New Perspectives Through Emerging Technologies

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Preliminaries

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Introduction:

Since Galenus (129-201 a.C., physician and philosopher in the Roman empire) approached the study of physical exercise and training of gladiators, classifying muscles and their function in his *De Motu Musclorum*, the assessment of motor activity and physical function has been the object of innumerate applied research. Great minds, such as Leonardo da Vinci (1452-1519), with his study of limb motion, and Galileo Galilei (1564-1642), in his *De Animalium Motibus*, opened the path to the systematic study of human motion, while Borelli, in his *De Motu Animalium* (1680; Figure 1), was the first to apply to a traditionally biological topic the rigorous analytic method developed by Galileo.

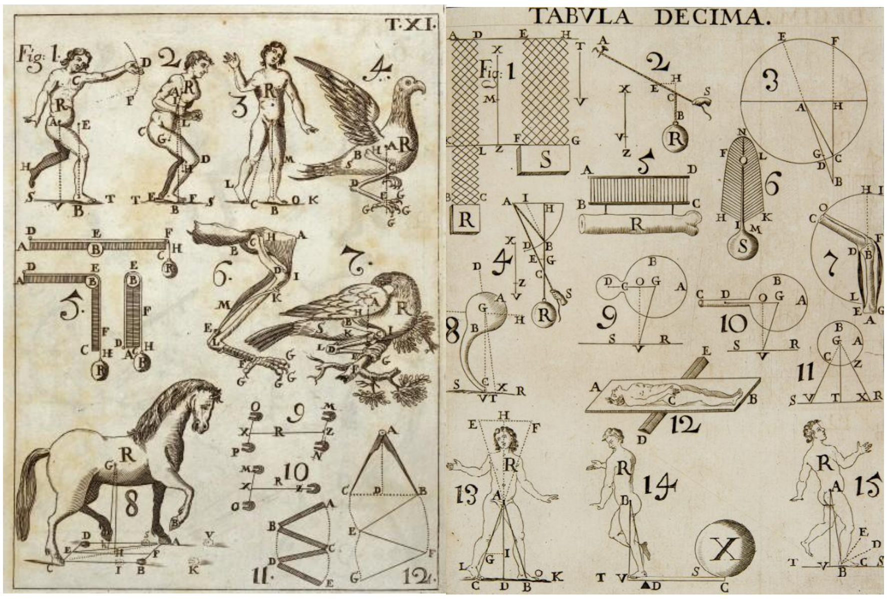
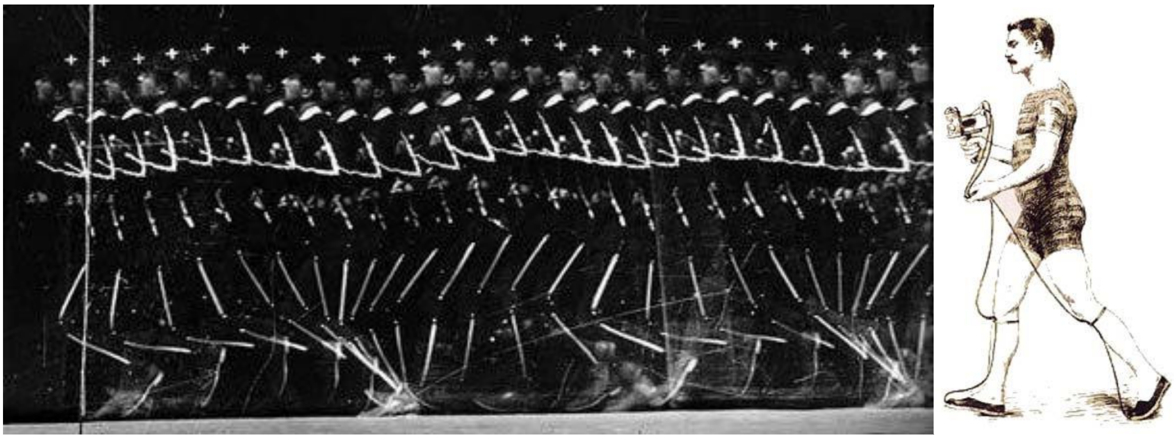


Figure 1: Giovanni Alfonso Borelli, *De Motu Animalium*.

From a scientific perspective, the assessment of motor activity entails the definition and measurement of objective descriptors (e.g., number of repetitions, durations, distances, angles), intended to characterize function, and the essential introduction of objective measurement tools demonstrated its disruptive potential since the pioneering studies by Etienne Jules Marey (1830-1904, physiologist and inventor) and Eadweard James Muybridge (1830-1904, photographer): their chrono-photogrammetric method exploited the innovation of the time in photographic technology to quantify, for the first time, segmental kinematics of living subjects during the execution of different motor tasks and is considered the starting point of modern quantitative motion analysis (Figures 2 a and b).



