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Wearable sensing for understanding and influencing human movement in ecological contexts

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Abstract
Wearable sensors offer a unique opportunity to study movement in ecological contexts—that is, outside the laboratory where movement happens in ordinary life. This article discusses the purpose, means, and impact of using wearable sensors to assess movement context, kinematics, and kinetics during locomotion, and how this information can be used to better understand and influence movement. We outline the types of information wearable sensors can gather and highlight recent developments in sensor technology, data analysis, and applications. We close with a vision for important future research and key questions the field will need to address to bring the potential benefits of wearable sensing to fruition.

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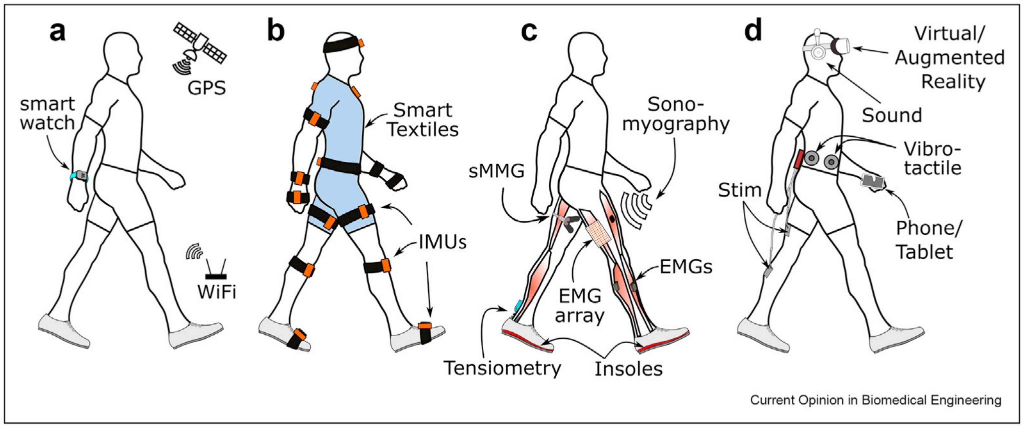
Introduction

Wearables are transforming the field of biomechanics, with new technologies providing the capacity to measure the kinematics and kinetics of movement in an ever-widening array of out-of-lab contexts. These technologies range from now-common systems like wearable inertial sensors and pressure insoles to emerging ones like sonomyography and shear wave tensiometry. The tremendous quantity of wearable data, generated across a variety of conditions, requires new ways to process, analyze, and understand the information. This rapid development also provides an opportunity to reenvision what it means to study movement mechanics, especially how to investigate motor control, performance, and tissue loading in ecological contexts (Figure 1).

One key question in using biomechanical measurements to understand and influence movement in ecological contexts is "why?" What drives the scientific community to do experiments that are less controlled and generate vast amounts of unstructured data, making it more challenging to interpret? What can be learned from implementing science in these contexts that cannot be learned in a lab? Collecting movement data outside the laboratory is motivated by the goal of investigating naturally emergent behavior, across a variety of conditions and behavioral states, and potentially with greater convenience. Wearable sensing can also be used to influence movement in real-world conditions, either indirectly through biofeedback, or directly as input to a real-time intervention. Wearable sensing enables a data-informed development cycle for these techniques and technologies, and real-world testing can ensure practical viability.

What is an "ecological context", anyway? As in all science, it is axiomatic that any effort to study a system will disturb that system in some way. The term "ecological context" is about continual improvement in how well experimental conditions approximate the "real-life" conditions that motivate a particular study. Thus, there is a topic-dependent continuum; considering the example of a walking study, perhaps the least ecological context is a motor imagery study in fMRI (functional magnetic resonance imaging), and more ecological contexts may progress to treadmill walking, walking throughout a building, walking outdoors, and, ultimately, unsupervised walking in everyday life. These contexts vary in their level of similarity to everyday life, level of experimental control, sensors that can be applied, duration of recording, and even how well the context itself can be documented. Future directions for both wearable sensor technology and data analysis techniques should be formed by considering these aspects of ecological contexts in light of what we, as a field, want to learn and what we want to influence. This review will focus on these questions specifically in relation to lower-body kinematics and kinetics in locomotion-related tasks.

