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Wearable Sensing for Solid Biomechanics

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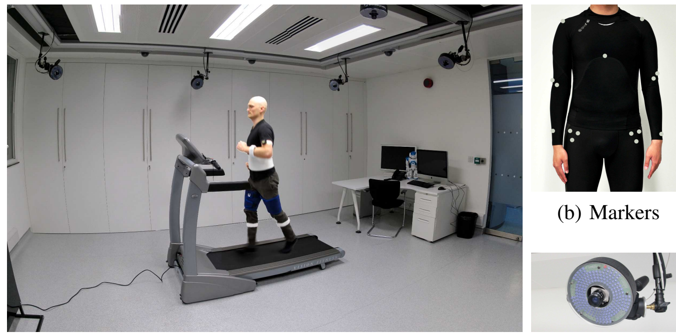
***Abstract*—Understanding the solid biomechanics of the human body is important to the study of structure and function of the body, which can have a range of applications in healthcare, sport, wellbeing, and workflow analysis. Conventional laboratory-based biomechanical analysis systems and observation-based tests are only designed to capture brief snapshots of the mechanics of movement. With recent developments in wearable sensing technologies, biomechanical analysis can be conducted in less constrained environments, thus allowing continuous monitoring and analysis beyond laboratory settings. In this paper, we review the current research in wearable sensing technologies for biomechanical analysis, focusing upon sensing and analytics that enable continuous, long-term monitoring of kinematics and kinetics in a free-living environment. The main technical challenges, including measurement drift, external interferences, nonlinear sensor properties, sensor placement, and muscle variations that can affect the accuracy and robustness of existing methods, and different methods for reducing the impact of these sources of errors are described in this review. Recent developments in motion estimation in kinematics, mobile force sensing in kinematics, sensor reduction for electromyography, as well as the future direction of sensing for biomechanics are also discussed.**

I. Introduction

Human biomechanics is the study of structure and function of the human body. The study of human biomechanics has been a subject of interest for centuries, as scientists seek to improve performance of the body and establish methods for diagnosis, recovery, and prevention of diseases through better understanding of the human body [1],. This plays an important role in healthcare, sports, wellbeing, and workflow analysis. Biomechanics studies may be oriented towards the biomechanics of solid bodies or fluids, for example, haemodynamics of the cardiovascular system [2][3]. In this review, we only focus upon solid biomechanics.

Two branches of biomechanics commonly studied are kinematics and kinetics, which study the description of motion and the cause of motion, respectively. Kinematics describes the overall motion of the body without considering the causes of motion. Thus far, human kinematics can be obtained at varying granularities and accuracy through a wide spectrum of technologies. For example, the movements of the head, hands, arms and legs can be measured using mechanical, magnetic, optical, and inertial systems. In contrast, kinetics studies the forces and torques that initiate the motion. When an accurate model of the musculoskeletal system is available, muscle force and muscle activation can be estimated using force measurement systems for kinetic analysis. Floor-mounted force plates, instrumented tools, and portable pressure sensors enable forces to be measured. Detailed measurement of muscle activations and forces can also be obtained through electromyography (EMG).



(a) Gait laboratory (b) Markers (c) IR camera

Fig. 1. (a) Gait laboratory equipped with an optical marker-based motion capture system and multi-view camera system for whole body kinematic analysis at The Hamlyn Centre, Imperial College London. The motion of (b) passive retro-reflective markers placed on the upper body are tracked using the optical system's (c) infrared cameras [29].

Thus far, many technologies, such as mechanical attachments, optical systems, floor-mounted instruments, and electrode arrays, have been developed to measure human biomechanics, but such systems are designed to capture brief periods of the movement in a laboratory setting. With the developments in wearable sensing technologies, continuous biomechanical analysis can be conducted in less constrained environments. In the rest of this section, we will briefly introduce the current sensing technologies used in the laboratory and typical applications of these technologies. A short summary of the previous surveys will also be provided.

A. Sensing Technologies

Conventional biomechanical analysis techniques have relied on subjective laboratory-based observation. Mechanical instruments [4]–[14], marker-based optical systems [15]–[20], force sensing walkways [21]–[25], and electromyography (EMG) [25]–[28] allow detailed quantification of movement and the cause of motion. Fig. 1 shows a typical example of a motion capture laboratory. These technologies enable a detailed study of human biomechanics with high accuracy. However, the complexity and technological constraints of laboratory-based instruments have prohibited their routine use in free-living environments.

The recovery of human biomechanics through natural video sequences has gained significant interest in the past as spe-

