsewhere [41].) Once macro recognition is achieved, the segmented signals can be examined for micro gait characteristics.

<Table 1 – see end of document>

Measurement of gait during free-living is difficult when using inertial sensor-based wearables only due to the lack of contextual information. Thus, initial work to quantify free-living gait started at low macro resolutions of 60-seconds [42], progressing to 10-seconds [43] ensuring, with a degree of certainty, that steady state gait was measured due to the cyclical nature of inertial gait signals. However, the majority of gait is accumulated in periods of time (bouts) <10s [44]. Thus, large portions of data may be excluded for micro analysis at low resolutions. Therefore, a methodology to quantify macro gait at a higher resolution (2.5-seconds) has been proposed, validated with a video recorder during extended periods of free-living [45] (Table 1) and subsequently used to compare micro gait in the clinic to free-living [38].

Realistically any number of possible micro gait outcomes can be quantified due to the range of mathematical permutations which could be applied to wearable data, which has hindered clinical use [46]. In general, micro outcomes can be classed as spatio-temporal and frequency-based (e.g. energy) with the former having more pragmatic utility due to the ease of interpretation for most healthcare professionals.

2.2.2 Micro gait

Recent reviews highlight the importance of measuring gait across the life course, from its development in children [47], link to fall risk [48, 49] and its relationship to dementia in adults [50]. While clinically assessed gait speed has been shown to have use in assessing longevity and cognitive function in older adults [51, 52], micro gait characteristics offer a more focused examination to differentiate pathology and identifying specific features of disease progression [53]. The latter reference identifies a number of studies which utilised data reduction techniques to define micro gait models. In brief, 16 spatio-temporal gait characteristics can be mapped to 5 domains: pace, rhythm, postural control, asymmetry and variability [54]. The latter (fluctuations in time or space e.g. step time or step length variability) has even shown alterations in brain structure and function in older adults when compared to neuroimaging techniques [55]. Thus, micro gait can be described as a complex task with important underlying mechanisms.

The detection of all features including initiation and termination across a range of physical capabilities (e.g. young fit to old frail) may only be attainable by multiple wearables [56] or by fusing different data streams [57] detecting slight changes in movement. While the use of complex/multiple wearables is not feasible during free-living, it highlights ongoing developments. Wearables for gait have generally been aligned to a single device worn on the trunk (typically the lower back: 5th lumbar vertebrae, L5) due to algorithm functionality and ease of use. Recent work highlighted the most effective algorithm for temporal characteristic estimation from L5 [58]. When utilised with a spatial algorithm [59] they have been validated as a suitable micro gait model for older adults and those with a movement disorder in clinic and during free-living [60]. However, that required tailoring algorithms to define step timing variables [61]. Of greater utility is the ability to freely transfer wearables with algorithms from one pathology to another. Recent attempts to be cohort agnostic were shown in Parkinson's disease (PD) and stroke with a wearable on the foot [62] as well as elderly, hemiparetic, PD and choreic gait with wearables on the ankles [63].

Frequency-based characteristics of gait have been investigated as novel micro gait outcomes. For example, harmonic ratio (HR) calculated for each stride has been examined for gait symmetry and smoothness of walking, with a perfect gait symmetry returning even harmonics in two planes of movement and odd in the third [64]. Recent work proposed standardised HR guidelines aimed to improve its mathematical definition and evaluation to enhance its use as a discriminative power between different cohorts [65]. However, frequency-based outcomes like HR remain difficult to interpret in everyday practice [66].

2.2.3 Micro gait: Commercial technology

A number of studies have utilised commercial smart devices (e.g. smartphone, mobile entertainment platforms) to record and quantify micro gait, Table 2. This facilitates a sustainable use of technology, rather than the ad-hoc creation of bespoke devices facilitating a cost effective, viable and scalable solution to penetrate healthcare structures [67]. Smartphone-based devices contain a range of sensors to assist mobile/ubiquitous health (mHealth/uHealth) and have been discussed as suitable platforms for delivering healthcare services, but remain in their infancy with a range of methodological and privacy issues [68]. To date, failings of smart devices as wearables can be attributed to deficiencies in applications (apps) [68, 69]. While data collection technologies have advanced (i.e. electronic hardware), potential exists for current/future clinically relevant algorithms. The latter must be translated from research software (e.g. MATLAB®, R) and used by smart devices to reach scalability for widespread use.