Figure 1



Uses of wearable sensors in ecological contexts. a: Location sensors, to determine context. b: Kinematic sensors to measure joint movements. c: Muscle and kinetic sensors to assess muscle activation patterns and loads on the body. d: Feedback and/or direct action to influence movement.

What do wearables help us understand?

How and where the body moves in space

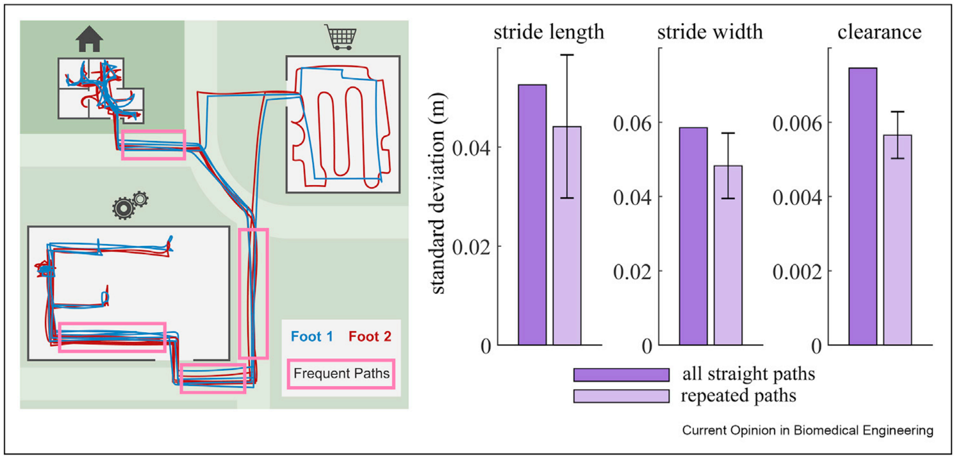
One of the most important aspects of understanding and interpreting movement measurements is knowing the context in which a movement was performed. Context includes many factors that can affect movement, such as: surroundings, terrain, path constraints, weather, time of day, movement purpose, motivation level, physiological state, and more. Our own team has emphasized the importance of focusing on comparable contexts when aggregating data over long periods of time, especially specific paths that are traversed repeatedly [1] (Figure 2). The most common way of generating data about this context is through GPS location tracking. Because GPS does not work in buildings, the indoor part of the movement is usually lumped together. To improve on that, wearable inertial measurement units (IMUs) have been used with pedestrian dead-reckoning techniques to reconstruct location within buildings [1], and localization using other available signals is also under investigation [2]. Future progress could be made by combining sub-centimeter real-time kinematic (RTK) GPS with scanning and vision to achieve simultaneous localization and mapping (SLAM). If there is need for terrain information, the situation becomes more difficult, as it is rarely available in maps at the precision needed for investigating legged locomotion. As an alternative, efforts have mounted scanners or cameras to the body to identify features like stairs [3,4] or even the relationship between viable footholds and gaze [5–7]. Other aspects of context, such as purpose or motivation, can be even more difficult. It may be necessary to glean information from test participants themselves, such as through voice recordings that report the salient context of interesting movements or events; for example, losses of balance [8–10].

How the joints move the body

In addition to the movement context discussed above, biomechanics focuses on analysis of joint-level movements. The critical aspect of the ecological context is that it is uncontrolled – for example, it may include a range of conditions that are irreproducible or unknown. Critical issues in understanding joint movement in ecological contexts include how to measure the movement, how to process and analyze the data, and how to combine it with contextual information and interpret it to generate meaningful knowledge.

The motion of the body in ecological contexts is now commonly measured using inertial measurement units (IMUs). Raw IMU measurements can be processed through sensor-fusion algorithms and kinematic models of the body to estimate a wide variety of movement parameters in a variety of ways. Advancements continue to be made in estimating and using joint kinematics [11–16], foot movement [17–19], center of mass mechanics [20,21] and other aspects of movement. Another novel way to characterize segment and whole body movements is using tactile textiles with piezoresistive fibers, interpreted through machine learning techniques [22]. Beyond the technical reconstruction of movement, an outstanding challenge of understanding wearable studies in ecological contexts lies in determining which data are meaningful for answering a given question. Here it is critical for researchers to choose instrumentation and data processing that can feasibly answer the questions under study. This means ensuring sufficient accuracy and precision in the measurements, including

Figure 2



Reducing gait data from ecological contexts to focus on frequently-repeated paths. Left: Conceptual diagram showing the reduction of variability by focusing analysis only on locations and paths that are used most frequently. Right: Example result (modified from Ref. [1] with permission) showing that eliminating data from other paths reduced variability in comparison to the set of all straight-line walking.

awareness of the strengths and limitations of each sensor type and algorithm.

