Engineering human gait and the potential role of wearable sensors to monitor falls

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Abstract

Falls and falls related injuries are the major causes of non-fatal injuries in older adults. With recent advances in mathematics, science, and technology, many scientists and engineers are devoting their efforts to prevent falls or to diminish the negative health outcomes after falls. In this chapter, we briefly review major engineering approaches to recover or augment the human gait function pre- and post-falls. Given the proliferation of wearable sensors and the availability of computational resources in the last decade, we focused on the role of wearable sensors to monitor gait instabilities and potentially prevent falls. We reviewed the general framework for gait monitoring using wearables and its utility in real-life settings such as homes or retirement communities. In the last part of the chapter, we focused on recent contributions that have proposed wearable sensors for gait monitoring and fall inferences.

Introduction

Falls and falls related injuries are the major cause of fatal and non-fatal injuries in older adults [1]. It is estimated that close to 640,000 people die from falls globally, and over 37 million falls require medical attention [2]. Falls also lead to fear of falling in older adults additionally limiting their mobility and productivity, which reduces the overall quality of life and causes further deteriorations in the overall health status [3]. A vicious circle of fear, reduced activity, decreased strength, poor posture, decreased balance and feelings of instability can create a downward spiral resulting in weight-loss, illness and depression [2], [4].

Fall risk factors are numerous with details and discussion relating to epidemiology and clinical management extensively covered elsewhere [5], [6], [7] in section I of the current book. In short, the most common fall risk factors include: older age, prior history of falls, functional impairment, cognitive impairment or dementia, balance abnormalities and impaired mobility [8]. The ability to discretely and robustly detect and monitor each of these is therefore paramount in the safety and care of patients at greatest risk.

Hence, it is obvious that gait represents one of the fundamental human functions needed for independent daily living, and any deteriorations in gait function can have drastic consequences on human health. The fundaments of gait performance in older adults and it relationship with impairments and falls is reviewed in chapter 6, section II, of the current book. Given recent technological advances that enable restoration or advancement of any functions, being human or artificial, this chapter will review approaches to "engineer" gait, which are based on the use of mathematics principles, science, technology and practical knowledge with the goal of restoring or augmenting gait function.

Engineering the human gain function is not a new idea, some of its original developments date back to the ancient Egyptian states [9]. In the last 20-30 years, many different techniques have been proposed and excellent contributions have been made ranging from simple mechanical devices to very complex devices involving multiple sensors and artificial intelligence. While many of these devices and approaches represent early stage technologies

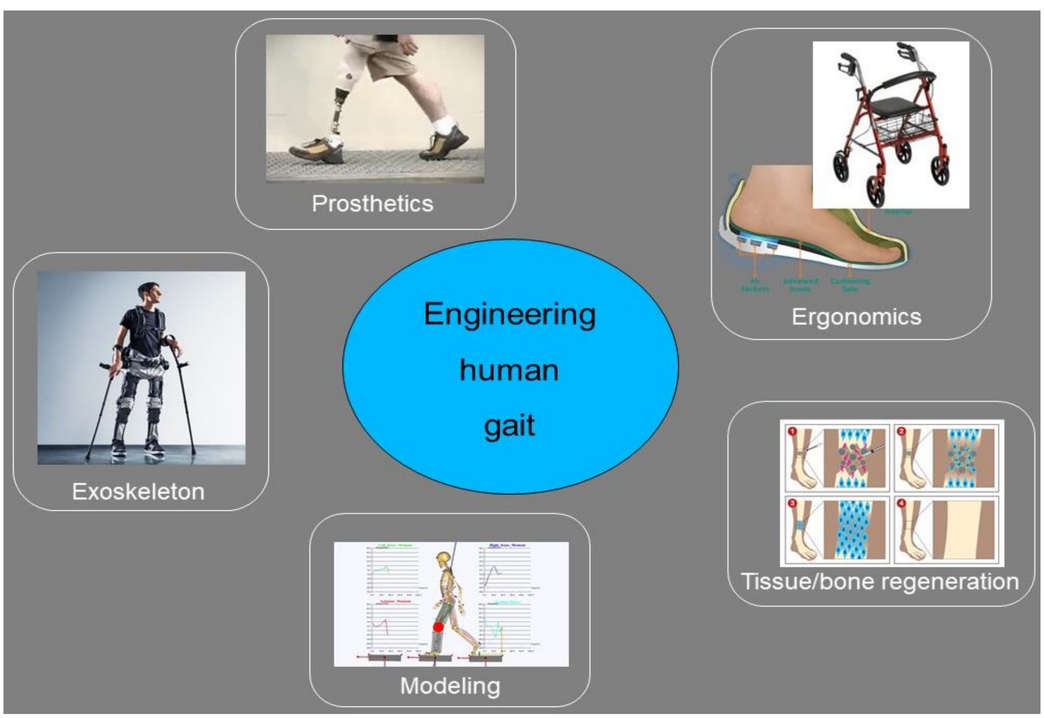

Figure 1 – Engineering human gait

that yet need to see its clinical implementations, Figure 1 describes the current approaches that have direct clinical applications and have already been somewhat clinically implemented: prosthetics, exoskeletons, wearables and modeling of human gait, augmentative devices and engineering and scientific approaches to regenerate tissue/bone.

Prosthetics are the oldest and most widely spread engineering solutions that were used for restoring/augmenting human gait [9]. Modern engineering developments in material sciences and other engineering areas have enabled us to develop prosthetics that are lightweight and easily adoptable to different patients, so that end users perform their daily duties with no major altercations [10]. In recent years, we have witnessed a double-leg amputee with prosthetic legs compete in both Paralympics and Olympic games. While the prosthetic devices used to restore and/or augment human gait have certainly improved in the last 30 years, there are still open questions to be resolved such as their price which limits their widespread use in developing countries [11], [12].