<Table 2 – see end of document >

2.2.4 Falls

Impaired gait is a major risk factor for falls in older adults [18]. The use of wearables and other technologies for fall prevention interventions [70], risk awareness [71], impact detection [72-74] in older adults [75] has been well documented. Although many challenges exist for fall detection systems [76], a recent taxonomy[1] aims to standardise future technologies and interventions in the field of fall prevention [77]. Importantly the taxonomy stipulates the need for individual requirements by drawing on older adult perceptions to ensure simplicity, reliability and effectiveness [78].

Wearable-based fall detection algorithms rely on inertial sensor data to detect fall events (Table 3, recent examples). Within clinically led research few studies have categorised falls based on fall related activity, e.g. walking, going up/down stairs or transition [79, 80]. This is an opportunity for inertial-based wearables as recent work has highlighted clinically defined falls classifications from (e.g.) macro gait and transitional tasks [81, 82] which can be quantified from existing algorithms [45, 83]. Pragmatic innovation lies in the exploitation and fusion of existing algorithms to better inform fall events and to reduce false positives that might be generated during gait related activities, Figure 1. For example, pilot work used multiple algorithms to reduce false fall detection events (e.g. gait during stair ascent/descent) when tested on younger adults during scripted tests and an older adult with PD during free-living [84]. The addition of automated stair ascent/descent identification [85], a common location for falls [86], would enhance efforts and provide free-living segmentation of stair descent which may offer better insight into fall risk compared to straight level gait [87]. Thus, the fusion of existing algorithms can identify discrete gait activities linked to fall risk assessment which may better inform/improve 'life-space' [88], i.e. environment modification for those at risk of falls [86].

<Table 3 – see end of document >

<Figure 1 – see end of document >

[1]FASEEING http://taxonomy.farseeingresearch.eu/

2.2.5 Pathology

Acceptance of wearables among older adults with chronic disease (e.g. diabetes, arthritis) is perceived as useful and acceptable [89] with the power to transform clinical trials [90]. Yet they have been described as underutilised solutions [91, 92] to treat healthcare needs. While the discussion of all wearables in pathological cohorts is beyond any one paper, their use in PD is an example worth presenting. The current state of the art for wearables [66], machine learning from big data [93] and other technologies within PD have been documented [94-96], with suggestions that application in PD are a suitable model for researchers of other cohorts to study/adopt [97].

The application of inertial-based wearables to monitor motoric decline within PD might seem obvious due to the impact of bradykinesia on gait. However, improvements of micro characteristics due to pharmacological intervention (e.g. levodopa) can also be observed [98] suggesting utility of wearables as clinical aides to help monitor medication adherence and response. Moreover, the use of wearables to facilitate free-living monitoring developments within the pharmaceutical industry was recently discussed [99, 100] with other technologies (e.g. smart packaging, visual tracking) to facilitate the concept of 'beyond the pill' [101], a means to manage patient adherence and disease management [99].

Challenges remain with wearables within all pathological cohorts such as the handling of large data sets, data visualisation [22] and selection of discrete moments of clinical interest rather than continuous streams of data. This centres on how data is presented in meaningful ways to different groups: wearers (generic feedback for continued use) versus healthcare (analytical platform for patient care) [22]. Regarding the latter, clinical observation remains gold standard for characterising freezing of gait (FOG) in PD despite attempts to provide objective detection with wearables [102, 103]. However, advances of FOG detection within habitual environments mean wearable algorithms should not go unutilised [104, 105] and be integrated to the type of analytical frameworks that could aid care [106, 107].