How the muscles move the joints

Kinematic characterization of movement is valuable, but deeper understanding is attained by knowing the control and mechanics of the muscles that generate and sustain the movement. As with kinematic analysis, the ability to measure musculoskeletal kinetics in ecological contexts is important because these contexts generate unusual scenarios that are uniquely relevant to injury, extremes of performance, and daily life. The key issue in kinetic analysis with wearables is how to assess load and power information without stationary force sensors such as in-ground force plates.

One approach to force sensing has been to incorporate miniature force plates in shoes; this can work, but it creates a bulky and stiff sole, which changes ground contact mechanics [23]. A common alternative is pressure insoles, which can be made thin and flexible [24,25]; however, current solutions provide only a subset of foot—floor reactions. A full solution must also measure shear stress, and this remains an unresolved area of research (e.g. Ref. [26]). To circumvent the limitations of these systems, modeling approaches have been proposed to estimate joint kinetics directly from movement kinematics [16,27,28] or from kinematics and sparse ground reactions [25]. In general, this still requires great expertise in the design, application, and interpretation of such inverse models. Further, tremendous amounts of data will be needed to make these approaches generalizable for diverse populations and ecological conditions.

A different approach to understanding movement kinetics is to measure, or estimate, the state of the body's tissues more directly. The most straightforward technology is electromyography (EMG). Muscle modeling approaches can attempt to use EMG data to estimate muscle forces [29,30]; however, the relationship between EMG signals and muscle forces can change over time, due to both intrinsic muscle state (e.g. length, velocity, fatigue) and extrinsic factors such as changes in skin impedance or sensor placement. Approaches using dense multi-channel EMG arrays [31,32] can reduce some of these limitations to better study muscle function with robustness to sensor placement error and the ability to decompose signals into fine motor units. Recently, shear wave tensiometry (SWT) has emerged to measure axial muscle-tendon loading via the speed of a wave propagating along the taut tendon [33]; SWT has been used to detect changes in tissue load in response to variable external conditions such as terrain slope or exosuit assistance [34,35]. Other recent approaches aim to use advances in portable ultrasound to understand both kinematic and kinetic muscle function [36]. Sonomyography uses ultrasound images of either a single depth line or a planar field, tracking features such as muscle thickness using computer vision techniques, to estimate kinematics and/or force [37,38] or classify movement [39,40].

Some emerging alternatives for assessing muscle state are worth considering as well. One is mechanomyography (MMG), a technique of measuring the low-frequency vibrations of contracting muscles, allowing for movement pattern recognition and subsequent biofeedback [41]. Another, different concept, coincidentally with a similar name, is surface mechanomyography, which uses stretch sensors wrapped over the skin to measure the bulging of muscles during movement [42]. While little-evaluated to date, these sensors are low-profile enough to potentially be mobile for ecological contexts. Finally, a recent novel technique focuses on joint contact forces rather than muscle loads, analyzing spontaneous acoustic emissions from joint articular surfaces (e.g. "knee sounds") together with machine learning to estimate joint loading during movement [43]. If proven reliable and repeatable, such an approach could address important questions about internal joint loads that are relevant to assess injury risk, while also providing valuable data to tune and validate musculoskeletal models.

One of the major challenges in understanding muscle kinetics in ecological contexts is to get sensors that are wearable enough to be part of an experiment beyond the lab. Most of the sensors described above are themselves small enough to be wearable, but few are readily packaged for ecological use. Making more of these systems small, lightweight, battery-powered, and with adequate portable data logging and synchronization capabilities would enable richer studies of how the body's tissues are loaded in the variable contexts of real-world activities. Another significant opportunity is to combine these systems together to answer questions about muscle-tendon energetics and mechanics during ecological movement (e.g. tensiometry and IMUs [44]; EMG and IMUs [30]; EMG and sonomyography [38,45,46]; MMG and IMUs [41]).