Another traditional line of work is the development of various ergonomical solutions [13], [14]. These range from purely mechanical devices such as a walker that person needs to lift and move with each step to more modern rolling walkers, which enable a person with walking difficulties to move more easily. In more recent years, there are a number of different ideas how to improve these walkers/rollers but most of them rely on imbedding additional sensors into the walkers [15]. The additional sensors will enable the development of “smart” walkers, which will be able to account for many different real-life cases (e.g., slippery floors) that can endanger the person with walking difficulties [16]. While the technology certainly exists to develop these “smart” walkers/rollers, possible high costs associated with such “smart” devices may prevent their wide-spread use. Similarly, shoe insoles have been used for many decades to help with walking, and traditional insoles are mechanical devices. In recent years, we have witnessed the development of instrumented insoles that can vibrate at various frequencies in order to stimulate the nerve ends in patients with diminished peripheral nerve sensations or accurately assess gait parameters in real-life settings [17], [18], [19]. These instrumented insoles are meant to enhance gait stability and potentially prevent falls in these patient groups. While there is a good clinical evidence that these may actually be very effective in specific clinical groups, there are still no viable commercial products.

More modern developments include exoskeletons, which were initially developed for military applications to augment the soldier’s gait while carrying heavy loads [20]. Soon after the initial development, the exoskeletons have crossed into medical applications, and they are typically used for restoring the gait functions in patients with stroke, spinal cord injuries or similar traumatic injuries [21]. The exoskeletons have not reached their full clinical potential as they remain costly, and there are open questions about their utilization [22], [23]. Namely, about a proper initialization of each step, and if the exoskeletons can be augmented by additional physiological sensors in order to synchronize the step initialization with the rest of the human body [24].

Complex and invasive regenerative medicine methods are emerging to restore/augment the human gait function [25]. These developments typically revolve around bone and/or tissue regeneration to restore the diminished function [26]. Most of the current success stories are focused on repairing a damaged knee cartilage, which will enable patients to walk again without major difficulties. Nevertheless, these tissue/bone regeneration methods are expected to flourish in the future. It is often argued that rehabilitation will play an active role in the development of regenerative medicine treatments of musculoskeletal disorders, similar to the role it currently plays in the development and the delivery of prosthetic devices or postoperative care.

The most widespread approach to engineer the human gait in recent years relies around the use of wearable sensors such as accelerometer, inertial measurement units (IMUs), and various other sensors such as electromyography sensors, respiratory belts, galvanic skin response sensors, just to name a few [27]. A sample set of sensors is shown in Figure 2. The use of wearable technology (defined here as wearables) facilitates the capture of traditional as well as more novel patient orientated outcomes for fall risk assessment. Indeed, the added benefit of (most) wearables is that the same underlying hardware (i.e. sensors) aids fall detection methodologies. Consequently, wearables offer a holistic tool for the assessment and monitoring of fall related outcomes. The main reason for the popularity of this approach stems from the fact that these sensors are very affordable, sometimes costing only a dollar or two, small and can easily interface with commodity electronics such as smartphones and tablets [28]. Using these sensors, different modeling approaches that have been adopted over the years to understand gait difficulties or two infer about potential falls. These modeling approaches range from simple one-sensor models such as modeling gait stability using accelerometers or IMUs [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39] to more complex multi-sensor monitoring to model the interaction among multiple physiological systems during walking [40], [41], [42], [43]. The additional benefit of wearable sensors is that they enable us to monitor the gait function even in real-life scenarios such as patients' houses or even when they are walking on a street. This provides an unprecedented opportunity to understand gait beyond typical well-controlled clinical settings, and to further understand patients' falls in community settings. It should be mentioned that wearable sensors (i.e., body worn sensors) can be combined with ambient sensors to assess patients in the home or hospital environment, but in this chapter, we will only focus on wearable sensors.

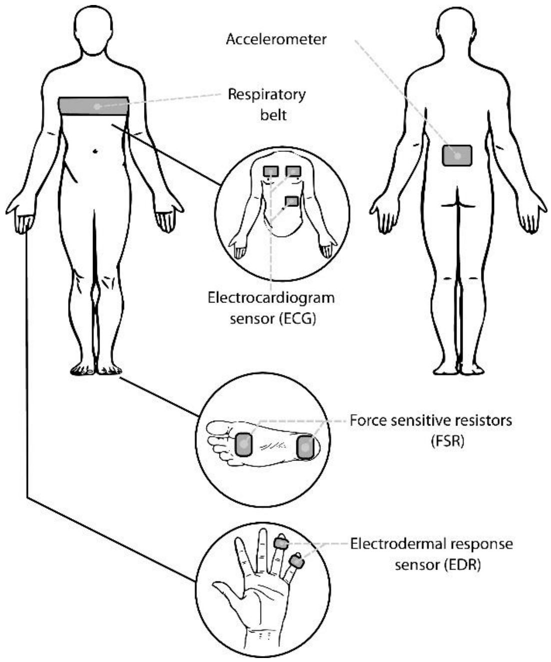

Figure 2 – A set of wearable sensors to assess the interaction between multiple physiological systems during walking [42].

While each of the aforementioned approaches to engineer the human gait function deserves a thorough coverage, we will focus on wearable sensors in this chapter and their potential to monitor and prevent falls. In the next section, we will introduce a general framework that describes how wearable sensors can be utilized for monitoring gait, and how this field will evolve over the years to improve the clinical outcomes. In the subsequent section, we will cover the most recent contributions dealing with falls monitoring using the wearable sensors. We will briefly review the technological aspects of these contributions, but we will primarily focus on the clinical outcomes.

Wearable sensors and gait

Remote monitoring of patients during walking is much needed in today's healthcare systems [44]. First, it will enable clinicians to fully understand how the environment affects the gait stability and potential reasons for falls. There is a need to understand how different environmental factors such as lighting, terrain or other auditory and visual distractions affect the gait stability in patients with gait instabilities. Second, remote monitoring also provides a way to monitor patients in rural areas, which often do not have an easy access to clinicians. With a proliferation of consumer electronics and wireless telephony, this until-recently-unattainable task is becoming reality and is enabling healthcare providers to go beyond “the walls” of their institutions and provide their services in remote areas. Therefore, wearable sensors and remote monitoring systems have a potential to address these issues, and recent technological and computational advances certainly provide hope for these advancements to address gait instabilities in patients.