3.0 Considerations

The use of wearables as tools for gait and fall quantification to facilitate independence for older adults is finely poised: the pragmatic aid for continuous monitoring during free-living or the white elephant of research due to the (non-focused) abundance of innovation, lack of standardisation and robust validation [66]. The former pushes the boundaries of technical achievements but could ultimately be the Achilles heel that forces healthcare professionals to remain with the tried and trusted, direct clinical observation.

3.1 Wearables: The gap between commercials and research

Wearables have been fuelled by the commercial development of fitness trackers where algorithms have remained limited to step count and periods/bouts of macro gait (walking). Typically there are no barriers (medical-based regulations) to entrepreneurs who develop fitness trackers and yet their inaccuracies may negatively impact a health conscious, self-medicating wearer or bring unreliable data to a technology accepting physician [108]. Similar concerns exist with research grade wearables and associated proprietary software in cohort studies, with non-disclosed/transparent analytics to quantify macro gait [109]. Regulation and transparency remains key for future developments to gain trust within healthcare settings as front line staff begin to learn benefits of using wearables for patient care [110, 111]. Nevertheless, developing wearables with more sensitive clinical outcomes (e.g. micro gait), although not easily done, facilitates more relevant data for healthcare professionals.

3.2 Existing challenges coupled with on-going innovation

Challenges to adopt/extend current wearables for free-living gait and fall assessment are faced with ethical and legal issues of data privacy/protection [112]. Yet the ability to gather data is only useful if the wearable can continuously sample at frequencies of sufficient magnitudes to ensure adequate accuracy (e.g. 100 data points/second). This negatively impacts battery life and free-living efficiency of wearables for gait and fall assessment [113]. Consequently, the demand for energy optimisation techniques [114] and new ways to configure wearable software functionality [115] are ongoing engineering challenges. Additionally, the concept of smarter sensing through context anticipation (rather than context recognition) is an emerging topic to enhance efficiency [116]. Alternatively, energy harvesting has been proposed as a means to utilise the dynamic energy of the wearer to continuously (months and years) power wearables through smart materials [117] (Figure 1) or microfluidics, miniaturized elements capable of performing numerous functions at a cellular or particle scale [118].

The emergence of the Internet of Things (IoT) and its impact on wearables has been enabled by using or integrating to smart devices [119], facilitating frameworks for uHealth and independent living [120]. This generates large volumes of data where efficient management has been proposed by health-based infrastructures in the cloud. For example, Wiki-Health aims to provide analytics with real-time capabilities for tracking existing conditions, facilitating a more pro-active approach to healthcare conditions through early detection [121]. However, challenges exist for storage and interconnectivity on current computing frameworks, where concepts have been labelled as insufficient [115]. Moreover, the pragmatic adoption and integration of wearables and/or future technologies within existing healthcare services remains the fundamental challenge given the existing constraints of standardisation and models of care [122].

4.0 Summary and conclusions

Wearables can play active roles for independent living in older adults by providing macro and micro gait estimations during free-living which are clinically relevant (bio) markers in ageing and pathology. Additionally, more accurate automated fall detection could improve life-space and lessen fall risk. However, diverse and sporadic innovation have generated many wearable (and algorithm) combinations to leave routine pragmatic use lacking. There is a need for consolidation on the use of wearables, establishment of a framework/taxonomy to inform deployment and ratification of sensitive gait characteristics (spatio-temporal or other) in older adult cohorts.