How can wearable sensing influence movement?

The measurements above of location, motion, and kinetics are keys to understanding ecological movement. The next step is to apply these technologies to influence movement, not just observe it. Three basic methods are available: using summary information to drive high-level behavioral change; using instantaneous measurements to change low-level movement patterns through biofeedback; and incorporating measurement technology into wearable devices that directly alter movement.

Driving behavioral change is the mechanism used by consumer wearables such as smart watches, rings or shoe pods, and some sports-related devices. These systems monitor movement quantity and sometimes detailed characteristics (e.g. cadence, impact acceleration), and provide summary data to help the user make decisions, such as whether to get more or less exercise, or to show whether performance is improving or degrading over time. Most of the wearable measurement systems can generate behavior-modifying information, so the question for each of them is how best to relate the specific signals to behavioral recommendations.

Biofeedback is a very intensive use of wearable sensor information, as it requires real-time processing and display to the user in a format that can be immediately acted on to modify a movement while it is happening. Because of the demands of real-time display, biofeedback applications are most suitable for raw or near-raw signals (to minimize processing latency) that are easily understood by a user. Examples include filtered EMG or sonomyography, single-joint kinematics from IMUs, or foot contact pressure, on one limb (for targeted improvements) or bilaterally (for symmetry). As embedded processing power increases, more sensors may become real-time capable, and ways of displaying information may advance from current screen-based, vibrotactile, or audible signals to advanced displays like augmented reality (see Figure 1d).

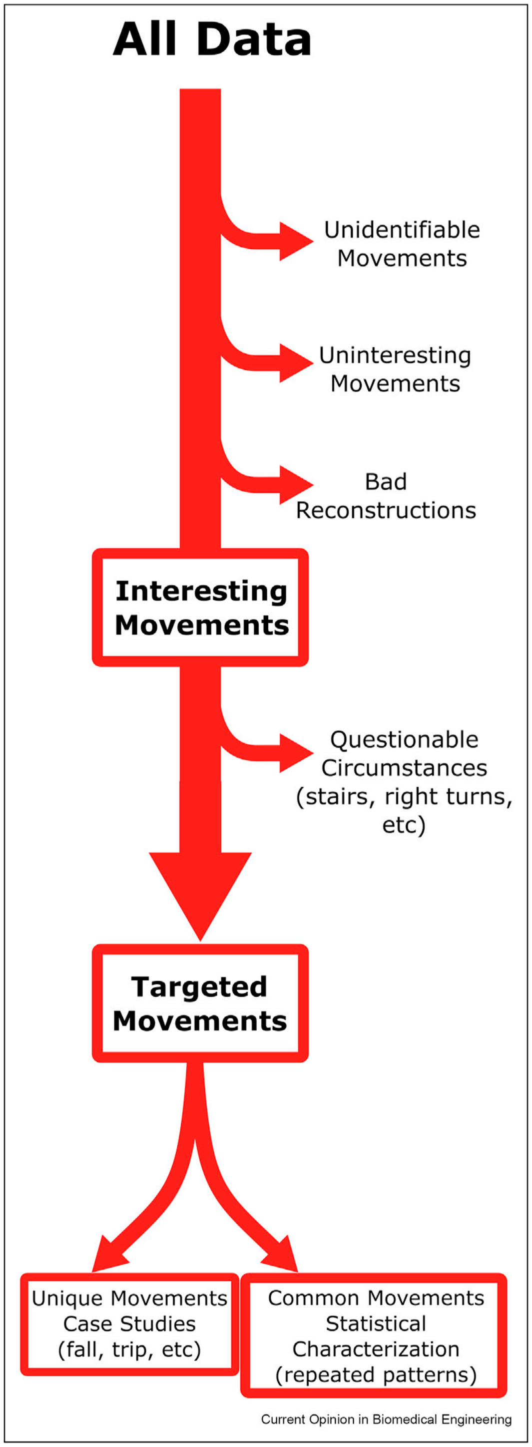
Finally, the incorporation of real-time measurements in devices that directly influence movement is an exciting present and near-future domain. In this case, the bandwidth problem of conveying information to a human user is circumvented; but it is replaced with a problem of intelligently using the measured information to control a device. Examples include exoskeletons and prostheses that respond to movement, EMG, or embedded force measurement signals [47–50], or electrical stimulation devices that modulate timing and/or amplitude in synchrony with measured movement [51–54]. A current frontier in this work is in truly bionic devices that include bidirectional information transfer as well as direct control or influence over movement in parallel with a human user [55].