TABLE I
APPLICATIONS OF WEARABLE SENSING FOR BIOMECHANICS

Application	Study size	Sensor type	Sensor placement	Pros	Cons
Pathology & Rehabilitation					
Gait analysis	8 – 28	Inertial, Pressure insole	Foot, Shank, Thigh	Inertial sensors allow gait analysis to be performed in free-living environments.	Floor-mounted force plates are still necessary for accurate force measurement.
Parkinson's disease	4 – 10	Inertial	Chest, Forearm, Hip, Shank, Thigh, Upper arm	Wearable sensors are essential for enabling continuous monitoring of Parkinson's disease patients. Inertial sensors also allow subtle movements to be captured. Studies have used inertial sensors to detecting freezing of gait (FOG) events and feedback optimising deep brain stimulation.	Additional contextual factors from the surrounding environment and physiological factors, which may affect Parkinson's patients, however, cannot be captured solely using inertial sensors.
Rehabilitation	2 – 15	Exoskeleton, Goniometer, Inertial	Forearm, Shank, Thigh, Upper arm	In addition to accurate motion measurement, robotic exoskeletons can also provide support for limb movement during rehabilitation. Goniometers and inertial sensors also enable accurate motion estimation.	Mechanical systems, such as exoskeletons and goniometers, can restrict natural motion and the cost of most exoskeletons remain high.
Stroke	12 – 15	Exoskeleton, Inertial	Chest, Forearm, Hand, Upper arm	Exoskeletons also can provide support for post-stroke rehabilitation and inertial sensors allow motor ability assessments to be performed outside the laboratory.	The nonlinear relationships between kinematics and existing clinical assessments for post-stroke patients mean that these assessments cannot be performed solely through wearable sensors.
Sports Performance					
Darts	3	Inertial	Forearm, Shank, Shoulder	Wearable sensors allow key biomechanical factors, such as speed, acceleration, and throw timing to be easily measured.	Measurement drift and external interferences, however, can affect measurement accuracy.
Rowing	1 – 5	Goniometer, Inertial	Hip, Thigh	Wearable sensors can provide an accurate estimate of the rower's posture and wireless connectivity enables real-time analysis. Inertial sensor nodes can also be easily adapted to fit different users.	Goniometers, however, can restrict the range of movement of the limbs, which is undesirable for sports.
Running	20	Inertial	Foot, Forearm, Hip, Shank, Shoulder, Thigh, Upper arm	Motion estimation in unconstrained environments can be achieved using wearable inertial sensors. Analysis of athlete skill and fatigue can also be achieved through classification of kinematic changes.	Measurement drift, external interference, and differences in sensor placement, however, can affect motion estimation and classification approaches.
Other					
Posture	9	Fibre optic	Spine		
Surgical skill assessment	30	Potentiometer, Force/Torque	Hand		
Workflow analysis	10 – 27	Inertial, Microphone, Ultrasonic, Ultra-wideband	Chest, Forearm, Hand, Neck, Shoulder	Ultrasonic and ultra-wideband enable low cost drift-free measurement of movement for multiple people	The accuracy and frequency of ultrasonic and ultra-wideband sensors, however, are typically lower than inertial sensors.

cialised markers and motion analysis laboratories are not necessary. Markerless vision-based systems using a single camera, multiple cameras, and depth cameras have been increasingly used recently for motion capture. Markerless solutions are less intrusive compared to other analysis methods. However, the estimation accuracy and robustness of the existing techniques are still lagging behind conventional marker-based optical systems.

In contrast to the current laboratory-based and vision sensing systems, wearable sensors offer much greater flexibility without spatial constraints. Developments in wearable technologies, such as inertial/magnetic motion capture, are enabling continuous capture of biomechanics beyond the typical laboratory setting. Advances in wearable sensing technologies and processing techniques have brought increasingly miniaturised sensors to measure human biomechanics with good accuracy. Flexible electrogoniometers, lightweight exoskeletons, wearable inertial systems, shoe-mounted pressure sensors, instrumented tools, and wireless electromyography (EMG) systems have brought continuous kinematic and kinetic analysis of daily life closer to reality. Current research platforms focusing upon challenges affecting the accuracy and robustness of wearable sensing technologies have explored the implementation of more detailed human models, more reliable motion estimation algorithms, and sensor fusion and estimation strategies, which we will elaborate on in Section II and III.

B. Applications

The development of sensing technologies and processing techniques for biomechanical analysis are used to enable study across a wide spectrum of applications. In this section, we will consider the following exemplars as shown in Table I on how one can use biomechanics to understand the effect of diseases and rehabilitation on patients, skills assessment in workplace and training on athletic performance.

Clinically, systems for kinematic and kinetic analysis are used for the diagnosis of disease and illness, such as the severity of symptoms in Parkinson's disease [30]–[33], assessment of patient recovery from treatment, such as the outcomes of training schemes for patient rehabilitation [34], and control of prostheses through identification of movement intention [35]–[37].

In workplace, existing processes and techniques can be optimised through biomechanical analysis of dexterity, body motion, and posture. In surgery, for example, studies of surgical workflow seek to describe and understand the surgical process such that the information can be used for training and skills assessment [38]. The application of biomechanical analysis techniques to acquire staff movement and interaction information can be used to gain a deeper understanding of activities that occur in the operating theatre such that communication and team interaction can be examined [39][40].

Biomechanical analysis technologies have been used in a wide range of sport applications, including overarm throw in darts [41], rowing [42][43], and golf swings [44]. This has enabled the performance of athletes to be quantified during training and in-game with unobtrusive devices.

C. Previous Surveys

Recent surveys of biomechanical analysis technologies used in patient assessment studies [45]–[47] and workflow analysis [48]–[51] have signified the importance of obtaining repeatable objective measures. These surveys focus mainly on the clinical application of analysis techniques rather than technical novelty of the sensing technologies.

Perez-Sala et al. [52] reviewed the state-of-the-art for vision-based motion capture. It provided an overview of the methods that describe appearance, resolve viewpoints, spatial models, temporal models, and human behaviour. For vision-based motion capture, determining activity and contextual information through the understanding of behaviour has been shown to improve visual pose estimation. However, behavioural cues from vision can also be used for improving the analysis using wearable sensors by providing contextual information.

Roriz et al. [53] reviewed the use of fibre optic sensors for measuring strain and forces in biomechanics. For sensing strain, fibre optic sensors that use wavelength modulation are used to substitute conventional strain sensors since they provide a linear response to axial strain, absolute measurements, and are promising for in vivo applications, particularly in minimally invasive and robotic assisted surgery. Fibre optic sensors are small, minimally invasive, and accurate, but involve complicated setup procedures and high costs. These limit the adoption of this technology for monitoring solid biomechanics in a free-living environment.