Figure 3 illustrates a general framework that can be used for gait monitoring via wearable sensors. This framework would consist of the main components: (1) sensors and other hardware components to collect motion and physiological signals; (2) communication systems to transfer data to and from patients; (3) data analysis methods to process these data streams and infer about the patient’s condition. More specifically, a person with gait difficulties would be typically instrumented with sensors to monitor motion and/or physiological signals during walking. A choice of the sensors would depend on a clinical application, but can include accelerometers (or IMUs), respiratory belts, galvanic skin response sensors, electrocardiograms and others. These sensors can interface with a communication device such as a smartphone, tablet or a computer, which would be connected to the Internet. A cloud-based solution can be then used to analyze streaming data and to infer about the patient’s condition and his/her walking. The results of such an analysis can be then conveyed to various entities such as family members, clinicians or even to alert an emergency service. Lastly, this framework can be potentially used to deliver novel therapies and to monitor the outcomes of such interventions.

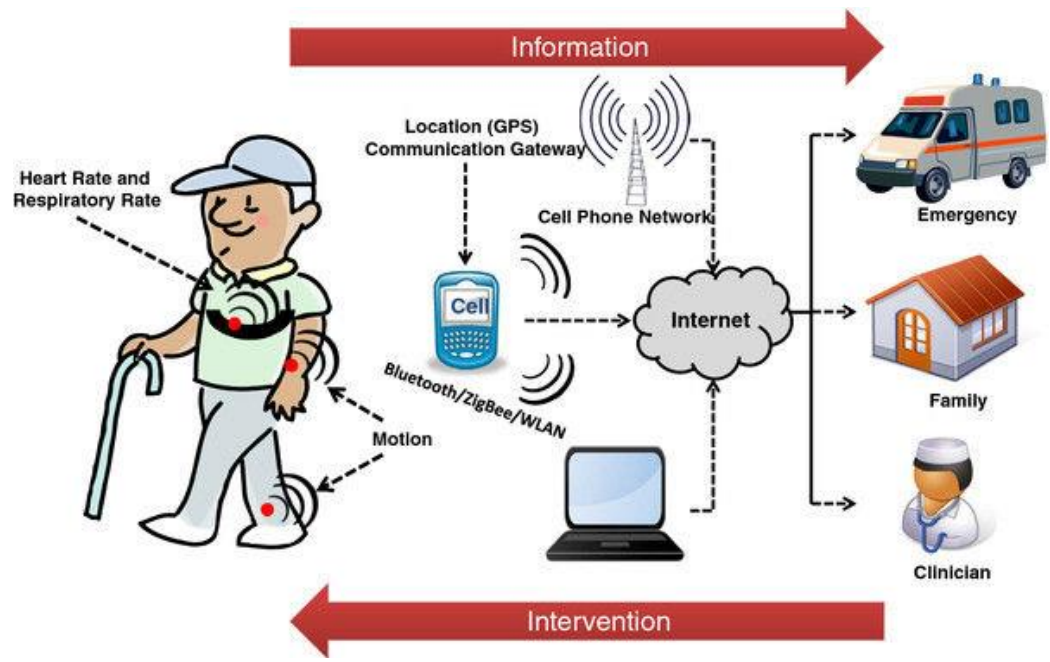

Figure 3 – A framework for gait monitoring using wearable sensors [44].

There are several open questions about the framework. First and foremost, are there technological barriers? Given the current state of wireless networks, from a data transfer point of view, we are finally at the stage where data transfer does not represent a major issue. Most of the commercial wireless providers have reliable networks with a sufficient bandwidth to support remote monitoring applications in real time. Next, what kind of wearable sensors can we consider? Any sensors that provide details about heart rate, blood pressure, respiratory rate, skin conductance, muscle activity and person's motion are useful, and recent technological developments have enabled us to obtain accurate, continuous real-time recordings in real-life scenarios. However, it needs to be pointed out that these sensors often require novel design ideas, and novel ways to implement them on patients, as many of these existing clinically used sensors to monitor these physiological signals suffer from various artifacts (e.g., due to motion). For example, novel design of sensors can entail that a sensor is a part of a clothing item [45], which also senses the changes in the environment and/or posture and potentially removes any artifacts. Lastly, from a technological point of view, one can ask if sufficient computational algorithms exist to reliably process these data points. Recent advances in machine learning and big data analytics certainly provide sufficient evidence that computational algorithms needed to process these real-time data streams conveying details about the patient's condition have certainly matured into robust algorithms, and researchers and clinicians can rely on them to complete these necessary tasks. Of course, it is understood that most of these algorithms need a certain level of tweaking to accomplish the task, as these algorithms were often developed with other applications in mind.

The second major question is: are there any clinical barriers to adopt the framework for remote monitoring? This is where the idea of remote monitoring becomes more complicated. Some wearable sensors, such as those for heart rate variability, provide traditional clinical measures that clinicians are familiar with and can easily interpret (e.g., heart rate). Sensor developers must often go through rigorous trials to prove that these wearable sensors provide clinically reliable and robust results comparable to the gold-standard equipment found in clinical settings, but once a sensor reliability is established, there are typically no clinical barriers to its implementation. However, sensors such as accelerometers provide novel types of measurements and outcomes [46], which are challenging for clinicians to understand. Many of these novel outcomes represent variables that are not physiological variables (e.g., Lempel-Ziv complexity), and engineers must work directly with clinicians to relate these computational outcomes to actual physiological outcomes, and to validate them in clinical trials. Similarly, novel machine learning approaches often consider hundreds of variables to come up with a reliable decision outcome, and these outcomes may not necessarily have a linear relationship with considered inputs. These non-linear input-output relationships often pose a problem to clinicians when trying to interpret the outcome in terms of traditional outcomes. Lastly, these machine learning techniques offer novel ways to consider the interaction between multiple physiological systems to understand how these interactions may influence the gait stability. However, these exciting opportunities provided by novel computational tools are not fully utilized by clinicians, which often focus on a single physiological system without attempting to understand how the interactions with other physiological systems may affect the functional outcome, in this case, gait.