Contributors

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Competing interest

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Tables

<Table 1>

Authors	Data collection environments	Length of test[1] (hours)	Algorithm functionality	Extracted wearable signal features (from inertial sensor signals)	Cohort Size	Cohort Age	Wearable locations	Macro gait accuracy and/or other information
Awais et al. [123]	Semi-structured within a laboratory and during free-living	5.52 (laboratory) 24.43 (free-living)	Tested 3 previous algorithms and varied the length of the sliding window to calculate different characteristics from the signals of the inertial sensors (opposite)	Mean, standard deviation, skewness, kurtosis, energy, frequency domain entropy, correlation between signals, minimum, maximum, mean and variance, spectral centroid, bandwidth, energy, gravitational component	20	76.4 ± 5.6 years	Chest, lower back, wrist, waist, thigh, foot	91.9-97.3%
Noor et al. [124]	Structured within controlled setting (house). Also utilised a range of public data sets[2]	1.5 (controlled setting)	Novel method based on dynamic variation of the length of a sliding window due to probability density function to help determine sequence of activity scenarios with classifiers	Slope, standard deviation, skewness, signal magnitude area, absolute slope, spectral energy, mean trend, windowed mean difference, maximum, minimum	6	33 ± 2.2 years (plus 1 child)	Waist	87.5-97.6%
Hickey et al. [45]	Free-living (including rural and urban environments)	20 (free-living)	Fusion of existing algorithms, including logical heuristics to determine upright and moving and then investigation of segmented signal to determine identification of micro and therefore macro gait	Upright and moving: Mean, standard deviation Micro: continuous wavelet transform to determine initial and final contact (IC and FC) events within the gait cycle. Macro gait: sequence of IC and FC define bouts of macro gait	10	27.5 ± 4.7 years	Lower back	$ICC_{2,1} \geq 0.941$
Segundo et al. [125]	Publically available scripted activity dataset gathered with a smartphone	3.7 (controlled setting)	Hidden Markov Models (HMM) derived classification of activities with cross-validation from a subset of the total cohort	Mean, correlation, signal magnitude area (SMA) and auto regression coefficients, energy of different frequency bands, frequency skewness, and the angle between vectors (e.g. mean body acceleration and vector)	30	19 – 48 years	Waist	Approx. 98%
Hammerla et al. [126]	Three publically available scripted activity	8-25 (controlled setting)	To test the performance of state-of-the-art deep learning approaches on three different	Adopted a non-manual approach (e.g. time series analysis using mean acceleration) to feature selection and	31	Younger and	Multiple locations	Convolutional networks recommended for

Authors	Data collection environments	Length of test[1] (hours)	Algorithm functionality	Extracted wearable signal features (from inertial sensor signals)	Cohort		Wearable locations	Macro gait accuracy and/or other information
					Size	*Age*		
	datasets with different wearables[3]		recognition problems: deep feed-forward networks, convolutional networks and recurrent networks	utilised machine learning approaches such as Restricted Boltzmann Machines and long short-term memory cells		older adults[3]		the detection of macro gait
Gonzalez et al. [127]	One scripted activity (TUG test) in a group of adults with stroke	--	Soft computing method involving: Information Correlation Coefficient (ICC) analysis, a wrapper feature selection (FS) and genetic fuzzy finite state machine	150 features generated with a filtered FS and ICC deployed to reduce to 20 which were used in a Genetic Fuzzy Finite State Machine to classify activities	3	--	Both wrists	--
Field et al. [128]	Scripted activities in a laboratory	1-2	Us of Gaussian Mixture Model to cluster motion data	Sets of joint angles. Segmentation involved partitioning temporal data into subsequence's by identifying modal changes, i.e. static poses, periodic motion or complex sequences such as walking	10	--	Multiple locations	Approx. 94%
Fida et al. [129]	Scripted activities within a controlled environment	1-2	Use of varying window sizes to determine effect on recognition of short and long gait activities with the additional use of classification models: decision tress, neural networks, support vector machines, k-nearest neighbour classifier, Naïve Bayes classifier	Mean value along each axis, average of mean values each axes, standard deviation each axis, average of the standard deviation values along each axes, skewness each axis, average skewness values each axes, kurtosis each axis, average kurtoses each axes, correlation at zero lag between each axis pairing and between each axis, magnitude acceleration	9	22-34 years	Waist	≥90% (with 1.5s window size with support vector machine classification model)

[1] Total time recorded in hours (inclusive of segmented gait activities)

[2] Data from a smartphone worn at the waist, gathered in controlled over 5hours in 30 subjects [130]