A review of wearable sensors for human posture and movement analysis by Wong et al. [54] highlighted the clinical applications as well as the major achievements of recent work and key challenges. It looked at alternatives to vision-based systems for measuring human movement and posture, and the possible clinical application of the sensors. The review considers physical activity monitoring, gait analysis, posture and trunk movement analysis, and upper limb movement analysis using a range of sensors, such as accelerometers, gyroscopes, flexible angular sensors, magnetic sensors, and smart fabrics. However, limitations in accuracy and environmental factors can affect all sensors depending on the environment. This can be overcome by fusion of different sensor information.

D. Content of This Paper

Different to previous surveys, this review focuses on developments in wearable technologies and processing techniques that facilitate continuous biomechanical analysis within, as well as beyond the hospital or laboratory settings. Three databases - IEEE Xplore [55], Google Scholar [56], and IEEE JBHI Topic Network [57] - were used for the literature search. A combination of keywords, such as biomechanics, solid biomechanics, kinematics, kinetics, wearable, motion capture, flexible exoskeleton, fibre/fiber optic, vision, pose estimation, drift, interference, inertial, ground reaction force, electromyography, surface electromyography, and muscle force, were used as search terms. Publications from 2009 – 2014 were preferred, however, this range was extended in some cases.

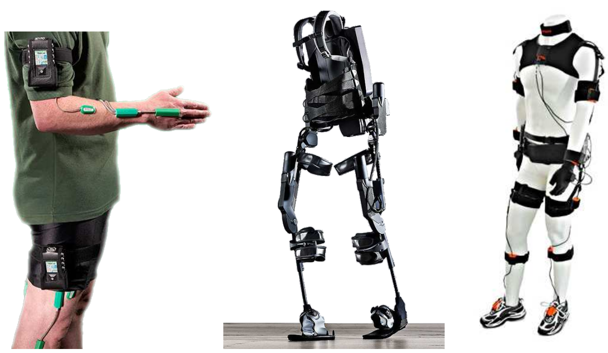
The rest of this paper is organised as follows: developments in sensing for kinematics are detailed in Section II and developments in mobile force sensing and electromyography are detailed in Section III. Section IV concludes the paper and discusses the future direction of wearable sensing in solid biomechanics.

II. Kinematics

Kinematics is the study of classical mechanics that describes the motion of human body without consideration of the causes of motion. Properties of the human joints, such as the trajectory, velocity, acceleration, joint angle, and angular velocity, are of interest in kinematics studies. Thus far, a number of wearable sensing technologies and processing techniques have

TABLE II
SENSOR PROPERTIES FOR KINEMATICS

Properties	Goniometer	Exoskeleton	Inertial
Sensor size	Length depends on joint measured	Full body suit	Multiple nodes $< 40mm^3$ each
Customisation	Flexible goniometer placement adjustable	Typically customised or adjusted to the subject for precise alignment	Sensor node positions adjustable
Setup	Precise alignment required at each joint	Precise alignment required at each joint	Calibration with known pose required
Accuracy	$< 2°$ at each joint	$< 2°$ at each joint	$< 2°$ at each joint
Variability	Accuracy can be affected if goniometer becomes misaligned	Accuracy can be affected if the exoskeleton becomes misaligned with the joints	Accuracy can be affected by measurement drift and external interference
Limb movement	Mechanical attachments can limit the range of motion of the subject's limbs	Mechanical attachments can limit the range of motion of the subject's limbs	Lightweight micro-inertial sensors allow free limb movement
Environment	Unconstrained	Some lightweight exoskeletons can be used within unconstrained environments	Micro-inertial sensor nodes can also be used within unconstrained environments
Power consumption	Low; batteries enable operation for several hours	High; high capacity batteries that enable the system to function for several hours are used	Low; small batteries enable most systems to operate from 1 day to 1 week



(a) Goniometer (b) Exoskeleton (c) Inertial

Fig. 2. (a) Flexible goniometers, such as the Biometrics Single/Twin Axis Goniometer [58], (b) exoskeletons, such as the Ekso Bionics suit [59], and (c) wearable inertial motion capture systems, such as Xsen's MVN suit [60], have been used for detailed analysis of human kinematics.

been have been developed to improve the robustness and accuracy of kinematic analysis systems. In this section, we will introduce the developments in wearable sensor technology and data processing techniques.

A. Wearable Sensors

For kinematics, marker-based optical motion capture systems are considered to be the gold standard and commonly used as a reference for validation. However, as shown in Fig. 2, the study of human kinematics outside the laboratory has only been made possible with the introduction of wearable sensors, lightweight exoskeletons, and micro-inertial/magnetic sensors. Table II summarises the typical properties of these sensors.

Exoskeletons, such as the Ekso Bionics suit [59], are rigid structures of jointed, straight metal or plastic rods, which are normally linked together with potentiometers or goniometers at the joints. Human kinematics can thus be directly measured using the potentiometers or goniometers. When the subject moves, the exoskeleton follows the same movement by measuring the subject's relative motion. It not only provides real-time kinematics estimation, but also supports limb movement, which is why many platforms are integrated as robotic platforms so as to provide mechanical support, feedback and control for limb rehabilitation applications. However, the complex setup procedures, poor wearability, and rigid construction of most exoskeletons affect routine usage and natural human movement. To this end, flexible and comfortable goniometers have also been used directly on the body to capture joint angles from specific parts of the body, such as the fingers [61] and legs [62], but flexible goniometers still suffer from complex setup procedures, requiring precise alignment across joints.

Unlike rigid exoskeletons or flexible goniometers, micro-inertial sensors typically have a more straightforward setup procedure and have minimal interference with natural human movement, which makes them the most widely used nowadays. Multiple inertial sensors are typically attached onto the surface of the human body for real-time capture of movement. Many systems incorporate other micro sensors, such as magnetometers [63], ultrasonic sensors [64], and cameras [65], to compensate for measurement drift which may be present. Extensive development of inertial/magnetic sensors has been witnessed over the last decade and some established commercial systems, such as Synertial [66], Perception [67], and Xsens [60], have been developed.