The third major question is: are there any socio-economical barriers to adopt the framework for remote monitoring? This is a big challenge facing us and not too much research has been completed to answer this question. First, wearables are future medical devices that will need to be prescribed, and the open question is who will issue these prescriptions, a family doctor or a specialist, or even some other healthcare professional such as a physical therapist. Second, wearable solutions are medical devices whose costs need to be covered. Some insurance entities (public or private) may see them as a great way to reduce costs associated with falls and falls-related injuries, and these entities may be willing to cover the costs of wearables if prescribed by a health professional. However, other insurance entities may not see the benefits and the patient will have to pay for these devices, which can decrease the adoption of a new technology. Third, adopting a new technology among older adults is always challenging, and manufacturers of these wearables will need to carefully address this issue, as patients may not feel comfortable wearing them (e.g., similarly to patients that need a CPAP machine at night). Lastly, many patients may feel that their privacy is violated, as they are equipped with wearables that track almost every move. This is a big concern, as the question is how we regulate sharing of data collected from these wearables. For example, can a GPS location obtained from an IMU be considered a private health data point protected under a legal framework (e.g., the Health Insurance Portability and Accountability Act in the United States)? If not, can these data points be sold by health insurances, sensor manufacturers, healthcare providers or any other entity that has access to this data? As we can see many open social-economic questions are open and will need to be answered before wearables are fully adopted in healthcare systems.

Wearables

Wearables come in all shapes and sizes but preferably, the form factor will be small to facilitate discretion for the wearer during everyday life. Early wearable concepts were bulky and too impractical for seriously consideration as pragmatic devices for monitoring in the home or community. However, the passage of time and advances in microelectromechanical systems ensured the manufacture of hardware components such as inertial sensors, capacitors and resistors became small enough to create wearables to fit neatly on the person. Typically, the user places wearables directly on the skin or by attaching to clothing with clips or other assorted devices. However, wearable placement is of paramount importance when considering the operation of inertial sensors due to their functionality, i.e. different sites of attachment will generate different data which impact analysis and sensitivity of detecting required outcomes [47]. The following sections present pragmatic and technical considerations relating to inertial sensor-based wearables, the most common for fall risk and detection. Here, inertial sensors comprise accelerometers and gyroscopes.

Inertial measurement unit (IMU)

The terminology surrounding wearables and affiliated technology is diverse. Generally, wearables are the physical unit attached to the wearer and its hardware could comprise any number of sensors and affiliated electrical components (hardware) depending on the measurement need. In the main, memory and battery configurations dictate wearable form factor, where the latter comprise the majority of weight and space within the wearable. However, future wearables will aim to overcome this pragmatic limitations by utilising energy harvested from the wearer [27]. IMUs are wearables that primarily utilise accelerometer or gyroscope sensors, which measure acceleration and angular rotation, respectively. These wearables are particularly useful for measuring all aspects of human movement such as duration and intensity. Hence, they have found great utility in measuring aspects of fall risk assessment as encountered earlier: functional impairment, balance abnormalities, and other aspects. Technical reading on inertial sensor functionality can be found elsewhere [48].

IMU development began with sensors attached/strapped to the person with wires/cables running across the body to data loggers attached at the waist. The latter were usually many inches in length, weighted several pounds and worn with a belt attached at that location only. Now, all the functionality exists in a single wearable device no bigger than the end of your thumb. The length of recording depends on the quantity of data recorded (memory) and length of monitoring period (battery life). An IMU for falls (and gait) gather/sample data many times a second (defined as sampling frequency and measured in hertz, Hz) due to the complexity of those activities and the need to define their patterns at high resolutions for more accurate and informed detection. Typically, high sampling rates/frequencies (e.g. 100Hz) achieve sufficient accuracies. Lower frequencies (e.g. 10Hz) have utility in movement analysis but generally

confined to broader aspects of human movement such as ambulatory activity or energy expenditure.
IMUs with multiple accelerometer and/or gyroscope sensors and high sampling frequencies are more readily suitable for laboratory use; collecting data in predefined patterns with the aid of structured testing protocols during short durations. Although they could be used in home-based environments it would greatly increase the logistical complexity of deployment, data management and deciphering/interpretation if not adequately supervised through direct observation or accompanied by video recording. To understand data and overcome complexity, i.e. understanding what movement is collected, IMUs have been developed for specific purposes/tasks, i.e. individual aspects of human movement. Typically, those tasks are informed by traditional *pen and papers* methods, tried and trusted techniques to inform patient diagnosis based on decades worth of research. In short, commercial IMUs generally align to testing specific aspects of traditional physical capability assessment e.g. gait (GaitUp[1]) or timed-up-and-go (TUG, Kinesis[2]) have shown utility in assessing frailty in older adults. The commercial technologies listed help quantify macro (broad) as well as the micro (fine) motor characteristics of movement. The latter traditionally attainable in bespoke facilities only (e.g. biomechanics laboratories) with more expensive, fixed location equipment. Of greater utility for future patient assessment will be the holistic approach to movement quantification with a single IMU gathering multiple macro and micro outcomes. This is possible with the fusion of numerous IMU algorithms to gather gait, TUG, balance and postural transitions [49]. The use of such innovative approaches can bring the expertise of an in-depth clinical assessment into the comforts of a patient's own natural surroundings, minimise disruption and ease burden. Nevertheless, the widespread adoption of such technologies remains sparse due to educational upskilling of frontline healthcare professionals and data privacy and control. The latter remains an ever-evolving quandary for this age of technology development with blurred lines between the use of IMUs/wearables as diagnostics and transfer of data between stakeholders and organisations in healthcare [50]. Indeed, wearable education needs to extend beyond frontline clinical staff to the direct beneficiaries of their use, elderly populations more prone to disease and in need of continuous monitoring to ensure good health. A recent study detailed a need to create awareness and knowledge among this group as wearables emerge as aids to detect and prevent medical [51].