[3] Opportunity dataset: 12 adults [131, 132], PAMAP2 dataset: 9 adults (27.22 ± 3.31 years) [133], Daphnet Gait dataset: 10 (66.4 ± 4.8 years) older adults with PD [134]

<Table 2>

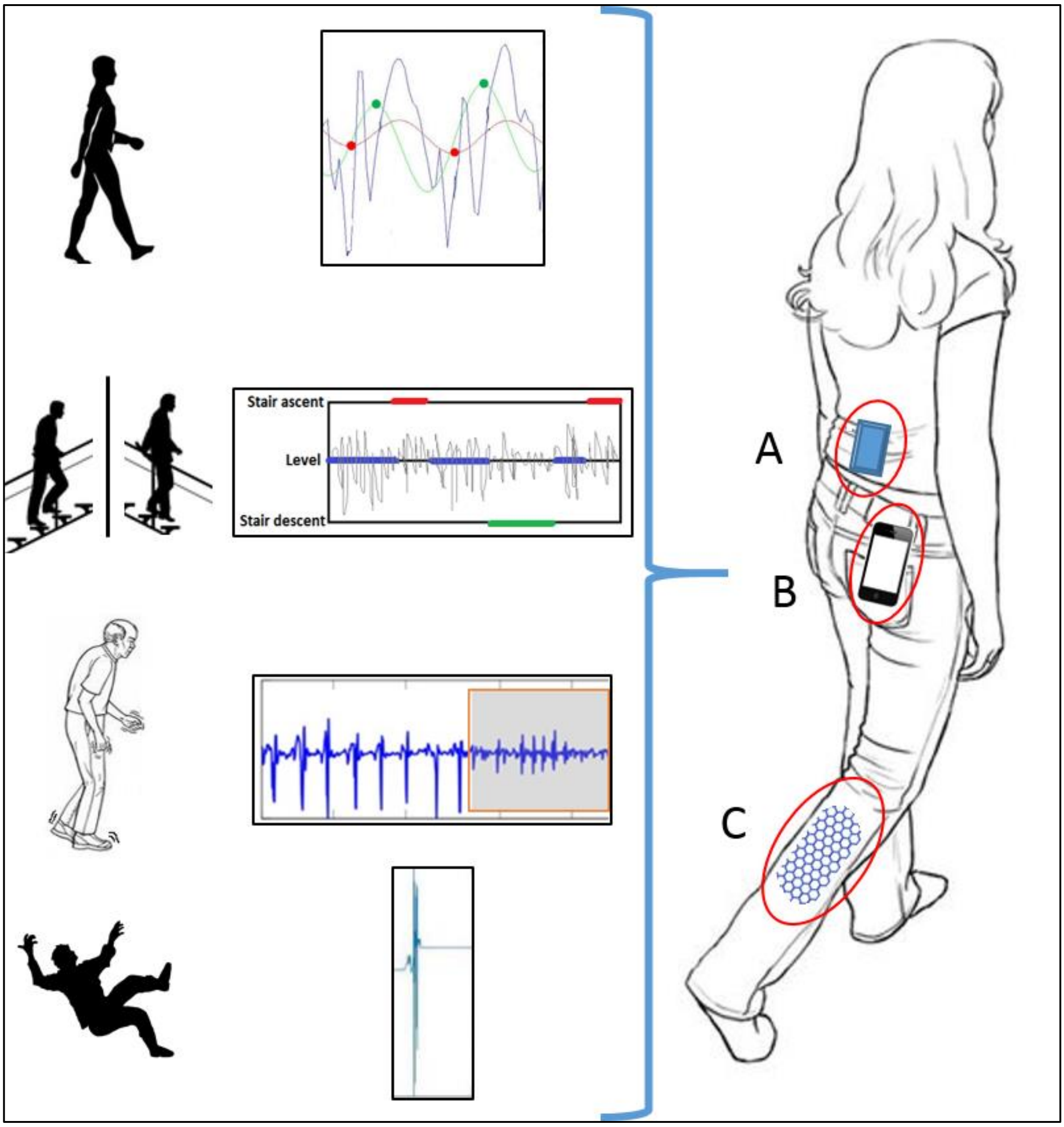
Authors	Technology	Location	Testing	Cohort	Macro or micro gait characteristics
Gadaleta et al. [135]	Asus Zenfone 2, Samsung S3 Neo, Samsung S4, LG G2, LG G4 and a Google Nexus 5	Pocket	5minute walking test	50 adults	Identification of walking cycles and the extraction of novel features to return a score
Hegde et al. [136]	Shoe based wearable (inertial and pressure sensors) with integration to Android application (app) on Google Nexus 5	Foot (phone location not described)	Scripted activities on a treadmill and cycling	4 adults	Real time activity classification of macro gait performed locally on the smartphone with 95.4% accuracy
Casamassima et al. [137] and Mazilu et al. [138]	Shoe based wearables with Bluetooth integration to a Samsung Galaxy S3 (Android)	Both feet and pocket	Lab training sessions and then in the homes to support gait exercises, but in free-living, e.g., walking in the park, as an assistive device	5 older adults with PD	Real time detection of (left and right) initial contact and foot-off events within the gait cycle. Specifically the system detects freezing of gait (FOG) and provides a rhythmic auditory cue to help resume normal gait
Kosse et al. [139]	iPod touch G4 with custom-made application installed on the iPod to collect and store accelerometer data which was post-processed	Trunk (3rd lumbar vertebrae, L3)	Twice walked back and forth along a 10-m long course with a one-meter wide curve at the two turns for three minutes at a self-selected habitual speed	29 young adults (19-41 years) and 30 older adults (47-75 years)	Left and right foot (initial) contact events with the gait cycle and the subsequent offline calculation of other outcomes, e.g. coefficient of variation and phase variability index