B. Processing Techniques

Measurement of joint movement through potentiometers and goniometers is relatively simple once they have been properly aligned to each joint. Kinematics through inertial sensing is more prone to error; therefore, in this section, we will only focus on the inertial sensor based processing techniques. Thus far, extensive research has been performed on how to fuse inertial and magnetic sensor measurements for accurate segment orientation and joint angle estimation [68]–[70]. The method can be further extended to estimate the global displacement and centre of mass as well [71]–[74]. However, the estimation accuracy can be severely affected by measurement drift and external interferences, which recent works have sought to resolve. Thus far, model constraints based methods and extra sensor-based methods have been proposed to further reduce drift, while interference estimation based solutions and noise adjustment methods have also been presented to handle external interference. In the rest of this section, we will explore these four areas developed for minimising estimation errors.

1) Model Constraints: Current skeleton models used in inertial capture systems are typically comprised of a simple structure of connected joints and segments [75], and each joint can admit three degrees-of-freedom. However, some joints, such as the elbow and knee, cannot rotate freely about three axes, thus geometric constraints should be taken into consideration for processing of processing inertial data.

Recently, some researchers have proposed to use these known physical limitations of the skeleton to further reduce inertial sensor drift. For example, Seel et al. [76] make use of the fact that the knee joint behaves approximately like a mechanical hinge joint. The kinematic constraints of the knee joint are exploited to align the inertial sensors to the body segments, which is crucial for precise joint angle calculation. Meng et al. [77] also used similar anatomical constraints for walking gait. The knee and ankle joints are modelled as soft hinges during walking, where the main axis of rotation is flexion/extension while inversion and abduction movements are limited to a small range. Similarly, Luinge et al. [78] uses constraints in the elbow to determine the exact orientation of each of the sensors with respect to the segment, thus improving the estimation accuracy of orientation of the lower arm with respect to the upper arm. Zhang et al. [79] proposes a link structure with five degrees of freedom to model the human upper-limb skeleton structure by limiting the elbow joint movement. Parameters are defined according to Denavit-Hartenberg convention, forward kinematics equations are derived, and an unscented Kalman filter is employed to estimate the human arm kinematics. Estimation errors of less than $3°$ and $12°$ were achieved, respectively, for upper-arm motion and forearm motion. Peppoloni et al. [80] and El-Gohary et al. [81] also present similar ideas for kinematic analysis using wearable inertial sensors.

These recent approaches demonstrate that by applying constraints on joint movement, which limit the degrees of freedom, range of motion, and body segment rotation, it is possible to reduce inertial sensor drift. However, these methods can only constrain movement to be within the defined range of each joint, while erroneous measurements within the defined ranges cannot be prevented. Furthermore, most works have only focused on constraining the motion of specific hinge joints, such as the elbow, knee, and ankle, meaning that drift my still be present within other segments of the body.

2) Multi Sensor-based method: In addition to constraint-based methods, researchers have considered the use of complementary information from other sensing devices. As discussed earlier, one of the key issues with inertial sensing is the measurement drift present in the estimation. To overcome this challenge, the use of drift-free sensors is combined with inertial sensing.

Drift-free sensors, such as global positioning system (GPS), laser range finders, and vision, have been used in recent works. For example, Brodie et al. [82] added Differential GPS (DGPS) to inertial sensing for biomechanical analysis of ski racing to reduce measurement drift of the subject positioning. In outdoor environments, where there is a clear view of the sky, DGPS systems have an accuracy of ± 5 metres, which can be used to reduce drift in position estimation. However, the accuracy of DGPS declines significantly in indoor environments due to interference. Schall et al. [83] extended this idea by combining DGPS and vision, which had an average error of $\sim 0.002°$ per pixel, with inertial sensing to compensate for measurement drift in outdoor and indoor environments, using vision to track sensor orientation where positioning information from DGPS is not available. Ziegler et al. [84] proposed to use a laser range finder instead to reduce drift in the position estimate. The human body posture captured using inertial sensing is combined with the location to obtain globally aligned full posture estimates. Position estimate error was reduced to less than 0.2m from 15m, where estimation was performed using only inertial measurements. However, leg detection methods in natural environments are likely to yield many false positives as a result of the laser range sensor's view of the environment. Tao and Hu [85] and Pons-Moll et al. [86] introduce vision to track image features on the human body to use as complementary information to reduce drift in the inertial estimation. Multi-camera and monocular systems are able provide drift-free tracking of the human body where the tracked segment is free from occlusion.

Other drift-free sensors, such as ultrasound, short-range radio - ultra-wideband (UWB) [87]–[90], radio frequency identification (RFID) [91], Wi-Fi [92][93], and Zigbee [94] - have also been explored in recent years. Regardless of the drift-free sensor type, the addition of complementary data from extra sensors has been shown to be effective towards reducing measurement drift from inertial sensing. These additional cues have enabled the study of human kinematics in both indoor and outdoor environments, where an accumulation of drift over long durations and distances can result in significant estimation errors. However, the suitability of each sensor also depends on the application and environment of kinematic analysis. For example, while the laser range finder is well suited for reducing measurement drift in large open areas, the interference present in more crowded environments would significantly reduce the efficacy of the sensor. Moreover, the use of additional sensing devices can be undesirable in a wearable sensing system as they often introduce further complexity and bulk to the system. This is especially true for methods that rely on ambient sensors, such as laser range finders and cameras, as these extra sensors can reduce the portability of the system.