Video

Perhaps the use and immediate transfer of IMU data is more readily achievable within health services due to the easier implementation of non-identifiable data. Commonly, IMUs with programming software will ask users/researchers to input generic study details, e.g. unique patient identification (ID) number, testing session ID, study name[3]. The patient ID will be recorded and referenced to a paper or digital record stored securely in a controlled and safe location accessible by the research team only via a key or password, respectively. Therefore, this aids patient confidentiality as no clearly identifiable information is recorded via the IMU. Alternatively, the use of video recording raises pragmatic questions for IMU development that remain unanswered. To date, IMUs are validated in controlled environments under direct observation, researchers manually observing or video recording activities. The latter are assessed against the direct output classification of IMU data with associated algorithms. One simple example includes number of steps manually counted vs. number of steps quantified by the IMU system (hardware, data and software/algorithms). Another example involves the use of

[1] www.gaitup.com
[2] www.kinesis.ie
[3] These data will be stored as metadata describing and giving information about the IMU sensor data

a volunteer performing numerous activities of daily living (ADL, e.g. walking upstairs, getting dressed) and performing a simulated fall onto crash mats. The second example usually involves a researcher video recording all activities and noting when the volunteer performed a fall. The type of fall[4] as well as the exact time will be checked against (i) the accuracy of the IMU data (does the data visually infer a fall event) and (ii) the output of the fall algorithm to verify it successfully detected a fall event from the same data, Figure 4.

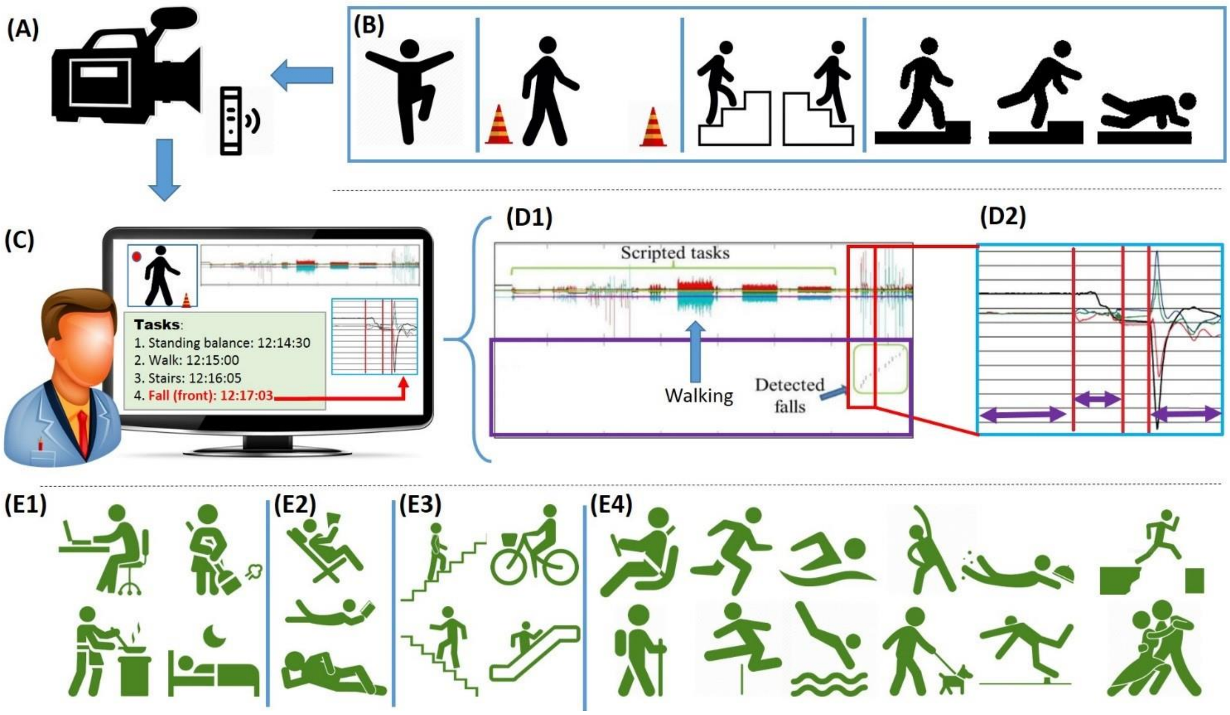

Figure 4 – The use of wearables with a camcorder (A) is standard validation processes within laboratory testing. Typically, the participant will performed a number of predefined tasks (B e.g. standing balance, walking between fixed points). Usually these are performed by young and older adults as they are deemed safe. The former usually perform falls in laboratories only to avoid risk of injury. Falls may usually be onto soft surfaces with participants under instruction to protect themselves (arms outstretched) to ensure safety but this can compromise algorithm accuracy and is not representative of real-world fall events.
A trained researcher will analyse wearable (IMU) and video data to ensure the automated recognition of falls are detected after or during scripted tasks (depending on the order of the protocol). The researcher will examine the algorithm output (D1) and often the raw IMU data (D2).
Generally, laboratory protocols will replicate as many activities of daily life (ADL) as possible (E1, e.g. sitting working at a desk, cleaning). However, people generally do not sit or lay on a bed in a laboratory like they do in habitual environments (E2) making real-world ADL and fall classification very difficult. Complex ADL such as stair ascent/descent, or dynamic seating and standing activities need to be considered for algorithm accuracy (E3). That extends to other more energetic activities including various forms of exercise, carrying loads, near falls (trips), jumping and even dancing (E4).

Use of video recording is key to help IMU system accuracy. Studies often compare the development of IMUs to *gold standards* but fail to recognise the fundamental differences between systems or the inherent error associated with all electronics-based systems [13].

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[4] Usually the fall will be predefined by a protocol. Development work will involve static falls, i.e. fall from a standing position with variations in how the volunteer falls. Additionally, protocols may ask the volunteer to simulate a trip, near fall or fall during a walking task or fall when arising from a chair to mimic a real-world, free-living fall event.

Regardless of video capture frequencies, video is currently the best standard as it can categorically and definitively record exact sequence of activities as well as provide the environmental context relating to the fall events. This is something IMU data cannot yet comprehensively provide due to the lack of real-world (free-living) fall studies involving robust algorithm deployment for all aspects of movement in all environments. Although recent developments have begun to use IMU data with complex machine learning algorithms to achieve that goal [52]. For now, multiple video deployment within the home is one suggestion but is far from ideal due to cost and burden of retrofitting equipment within a person's home. Alternatively, wearable cameras are aiding context description helping to categorise falls in the home and beyond. Yet, this is no easy or quick solution as trained observers must carefully study longitudinal recordings to categorise and label periods of activity and cross-reference with algorithm outputs. Automated video-based algorithms will help overcome this manual process but are in early stages of development and must undergo robust validation and reliability checking before used as a (gold) standard for comparison.