Watanabe [140] and Watanabe et al. [141]	iOS-based platform to record data and to correct for misalignment due to variable orientation in the pocket	Pocket, holding phone to ear, holding while typing	Flat level walking, walking up and down stairs with the phone hand held or placed in pocket	4-15 adults	Use of a range of inertial sensor features with different classifiers to achieve walking accuracy 60.7-90.0% (depending on walking condition)
Sejdic et al. [142]	Shoe based wearable (inertial and pressure sensors) with USB connection to a Samsung Galaxy Nexus (Android)	Foot and lower back	Two, 15-min walking sessions around a closed corridor with a 10-min break in-between	15 younger adults (18-35 years)	Pressure sensors gathered characteristics and inertial sensor (lower back) stability analysis during gait
Steins et al. [143]	4th generation iPod touch	Trunk (3rd lumbar vertebrae, L3)	Four 10 m straight walks at self-selected speeds in a gait laboratory.	10 younger adults (26 ± 4 years)	Identification of gait patterns and steps but no micro characteristics estimated
Del Rosario et al. [113]	Samsung Galaxy Nexus with Android software to sample and store data which were post processed but also tried in real-time	Pocket	Free-living data collection up to 30mins per participant within laboratory, general university and habitual environments	20 younger (22 ± 2 years), 37 older (84 ± 3 years)	Walking activities (level, up and down stairs) sensitivity/specificity ranged 58-90%/96-99%. Real-time possible but smartphone functionality and battery life a concern