3) Interference estimation: External interference is also an issue that can greatly impact the kinematics estimation accuracy of micro-inertial sensors. Most inertial sensors comprise of accelerometers, gyroscopes, and magnetometers. The accelerometer is generally assumed to only measure gravity while the magnetometer only measures local magnetic field, and the linear acceleration of the rigid body and magnetic disturbance are assumed to be negligible. However, such assumptions are not applicable to real word kinematic studies where relatively large linear acceleration exists due to dynamic motion or magnetic disturbances due to ferromagnetic material.

To this end, many methods have considered estimating the interference by adding it as part of the state vector in the framework of Bayesian filter. For example, Young [95] combines the human body model with the rotational parameters of each inertial sensor worn on the body to more accurately estimate acceleration. The linear acceleration at each joint is estimated recursively through a tree of connected joints used to represent the skeleton. Mean root-mean-square (RMS) errors of 0.54° and 0.72° at the pelvis were achieved for walking and running, respectively. Roetenberg et al. [96] proposed a model which separates gravitational acceleration and linear acceleration to handle interference from acceleration, and a magnetometer model for preventing heading drift and interference from magnetic disturbances. RMS errors of 2.7° and 11.9° were observed for orientation estimation with and without magnetic disturbance compensation, respectively. Ren and Kazanzides [97] used Kalman filters to estimate gravity and magnetic field measurements, and an extended Kalman filter for estimating the orientation of a hand-held surgical instrument tracked using an inertial and magnetic navigation system. Estimating magnetometer measurements using a Kalman filter can eliminate the influence of brief periods of magnetic interference. Overall RMS tracking errors of 0.76° - 1.06° were obtained. Sun et al. [98] proposed a quaternion-based adaptive Kalman filter for drift-free orientation estimation. In the filter, the motion acceleration is included in the state vector to compensate the effects of human body linear acceleration. Lee et al. [99] also presented similar ideas to estimate the external linear acceleration with RMS errors ranging from 0.92° – 5.28° for low interference, to 1.2° – 44.13° for high interference.

These methods show that interference from acceleration and magnetic disturbances can be estimated and thus compensated for by using Bayesian estimation models. However, the effectiveness of compensation from interference through adaptation of process noise and filtering of sensor measurements is limited where external interference is sustained for prolonged periods of time. The other disadvantage of these methods is that they can only deal with relatively small interferences, which is problematic where the magnitude of the interference is large.

4) Noise adjustment: Another approach used to minimise errors introduced through interference and disturbances is measurement noise adjustment, which adapts measurement noise based on the estimated level of interference. In general, when interference is detected, the covariance matrix of the measurement noise is increased to reflect the noisier sensor measurements.

Similar to interference estimation methods, noise adjustment has also been widely explored in recent years. For instance, Sabatini [100] proposed an approach which modifies the measurement noise covariance matrix of the quaternion-based extended Kalman filter to handle interference in accelerometer and magnetometer measurements. The approach achieved RMS errors of 1.31°, 1.4°, and 4.13° for roll, pitch, yaw orientation estimates. Sun et al. [101] also proposes an adaptive quaternion-based complementary Kalman filter. To optimise the performance under interference, the filter changes the covariances of accelerometer and magnetometer measurement noises based on the information confidence, which is evaluated by computing interference level. Compared against three other methods - FQA [102], Quaternion-based UKF [103], and direct gyroscope integration - their method is shown to be accurate under motion acceleration and magnetic disturbance with RMS errors of 0.56° and 1.19° achieved for roll and pitch. Zhang et al. [104] implements an acceleration interference detection scheme based on the exponentially discounted average of the normalised innovation squared (NIS) in the Kalman filter framework. According to the detection results, process and measurement noise levels are then scaled up or down automatically. Their results show that before noise adjustment, measurement errors can exceed 40° compared to errors of less than 20° with compensation. However, the main disadvantage of the aforementioned solutions is the response speed, as the covariance matrix increment is not fast enough to handle the outburst of large interferences. For this purpose, some variations of noise adjustment, such as vector selection schemes, have also been proposed. The basic idea for such schemes is to detect whether the sensor measurements are perturbed and then replace the degraded measurements with more reliable ones. Lee et al. [105] and Zhang et al. [106] have explored such ideas in their work. In general, noise adjustment has shown better performance in reducing the effects of interference from acceleration and magnetic disturbances than interference estimation methods. On the other hand, similarly to interference estimation methods, they cannot handle significant and sustained interferences either.

In addition to kinematics, kinetics is another important branch of biomechanics, which studies the cause of motion in the human body. It considers the forces generated internally in the body that result in human movement. Thus far, a number of wearable sensing technologies and processing techniques have brought greater mobility for kinetic analysis. In this section, we will review the developments in wearable sensor technology and data processing techniques for kinetics.

In summary, interference estimation and noise adjustment methods have been shown to minimise measurement errors introduced through interference from acceleration and magnetic disturbances, which may be prevalent beyond the controlled laboratory environment, where the interference is usually small and transient. Small changes in the magnetic field due to positional variations and interference from acceleration can be handled as demonstrated by Roetenberg et al. [96] who achieved a 9.2° reduction in error through magnetic compensation. However, where significant external interferences are present or interference is sustained for prolonged time periods, interference estimation and noise adjustment methods become ineffective for reducing measurement error. For more significant and prolonged interferences, model constraints and additional sensor information can be used minimise error and measurement drift. Model constraints and the inclusion of data from extra drift-free sensors have been shown to reduce measurement drift from 15m to 0.2m in some experiments. To improve accuracy and enable greater resilience against measurement drift and external interference in kinematic analysis, it is necessary to consider drift and interference reduction methods together.