Algorithms

Fall detection

Here, IMU-based fall detection algorithms are presented from early designs with a focus on the current state-of-the-art. To date fall detection research has primarily focused on laboratory testing with young healthy volunteers performing static or simulated falls during walking or transitional-based tasks. The obviously limitation here is the use of younger adults within controlled settings trying to replicate free-living events which is unrepresentative of those who are to benefit from the research, the natural settings they reside and the range of fall related circumstances [53]. Indeed, this is corroborated by a recent scoping review which found testing/evaluation settings are greatly different from real-life context and research should focus on evaluating technologies to detect older adult falls in free-living environments [54]. Nonetheless, developments to date have aided innovation and provided numerous methodologies to aid falls research.

IMU - Thresholds

Early work with IMUs concentrated on the detection of a fall only. One prominent work includes the use of IMUs attached to various body locations (e.g. trunk, thigh) during eight different fall types: forward falls, backward falls and lateral falls left and right, performed with legs straight and flexed [55]. In addition, the referenced study had volunteers perform ADL (e.g. walking, transfer in/out of a car). Thresholds (cut-points) were applied to all IMU acceleration data which resulted in the trunk-based IMU better able to distinguish falls from ADL compared to the IMU on the thigh. Examples of other earlier work are shown in Table 1.

Table 1: Some threshold-based fall detection algorithms

Study	IMU location	Details	Algorithm	Accuracy
Bourke et al [55~~55~~]	Tri-axial accelerometer on the trunk and thigh	Discriminated between falls and activities of daily living (ADL). Young adults (n=10) used for falls data but older	Root sum of squares (RMS) calculated from each IMU. Thresholds applied to upper and lower peak accelerations	Thresholds determined from examining peak accelerations during all activities. Overall: trunk UFT = 100%[a] trunk LFT = 91.3%[a] thigh UFT = 83.3%[a]

		adults (n=10) for ADL in own homes.	UFT and LFT respectively	thigh LFT = 67.1% [a]
Kangas et al [56~~56~~]	Tri-axial accelerometer on the waist, wrist and head (forehead)	Discriminated between falls and activities of daily living (ADL). Two young adults for falls and ADL.	Used RMS (detailed as total sum vector, SV_{TOT}), difference between max and min acceleration (SV_{max}), dynamic sum vector (SV_D), vertical acceleration (Z_2), velocity and posture after the fall to improve fall detection	Waist: SV_{TOT} = 100% [a] /100%[b] SV_D = 100% [a] /100%[b] SV_{max} = 100% [a] /100%[b] Z_2 = 95% [a] /100%[b] Wrist: SV_{TOT} = 45% [a] /100%[b] SV_D = 32% [a] /100%[b] SV_{max} = 41% [a] /100%[b] Z_2 = 75% [a] /100%[b] Head: SV_{TOT} = 100% [a] /100%[b] SV_D = 100% [a] /100%[b] SV_{max} = 100% [a] /100%[b] Z_2 = 100% [a] /100%[b]
Bourke et al [57~~57~~]	Bi-axial gyroscope on the trunk	Distinguished between ADL and falls. Young adults (n=10) used for falls data but older adults (n=10) for ADL in own homes.	Applied 3: FT1: threshold lowest recorded resultant angular velocity (ω_{res}) FT2: threshold resultant angular acceleration (α_{res}, integrate velocity) FT3: threshold resultant change in trunk angle signal (Θ_{res})	Three fall thresholds combined identified 100% of falls (100%[a]/100%[b]). FT1 correctly identified 97.5% of ADL as non-falls (97.5%[b]) Combining FT1 and FT2 obtained 99.2%[b]
Wang et al [58~~58~~]	Tri-axial accelerometer on the head (above the ear)	Distinguish seven acts of ADL (inc. jumping) from falls. Younger adults (n=5)	Four criteria based on RMS/sum vector: 1. sum vector (SV) of all 3 axes 2. SV of horizontal plane (S_h) 3. Timestamp of falling body at rest (T_{rs}) and timestamp of initial contact with ground (T_{ic}) 4. Backward integration of reference velocity (V_{max})	True accuracy unclear but authors detail their experimental results as effective by precisely distinguishing the eight types of fall and seven ADL.
Li et al [59~~59~~]	Tri-axial accelerometer and tri-axial gyroscope on the chest and thigh	Distinguish ADL (e.g. walk on stairs, jump, run), falls and fall-like activities (e.g. quickly sit-down upright, sit down reclined). Three young healthy	Algorithm divided into three: 1. activity intensity analysis (using RMS on chest and thigh accelerations and angular velocities) 2. posture analysis	Authors present two special cases normally difficult to classify as ADL (from a fall) but distinguishable using their method/system. 1. Sit down fast and 2. Fall on stairs Generally accuracies

		males.	(angle of trunk and thigh) 3. transition Analysis (intentional vs. unintentional/fall) apply thresholds to peak values of acceleration and angular velocity, chest and thigh	91%[a]/92%[b] for ADL and fall detection, respectively.

[a] sensitivity
[b] specificity

IMU - Machine learning

Although threshold-based algorithms first shed light on the utility of IMU data detecting fall related events they have been recently compared to complex but more adaptable machine learning (ML) algorithms. The latter can be simply defined as methodologies to enable a computer (or IMU internal processing hardware) to automatically detect a fall if given a set of training data from which to learn what falls data are. The comparison study found that the performance of the ML algorithms was greater compared to thresholds. Specifically, the study investigated logistic regression, decision tree, Naïve Bayes, K-nearest neighbour and support vector machines with the latter providing the highest combination of sensitivity and specificity [31].