Vision: future priorities and philosophical questions

The many current and potential technologies for field-based wearable instrumentation lead to the question: What should be the priorities for near-term research? Several areas of critical need are outlined here.

- Deep tissue measurements: Most current wearable muscle or tendon measurements are most sensitive to and representative of the superficial tissues they are near. For fuller understanding, it will remain valuable to continue developing technologies to look deeper into the body during movement.
- Novel phenomena: The range of sensors that can potentially be made wearable opens a wealth of opportunities to measure phenomena that could not previously be observed. By addressing questions of movement and loading from multiple different angles, new richness could be added to mechanistic studies and to advanced modeling techniques.
- Convenience: Battery life, automatic record/sleep modes, cleanability, error recovery, and other issues that burden the user need to be improved if wearable sensing is to achieve continual use.
- Data quality and robustness: Using wearable systems in ecological contexts challenges the technology

Figure 3



Information flow to generate insight about common or unique movements from wearable sensor data.

substantially, in areas from limited computing power and communication, to severe movement and environmental conditions, and even to use with varied and conflicting equipment (e.g. boots, sports equipment, outerwear, tools). It is critical to make sensing systems easily deployable and robust, and also to understand their limitations when choosing what to use in a given study.

- Data standardization and reduction: Modern science and industry draw great value from data-driven applications, but variable, poorly curated, or uninteresting data are a major challenge to these endeavors. Researchers and practitioners should take great care to define standard procedures for wearable technologies, so that data representing different ecological contexts is sure to represent the context, and not just variable test protocols.
- Statistical and interpretive approaches: Especially in long-term studies that involve multiple types of movements, simple statistics cannot justly describe the recorded data. Continued development or adaptation of richer statistical interpretive tools, such as whole-sample histogram analysis, or classification-based or cluster-based subset analysis and other machine learning approaches, will be very important for generating meaning from the rich data sets collected.

In addition to these practical concerns, we see several overarching philosophical questions the field should address.

- Richness vs. simplicity: The many potential options available make it tempting to heavily instrument test participants, but even wearable instrumentation can become cumbersome in quantity. Researchers should be cognizant of the trade-off between data richness (from many sensors) and true ecological validity (few enough sensors to forget about them).
- Typical signals vs. outlier events: Wearable data from ecological contexts is likely to capture a great deal of common movement, plus a few strange and unique events. Both categories are interesting: the first, to understand typical movement patterns and coordination; and the second to study real-life occurrences that are extremely rare in the lab, such as falls or injurious movements. For greatest insight, researchers should be attentive to finding and interpreting both (see Figure 3).
- Understanding variability vs. rejecting variability: Even within typical movement, there is variation, and some aspects of the variation are important while others may not be. Researchers should attend to methods of understanding why different types of variability arise, but should also attend to improving methods for obtaining the most accurate measures of “typical movement” by filtering irrelevant variability.
- Usability vs. insight: Many of the most successful recent advancements include machine learning in at least some component of data analysis or device control. While these techniques are powerful, the common complaint is that the underlying models are

usually uninterpretable, severely limiting the insight that can be gleaned. As in other fields, researchers should advance on both fronts—enabling important applications while still creating generalizable knowledge.
- Privacy vs. data sharing: With better resolution, improving data richness, and longer-term real-world collection come privacy risks that are not prevalent in current wearable data sets. In particular, context information (e.g. location, time of day) is enough to disclose identity and lifestyle choices. The legal, ethical, and practical management of privacy while making the most of each data set is an area worthy of dedicated attention and standardization in the field.

Conclusion

A variety of traditional and emerging technologies are enabling new ways of studying movement in ecological contexts, outside the laboratory. With these capabilities come challenges with respect to the sensors themselves, including interfacing, processing, statistical and interpretation approaches; and to the scientific and philosophical underpinnings of these approaches. A rich variety of research endeavors are motivated, to enable a future where biomechanical data have maximal meaning and relevance to solving problems and improving lives.

Declaration of Competing Interest

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Data availability

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