Advances in wearable sensing technologies have led to the development of smaller, lighter, and low-power systems for enabling the study of kinematics beyond the laboratory. Many different lightweight exoskeletons and micro-inertial sensors have already been developed by researchers and commercial entities. Accuracies comparable to those offered by commercial marker-based optical systems have been achieved for estimation certain joint movements. However, the use of mechanical attachments across multiple joints in exoskeletons and the number of sensor nodes required for inertial motion capture still limit the widespread adoption of these technologies for certain kinematic studies. Continued development of smaller, lighter, and more accurate wearable systems that are more comfortable, with better wearability, and rely on fewer sensor nodes is essential for widespread adoption.

III. Kinetics

A. *Wearable Sensors*

For kinetics, ground reaction force (GRF), the force exerted onto the ground, is essential for inferring the internal forces generated at each joint in the body, which is typically measured using floor-mounted force plates. In addition, muscle activity, which can be captured through electromyography (EMG), also allows more in-depth study of the cause of motion and detailed force analysis. Similar to kinematics measurement, kinetic analysis is so far mainly confined to the laboratory environment. However, as shown in Fig. 3, with the development of portable and wearable sensors in the past decade, kinetic analysis beyond the laboratory is becoming possible. In this section, we will briefly introduce some of the portable and wearable sensors, including mobile force plates, wearable pressure insoles, micro-inertial sensors, and wearable surface EMG. Table III summarises the typical properties of these sensors.

The development of low-cost and lightweight force plates has made technology GRF measurement more accessible and portable. Commercially available portable force plates from AMTI [107], Bertec [111], and Kistler [112] enable human kinetics to be studied outside of the controlled laboratory

(a) Mobile force plate (b) Pressure insole (c) Inertial

(d) High-density EMG (e) Sparse EMG

Fig. 3. (a) Mobile force plates, such as the AccuGait portable system from AMTI [107], (b) pressure insoles, such as the Parotec system from Paromed [108], (c) inertial sensors, such as the ear-worn accelerometer used by Lo et al. [109], (d) high-density surface EMG, such as the used by Rojas-Martínez et al. [110], and (e) sparse surface EMG, such as the wireless FREEEMG system from BTS Bioengineering [29], have allowed human kinetics to be captured.

environment. However, while GRF can be captured for a more diverse range of applications, portable force plates can only capture the force exerted over very small areas, which places significant restrictions on the activities that can be studied.

As an alternative to portable force plates, wearable pressure sensing insoles and inertial sensors have been developed to measure GRF within free-living environments. Thus far, a number of research platforms have been reported. For instance, Liu et al. [113] develop a mobile force plate that can be attached onto a shoe which combines three triaxial force sensors, one triaxial accelerometer, and three uniaxial gyroscopes to measure GRF, centre of pressure (CoP), acceleration, and angular velocity. Morris Bamberg et al. [114] present an insole which incorporates two dual-axis accelerometers, three gyroscopes, four force sensitive resistors, two polyvinylidene fluoride strips, two bend sensors, and an electric field sensor for the analysis of Parkinsonian gait. Pressure sensing shoes and insoles are also presented by Howell et al. [115] and Strohrmann et al. [116] to study the motion of stroke and Cerebral Palsy patients, respectively.

Both Lo et al. [109] and Neugebauer et al. [117] propose to further simplify kinetic analysis using micro-inertial sensors for GRF measurement. Although GRF is critically important for kinetics analysis, it can only be used to infer virtual force generated at each joint by inverse dynamics, which may not be enough in practice.

In addition to GRF, surface EMG (sEMG) systems can be used to measure muscle activity for better understanding of muscle characteristics, muscle force estimation, and movement

TABLE III
SENSOR PROPERTIES FOR KINETICS FORCE ESTIMATION

Properties	Mobile force plate	Pressure insole	Inertial	High-density EMG	Sparse EMG
Sensor size	$> 40cm^2$	Shoe size	$< 4cm^3$	Area of muscles monitored typically covered	$< 4cm^2$
Customisation	Multiple force plates may be used depending on assessment	Customised to subject's shoe/shoe size	Sensor node positions adjustable	Electrode placement depends on study	Electrode placement depends on study
Setup	Initial calibration required	Calibration required	Per subject calibration required	Precise placement required	Precise placement required
Accuracy	$> 99.5\%$	$> 90\%$	$80 \sim 90\%$	–	–
Variability	Low	Can increase due to wear of insole materials	Subject variation	Yes; across different subjects and placement	Yes; across different subjects, placement, and external interference
Limb movement	Unlimited, however, force measurement is constrained to the force plate area	Unlimited	Unlimited	Free movement limited due to large surface electrode array	Unlimited
Environment	Limited to area of force plate	Unconstrained	Unconstrained	Limited to laboratory setting	Unconstrained
Power consumption	Moderate; most systems are wired or operate for several hours	Low; batteries enable monitoring from several hours to days	Low; small batteries enable most systems to operate from 1 day to 1 week	High; most systems are wired	Low; small batteries enable wireless measurement for several hours

identification. Previous studies capture myoelectric signals through high density arrays of surface electrodes as they are less invasive than intramuscular electrodes and provide high resolution measurements. Recently, electrode placement studies [118] have enabled the usage of sparse sEMG to improve setup times and the convenience of capturing muscle activities. Some established commercial systems, such as the BTS Bioengineering FREEEMG system [29], Delsys Trigno Wireless EMG [119], and Shimmer3 ExG [120], are already available on the market.