Additionally, Khan and colleagues [60] ~~present an interesting paper with the use of a~~ combined ML and data mining methodology, Hidden Markov Model. However, the authors introduce an added dimensionality to model unseen fall events within the Hidden Markov Model, which they describe as X-factor. This is derived from previous work to deal with un-modelled variations from normal events that may not have been analysed [61]. Thus, Khan et al. proposed the recognition of falls by observing normal ADL only with no training data. This approach is particularly insightful where the robust detection and classification of real fall data is sparse or unavailable and once detected incrementally adapts and updates its parameters to improve performance. However, the approach needs more stringent investigation as it was investigated with open datasets on younger adults in semi-structured testing situations [60]. Of note, was the collection of data from a smartphone, which often contain the same inertial sensors as generic IMUs. Smartphones are an important tool in wearable and fall research as they come readymade with the additional technologies for onwards integration of data to communication frameworks. Although most smartphones are powerful enough to process data one recent example offloads/transmits data to a computer as it investigates numerous ML algorithms for ADL and fall analysis [62]. In fact, this example highlights the need for algorithms to be combined. Given the complexity of real-world data collection but diversity and richness of wearable/IMU algorithms, they must be used jointly to aid free-living fall research as fall-based IMUs are hampered by a lack of accuracy. In fact, this was previously suggested but not yet widely implemented [63].

IMU - Fusion

The ability of IMUs to gather data to inform many human movement related activities has been previously highlighted. Thus, fusing or implementing different algorithms on the same data can provide more informed activity recognition that may lead to a fall. Typically, gait research has aligned to use a single IMU on the lower back to capture a range of micro gait outcomes, sensitive to ageing and pathology [64], [65], [66]. This led to the investigation of gait and falls from IMU data at the same location, showing a reduced number of false positives (false fall detection events) by understanding the broader activities performed [67]. Similarly, ML algorithms and smartphones have been used to help characterise walking patterns and falls. Approaches such as these highlight how a combination of traditional and/or more novel approaches can help improve fall detection rates while showing holistic use of IMUs for various outcomes. If algorithms cannot be fused, fall detection knowledge may also be supplemented by data fusion approaches through ubiquitous sensing. Although significant technology integration challenges exist within that field [68].

IMU & Video

Of course, data and algorithm fusion extends to IMU and video. Algorithms from the latter are quite complex given the heterogeneity of (e.g.) scenes and lighting conditions that are captured within free-living environments. Feature extraction to aid fall detection in new and cluttered environments is difficult and continuously gathering video data significantly affects memory and battery capabilities for all wearables. Recent work fused video from a smartphone (worn at the waist) and its embedded inertial sensors to create a robust and reliable fall detection algorithm [43]. Although the study achieved high sensitivity and specificity (>90%) during basic scripted tasks with a generic video recorder and a low number of false positives with the smartphone during more complex ADLs, it estimated a use time of less than 5-hours. Here, suggestions to improve/extend battery life include using the accelerometer (IMU) data only to continuously sample movement (uses less battery and memory) and once detected, switching the camera to record. That would greatly limit video data and extend smartphone recording capabilities.

Fall prediction

Gait

The ability to predict falls has obvious implications for patient care and is the focus of instrumented gait assessment. As previously discussed, the ability to robustly quantify gait with a single IMU is achievable, as well as its longitudinal deployment in free-living to investigate habitual micro characteristics in comparison to clinical/laboratory settings with arguments to target the former as the optimal environment for more informed patient assessment [69]. Although the best predictor is falls history, it would be ideal to ensure the patient does not experience any fall. To date numerous studies investigated wearable-based predictive models, including combination with clinical assessments and showed enhanced fall-risk prediction compared to clinical assessment only [70], [71], [72].

Sway

IMUs have shown utility to capture even discrete human movement, body/postural sway during periods of standing [73]. In fact, recent work suggests this approach should be the preferred method of assessing postural sway (for vestibular function) during standing balance tests across the age continuum [74]. In short, recent work has shown IMU-based outcomes can reliably estimate balance impairment and associated fall-risk [75] when compared to a traditional method[5] during solitary or repeated testing scenarios [76]. Moreover, work is extending postural sway assessment beyond standing to dynamic balance (during gait) where novel IMU outcomes like root mean square (RMS) of acceleration are complimenting best practise outcomes such as

[5] Berg Balance Scale

step width or step length [77]. Complementing new with well-known outcomes is key to understanding how the former can add pragmatic insight to daily clinical practise. It is important newly derived outcomes remain tethered/grounded to established conceptual models [78] ensuring translation from engineering to medical professionals and uptake by the latter.

Near falls

Although fall detection is of utmost importance to ensure the continuing health and safety of those at risk of falling [55], the ability to detect near falls or predict them before they occur is of growing interest. The latter can target physiotherapy-based strategies such as muscle strengthening exercises to avoid injury [79]. Yet, falls are difficult to quantify with traditional patient self-report often grossly underestimate the number of falls experienced. This is hampered by the variation of how falls are defined with efforts to standardise falls classification through self-report [79]. The referenced study presents a simplified classification defined by transitional, combined and advanced falls where the latter identifies complex high-risk motor tasks with significant environmental challenges, e.g. hill walking. It is reasonable to assume that near falls are more likely to occur in this situation resulting in a trip, slip, misstep or loss of balance. Near falls with wearables was systematically reviewed by Pang et al and found insufficient evidence to determine that near falls can be accurately detected and distinguished from actual falls and ADLs in older adults (>60yrs). However, it was found laboratory-induced near falls can be distinguished from actual falls and other ADLs in younger adults (<30yrs). The authors concluded that there is a dearth of large, high-quality studies investigating near falls with wearables in real-life settings with older people [80].

Brief case studies

Parkinson’s disease

Falls are prevalent in pathological cohorts but notably Parkinson’s disease (PD) where recent work has expertly examined the use of wearables and associated technologies where notable opportunities exist [7], [81], [82], [83], [84]. However, perhaps due to wearable fall system heterogeneity, it is recognised that a gold-standard for fall risk detection remains a major unmet need [85]. Although self-report (diaries) are subjective with high attrition rates [86], they remain “state-of-the-art” (i.e. simple but effective).