Authors	Technology	Location	Testing	Cohort	Macro or micro gait characteristics
Mellone et al. [144]	HTC Desire with Android-based data acquisition to store accelerometer data, post-processed	Lower back	Performed the TUG test and the gait segment extracted	49 older adults (59 ± 16 years)	Identification of micro gait characteristics from a TUG task: including mean step time, step time variability (standard deviation)

<Table 3>

Authors	Technology / data / methods	Cohort	Falls accuracy	Comments
Gjoreski et al. [145]	Compared 5 machine learning algorithms with a range on features on 4 datasets containing scripted (laboratory) and simulated free-living activities. Wearables located at chest, waist, (left & right) wrists, thighs, ankles and upper arms. Up to 1367hours of data.	21 adults (average age, late 20's)	85% on one dataset where falls present	Non-dominant wrist optimal for fall detection at that location
Pannurat et al. [146]	Real-time method for fall detection and reports the classification performance when the sensor is placed on different body parts: waist, chest, head, wrist, ankle, thigh, upper arm. Tested 14 fall types, e.g. fall on knees, collapse into bed.	16 (younger adults)	87-91% (pre-impacts, impacts, post-impacts	Side waist best for post-impact detection. Most false alarms during transitions of lying postures
Hsieh et al. [147]	One wearable attached to the waist with 7 types of falls performed and scripted tasks. Hierarchical fall detection algorithm involving threshold-based and knowledge-based approach (free-fall, impact, and rest phases).	8 (all males, 22 ± 1.3 years	98.7-99.8%	Method improved overall performance by up to 0.55%, compared to machine learning
Khan et al. [148]	Used a new form of Hidden Markov Models (HMM) to identify falls in the absence of training data (i.e. data for machine-learning approach to model activity or falls classification). Utilised two scripted activity and falls datasets from the waist or pocket.	30 adults	Improved fall algorithm with HMM	HMM thresholds to identify falls not suitable. New method can be used without training data
Gibson et al. [149, 150]	Wearable on the chest during scripted falls (hard and soft surfaces/pacts) and activities. Compared new multiresolution, principal component analysis and classifier to a threshold-based approach.	14 adults (27 ± 8 years)	Up to 99% for new method compared to 93%	New method facilitated data reduction of over 70% yielding good energy efficiency
Concepcion et al. [151]	Iterative work by the authors using an optimised version of a previous algorithm (Ameva). Data gathered on large cohort with smartphone but only 1 case study presented. Algorithm classified falls and activities from combined version of inertial signals	31 year old	98%	Optimised for efficient smartphone use, longitudinal monitoring with 95% accuracy all activities
Dias et al. [152]	Wearable placed at the waist and used in conjunction with a network of sensors for issuing the fall alarm. The network are used for obtaining (triangulating) the fall location (room of a house). Utilised low-cost technology (Arduino) to implement system.	Younger adults	90% & nearly all alerts reported the correct room	Absolute accuracy not achieved due to difficulties found to detect falls with rotation movement
Sabatini et al. [153]	Wearable (inertial sensors and barometric altimeter) worn on the waist which linked with a smartphone (Samsung Galaxy SII, GT-I9100) via Bluetooth. Scripted falls and activities. Estimated vertical velocities (with thresholds), height, posture and impact detected falls.	25 (28 ± 3 years)	80-100%	No single feature (e.g. impact or vertical velocities) allowed for 100% accuracy
Harris et al. [154]	Wearables (linked to iOS software platform) worn on the sternum, waist, and right leg. 54 statistical features calculated, filtered and applied to a classifier (e.g. Random Forest, Linear Support Vector Machine). Scripted falls and activities.	14 adults (22-50 years)	Up to 98.3%	Using more than one wearable better than using one. But waist placement optimal

Figure



<Figure 1>

Table captions

Table 1: Examples of recent approaches to macro gait detection with wearables.

Table 2: Some recent studies utilising smartphones as wearables to gather and store macro and micro gait related data or process for real time characteristics estimation

Table 3: Recent falls algorithms from inertial sensor-based wearables.

Figure caption

Figure 1: An algorithm fusion approach on one wearable for (left, top-bottom) indoor and outdoor gait (blue), stair ascent (red) & decent (green), pathological gait (e.g. FOG in PD) and fall detection during free-living on a dedicated wearable (A, fixed or variable location) or smart device (B) placed generically on the person (e.g. back pocket). The smartphone facilitates synchronisation to A and relay of information to healthcare professional (analytics framework) via communication networks. Alternatively the smart device could be the sole wearable. Smart materials embedded in clothing could be the viable solution to continuously power wearables (C).

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