B. Processing Techniques

Obtaining accurate GRF measurements for kinetic analysis from portable force plates is normally straightforward once the system has been calibrated. However, obtaining an accurate GRF measurement from pressure sensing insoles and inertial sensors is more challenging as the relationship between force and measurements from deforming insoles and inertial sensors are nonlinear. To this end, calibration and force estimation from insole and inertial data is important for enabling GRF measurement through wearable sensing. Meanwhile, accurate muscle force estimation and movement identification through sEMG is challenging due to signal variation across the muscle and crosstalk. The routine measurement of myoelectric signals using sEMG is also challenging as the electrode arrays typically used for detailed analysis are cumbersome to setup and may affect natural human movement. Therefore, in this section, processing techniques for pressure insole calibration and force estimation, and inertial force estimation methods for GRF measurement, and muscle force estimation and motion classification methods for surface EMG measurement are detailed.

1) Pressure insole GRF estimation: Ground reaction force measurements from force-sensitive resistors used in pressure insoles are nonlinear and may change as the materials within the insole deform and become worn with use. Therefore, careful sensor calibration and force estimation methods are necessary to ensure accurate GRF measurement.

For example, Morris Bamberg et al. [114] fit sensor measurements with known forces generated from Stable Micro Systems' TA-XT Texture Analyser onto a curve for sensor calibration. Four force-sensitive resistors and a polyvinylidene fluoride strip are used in the insole to obtain timing and pressure distribution across the foot. Howell et al. [115] use an iLoad Mini 50 pound miniature load cell for calibration. Least squares linear regression is used to find the weighting coefficients to match the measurements to ground truth GRF measurements. Similarly, multiple force-sensitive resistors are used to capture plantar pressure distribution and GRF - 12 resistors are mounted on a flexible circuit board. An overall RMS error of 5.4% and 6.4% was obtained for GRF estimation of the control subjects and stroke patients, respectively. Rouhani et al. [121] compares GRF estimation using linear regression and nonlinear mapping functions - multi-layer perceptron (MLP) network and locally linear neuro-fuzzy (LLNF) model. Nonlinear mapping functions are shown to have lower Normalised RMS errors of $7.28N$ for MLP and $7.66N$ for LLNF in comparison to $10.69N$ for linear regression where stance time percentage is also used as an additional input.

Pressure sensing insoles are used to capture not only GRF, but also more detailed characteristics of force distribution by typically using multiple force-sensitive resistors in their implementations. Calibration is commonly performed for each force-sensitive resistor against ground truth values before use to correct for variations in measurement arising from wear of the insole. Linear and nonlinear approximation models are used and compared for GRF estimation. Due to the nonlinear nature of insole measurements, nonlinear approximation and input selection using principal component analysis (PCA) showed better performance. However, the high cost of commercial pressure insole systems and modifications required to the subject's footwear limit their widespread use.

2) Ground reaction force estimation from inertial data: The use of micro-inertial sensors for estimating ground reaction force has also been explored by researchers as the low cost and size of the sensors make them ideal for routine use in kinetic studies.

Recent research has used statistical models, such as Bayesian networks and regression models, to derive GRF measurement estimation from acceleration. For example, Lo et al. [109] use an ear-worn triaxial accelerometer to estimate the plantar force distribution across each foot, which is divided into eight sub-plantar regions. A hierarchical Bayesian network is used to detect footsteps, heel strikes, and lateral hindfoot strikes. A relatively high sensitivity and specificity of 88% and 83%, respectively, were achieved for detecting pressure transitions, and a specificity of 77% was achieved for detecting medial and lateral contact. Similarly, Neugebauer et al. [117] used a waist-worn accelerometer to estimate GRF. A mixed effect and generalised regression model, which is not subject specific, is used to predict the peak vertical GRF from the waist-worn sensor. Results from the patient cohort show that the predicted force measurement for most subjects were within 11% of the fitted mean. Other studies have also considered the use of multiple sensors for GRF estimation. Rowlands and Stiles [122] used five accelerometers - three on the hip and one on each wrist - to consider different sensor placements on the body. Their findings showed that measurements from accelerometers on the wrist and hip were similar. This suggests that it is possible to also capture GRF using wrist-worn inertial sensors. Charry et al. [123] attached inertial sensors to the medial tibia of each leg to more accurately capture peak GRF along the tibial axis, achieving an average RMS error of $151N$, $106N$, and $130N$, for each subject in their experiments.

These studies demonstrate that GRF estimation using inertial sensors is possible from sensors mounted on multiple locations of the body, such as the ear, waist, hip, wrist, and legs, which may be useful when considering different applications. However, most papers only assume a steady activity state for estimation, which means that GRF for mixed activities is not accurately estimated. For less controlled continuous monitoring applications in the natural environment, the use of activity classification techniques can be incorporated to handle different activities. Furthermore, while it has been shown that plantar pressure distribution can be determined through an ear-worn accelerometer, accurate measurements were not obtained throughout the sub-plantar regions of the foot.

3) Electromyography: Surface electromyography offers a less invasive means of capturing muscle activity, however, since surface electrodes can only measure activity from superficial muscles near the electrode, estimating overall muscle force and identifying joint movement using sEMG is not straightforward. Muscle models and a number of machine learning techniques are used by researchers to estimate muscle forces and identify joint movement.

To estimate muscle forces using sEMG, musculoskeletal models and learning methods are typically used. For example, Staudenmann et al. [124] used a high density electrode array and principal component analysis (PCA) to estimate muscle force. PCA was used transform the spatial distribution of muscle activations into linearly independent ranked modes, split into a sum of higher modes and lower modes, for muscle force estimation. Shao et al. [125] used a modified Hill-type muscle model [126] for describing lower limb anatomy. High-pass filtering, full wave rectification, normalisation using peak rectified EMG measurements, and low-pass filtering are used to process the measurements. A calibration process which incorporates EMG and kinematics was used to determine parameters between EMG and muscle activation of the muscle model to achieve RMS errors between 9.7% and 14.7%. Similarly, Naeem et al. [127] also rectified smooth EMG measurements, which are combined with a back-propagation neural network. The artificial neural network learns the exerted muscle force from the rectified EMG measurements. A comparison of the Hill-type muscle model with the proposed neural network is also provided. Recent works show that while muscle models, such as Hill's muscle model, are important and still commonly used, the addition of machine learning techniques and calibration for each individual subject is vital for muscle force measurement due to muscle variations between each subject.