The role of algorithm/data fusion becomes clear within PD when considering the spectrum of motor related disease characteristics, e.g. bradykinesia, shuffling gait, slow ADL [87]. Of additional note is freezing of gait (FOG). That affects the legs during walking, manifested as a sudden and temporary inability to move [87] that may result in a fall. Current stand-alone technological efforts on this topic utilise deep learning (ML methodology) in a home environment to achieve high FOG detection accuracies [88] but should complement other approaches of assessment [89], [90], [91], [92] for more rounded technology development in this field. Interestingly, eye-tracking technology recently provided evidence for route previewing as a potential intervention to reduce risk of tripping and falling in older adults [93]. Although replication of those findings within PD is difficult due to visuo-cognitive challenges [94], recommendations were made for the composite use of instruments to achieve reliability and validity of visual sampling outcomes but that (again) is hindered by a lack of standardisation [95].

European projects

A few European fall related projects have recently come to completion. Here, descriptions and general findings of two prominent collaborations are given, representing the latest in large multi-disciplinary projects networking across several boarders.

FARSEEING[6]

This included ten partners across five countries and aimed to improve fall identification, prediction and prevention. There was a focus on information and communications technology devices and the opportunities they can provide to support older adults in their own environment. The project was divided across nine work packages (WP) with different partners leading on each, Table 2.

Table 2: FARSEEING work packages

Project Management (WP1)
User perspectives and psychological aspects about ICT technologies for “ageing well” (WP2)
Technological development (WP3)
Implementation and operational validation of longitudinal monitoring of mobility to early predict mobility disability & falls. (WP4)
Tele-medical service models (WP5)
Knowledge acquisition, consolidation and generalisation about falls through a meta-database (WP6)
Designing and testing a complex/self-adaptive intervention to reduce fall risks (WP7)
Dissemination (WP8)
Business models (WP9)

Readers are directed to the project website for full publication listings but two papers are highlighted here that may interest readers. The first compared self-recovered falls and non-recovered falls with long lies, examining frequency of unrecovered falls and resting duration [96]. This study also provided some useful algorithm development insights such as updating the assumption that a horizontal trunk position classifies a resting phase. The authors found that fallers with long lying periods often attempted to stand or adopt upright sitting positions but were not adequate to facilitate a successful recovery to a standing position. New insights such as this were possible due to a rich IMU-based database collected during the project. Currently, a dataset of twenty selected fall events is now available for researchers on request which may be useful for those developing algorithms but with little or no access to patient recruitment[7]. The second FARSEEING study of interest relates to development of a taxonomy of technologies to classify and characterise components of falls related studies and interventions. Specifically, the taxonomy is a tool detailing a common language and classification system to standardise the approach to reporting studies in the fields of biomedical informatics and fall prevention [97]. The latter study is vital to ensure the field moves in a co-ordinated and linear manner where consistency is key.

[6] FARSEEING: FAll Repository for the design of Smart and sElf-adaptive Environments prolonging Independent living: http://farseeingresearch.eu/

[7] http://farseeingresearch.eu/the-farseeing-real-world-fall-repository-a-large-scale-collaborative-database-to-collect-and-share-sensor-signals-from-real-world-falls

V-Time[8]

This randomised controlled trial aimed to evaluate two walking interventions to reduce falls incidence while improving walking, balance and cognition. A 6-week treadmill training programmed augmented by virtual reality was compared with a conventional treadmill training program. Three-hundred participants across three cohorts in five clinical centres across Europe were recruited: older adults who fall with and without mild cognitive impairments (MCI); and, people with PD who fall [98]. The primary outcome of the study was fall rate, quantified by falls diary/calendar post intervention where a fall was defined with the recommendations Prevention of Falls Network Europe[9]. Gait, balance and a range of other outcomes were also collected [98]. RCT findings showed that in a diverse group of those at high risk for falls, treadmill training with virtual reality led to reduced fall rates [99].

Remote monitoring: the great beyond

Only when common currency exists between wearables (including outcomes) will they be suitable for onward integration to communal communication frameworks, currently defined by the Internet of Things (IoT).

The IoT

Developments for relay of fall related detection currently consider IoT functionality, creation of real-time warning systems alerting a carer or medical service. Currently, work focuses on improving energy efficiency of wearables and associated technologies [100]. Additionally, other work implements a pre-fall detection IoT system, detecting human falls approximately 250-milliseconds before it occurs [101]. The purpose of the latter methodology is to integrate into wearable airbag systems to protect the faller before impact with the ground[10].

Big data

Use of any wearable facilitates the collection of data, lots and lots of data. This can be a double-edged sword. The collection of big data provides opportunities for in-depth patient analysis but the proliferation of information, which many healthcare professionals may struggle to deal with or understand within the context of current patient care pathways [102]. How big is big? Consider an IMU with a tri-axial accelerometer only, sampling continuously at 100Hz for 7 days (the norm). That is 3 channels (tri-axial) at 100 data points/second each for 24-hours/day for 7 days which equates to >181-million data points. This is increased by repeated testing (follow-up), making data management key for wearable studies. Thus, the robust/accurate detection of a single or even multiple near fall or fall event(s) is extremely difficult but understanding the volume, variety, velocity, and veracity of big data is key [103]. Yet, data sharing between research groups and/or commercial systems to promote integration into health information systems is currently lacking [104]. This is of importance where pooling of diverse data sets (e.g. interviews, family histories, muscle strength, bioelectrical impedance, blood and urine assays) can play a key role in the development of fall prediction tools [105].

Validation

Innovation is rife with wearable research. The novelty of devices, their application in various cohorts and coding of algorithms makes this an exciting and constantly evolving field. Yet, the

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[8] https://cordis.europa.eu/project/rcn/101785_en.html
[9] ProFaNE: www.profane.eu.org
[10] E.G. https://activeprotective.com/

abundance of creation is leading to heterogeneous development where established and emerging groups are competing to create the next wearable-based diagnostic. Many recent literature reviews conclude that the field needs to be harmonised with the creation of standardised protocols for wearable design, validation and reliability testing [51], [54], [106]. This extends to the description of studies including wearable outcomes[11] where the richness of data means it can be analysed and presented in a plethora of ways [27], [51], [54], [107]. In short, innovation supply often exceeds pragmatic demand.

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