To identify movement intention using sEMG, learning methods are typically used to classify observed muscle activations into actions. For example, Rojas-Martínez et al. [110] used high density electrode arrays with around 350 channels to classify activations from upper-arm and forearm muscles into four movement directions at the elbow at different strengths. A linear discriminant classifier (LDC) was used to classify the activation maps into 12 groups based on the spatial distribution and intensity of the map, with classification accuracies of up to 96.3% achieved. Similarly, Boschmann and Platzner [128] used a 96 channel high density electrode array to identify 11 hand and wrist movements. Three classifiers - linear discriminant analysis (LDA), support vector machines (SVM), and k-nearest neighbour (k-NN) - are compared and used to identify the different movements. Using a subset of 20 EMG channels, classification accuracies of up to 85% were achieved, while a 77% accuracy was attained using just four EMG channels. An electrode placement study by Mesin et al. [118] considered the importance of precise electrode placement, avoiding the muscle innervation zone where the muscle bulges, and proposes a search method for locating optimal detection positions for surface electrodes using multichannel surface EMG. To further simplify EMG embodiment for routine analysis, high density electrode arrays are not used in some recent works for movement identification. Precise electrode placement is important where the number of electrodes used is reduced. For example, Landry et al. [28] and Man et al. [129] used smaller electrode arrays to capture muscle activity from the foot and fingers, respectively. Zhang et al. [130] proposed a further reduction through a combination of careful placement of surface electrodes on the forearm and feature dimensionality reduction using uncorrelated linear discriminant analysis (ULDA), which seeks to maximise the separation among different classes, to classify six forearm movements using five electrodes. An overall classification accuracy of 97.9% was obtained using 8 EMG channels, which was reduced to 95% when using a subset of five EMG channels. Reducing the number of electrodes required for muscle activity analysis makes routine clinical use more practical, however, the lack of redundancy means that placement and error recovery from noisy measurements becomes even more essential.

In summary, high-density electrode arrays are commonly used for detailed muscle activity monitoring in the laboratory as they have been shown to achieve activity classification accuracies of up to 90% – 96.3%, however, large electrode arrays are time consuming to setup and not suited for long-term or routine use beyond the laboratory. To enable the capture of muscle activity beyond the laboratory, recent works have demonstrated that by locating optimal positions on the muscle for measuring activity and targeting specific areas on the muscle using wireless sEMG sensor nodes or small electrode arrays, movement identification can also be obtained using significantly fewer surface EMG electrodes for routine muscle activity monitoring with 77% – 97% classification accuracy achievable using 4 – 20 EMG channels. The development of muscle models and machine learning techniques, such as neural networks, also allow sEMG to be used to estimate muscle force. However, due to variations between subjects, per subject training of estimation models is still necessary for obtaining muscle force estimates with RMS errors from 9.7%. While these developments alleviate some of the challenges associated with monitoring outside laboratories, continuous monitoring of daily activities in a free-living environment is still a major challenge as error recovery techniques from EMG signal interference and skin motion, which alters the muscle position of the electrode, still require further work.

Advances in ground reaction force estimation using pressure insoles and inertial sensors have also enabled kinetic analysis beyond the laboratory. Calibration methods and approximation models have enabled pressure insoles to capture detailed foot pressure information, including GRF and pressure distribution, with greater consistency. Nonlinear approximation models, such as multi-layer perceptron (MLP) network and locally linear neuro-fuzzy (LLNF) model, were found to result in greater prediction accuracies when compared with a linear model. The proposition of force estimation from inertial sensing creates an opportunity for realising low cost continuous kinetic analysis beyond the laboratory with GRF estimates within 11% of the fitted mean obtained, however, accuracy is limited for complex movement, and further developments are still necessary to improve estimation accuracies for a greater range of activities.

IV. Conclusion

The study of solid human biomechanics enables the assessment of the structure and function of the human body, which is important for monitoring a person's health and wellbeing, and also monitoring performance in the workplace and in sports. Established analysis techniques have traditionally relied upon laboratory-based observation and instruments, which are costly and limit the range of applications that can be studied. Fortunately, advances in wearable sensing technologies and processing techniques have enabled the study of biomechanics beyond the laboratory.

The development of lightweight exoskeletons, micro-inertial sensors, mobile force plates, pressure insoles, and wireless surface electromyography have made monitoring kinematics and kinetics in the natural free living environment more feasible. However, costs, complex and time consuming setup procedures, and reliance on multiple sensor nodes still limits the widespread use of these technologies for continuous monitoring of biomechanics. For example, while micro-inertial sensors are small, lightweight, and have demonstrated the ability to capture human kinematics and ground reaction force for kinetics, the number of sensor nodes typically required is undesirable for long-term use, and makes setup complex and time consuming. A number of challenges, such as measurement drift, external interferences, and muscle variations, also affect the accuracy and resilience of these technologies.

To realise practical wearable sensing technologies that can be used in routine human biomechanics studies, further work is still necessary to improve both the sensing hardware and software. Further work to improve drift compensation, error recovery, and estimation accuracy in uncontrolled natural environments is necessary. Multi-sensor fusion techniques that fuse complementary sources of information to further improve accuracy and resilience against interference is also an important consideration for future research.

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