(a) (b)

Figure 2: a) Chrono-photogrammetry (E.J.Marey and E.J.Muybridge); b) device for the quantification of foot pressure (E.J.Marey).

Ever since, a number of different tools and approaches have been exploited to further develop and integrate the quantitative assessment of human motion, from the simple use of paper stripes and inked feet for the quantification of step and stride length, and chronographers for speed, to the more advanced technological solutions allowed by the spread use of personal computers in the early 1980s. The progressive advances in the field of electronics and computer sciences, together with the concurrent reduction of costs, led, in the following decades from the first two camera stereophotogrammetric systems, for the automatic quantification of segmental kinematics, to the most advanced modern systems integrating multiple cameras together with several other measurement devices, such as load cells and platforms for the quantification of reaction forces, electromyography for muscle activity, pressure insoles, and many others.

Nowadays, integrated motion analysis systems have reached a high technological level and simplicity of use, becoming a *de-facto* standard for the detailed and accurate quantification of human motion in laboratory conditions. They are extensively used for the characterization of motor alterations, the design and evaluation of clinical interventions, and the monitoring of the follow-up in specific pathological conditions (e.g., arthritis, stroke, cerebral palsy, Parkinson disease), as well as for the evaluation of performance, the optimization of training, and the prevention of injuries in sport applications.

Despite the valuable quantitative information provided by these systems, their use remains limited to laboratory, or, at least, to controlled environment conditions, while the assessment of motor activity and performance is expected to describe what people do in real life.

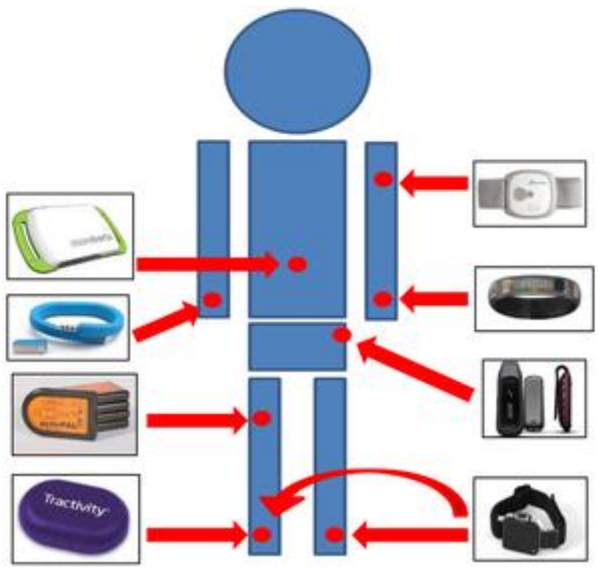
The technological solution required to respond to this need must:

- be un-obstructive and self-contained, not to alter the natural performance of motor activities in real life conditions;

- allow long recordings with sufficient sampling frequency, to guarantee an appropriate description of motion and take into account physiological variability;
- be simple to use and low-cost, to support extensive assessment by non-technical operators in different contexts.

Despite the several attempts to produce measurement systems with these characteristics in the past decades (e.g., portable systems integrating electro-goniometers, foot-switches, pressure insoles, and/or electromyography), none of them actually satisfied all the afore-mentioned requirements. Only in recent years, the disruptive development of mobile technologies provided the first effective response to the need of pervasive real-time motor assessment.

Wireless wearable sensors have become available on the market, ready to be exploited in a number of technological solutions aiming at the quantitative assessment of motor activity and performance. Among these, magneto-inertial measurement units have certainly gained a key role; providing miniaturized measurement units integrated in minimally invasive set-ups (i.e., a single wireless tri-axial sensor or a small network, mounted on bands or straps, with integrated power supply and data transmission), allowing the measurement and recording of real-time orientation, angular velocity and acceleration of body segments in free environment. They have found application for different types of motion analysis assessment, from activity monitoring to traditional motion analysis, also opening the path to novel approaches to the objective assessment of motor control (Figure 3). In addition to this, an innovation coming from the gaming industry (Kinect, Microsoft) has served motion analysis researchers with the first low cost video-based solution allowing the automatic reconstruction of segmental kinematics not requiring the placement of any markers on the analyzed subject.



<u>Figure 3: numerous wireless sensors and body worn locations</u>

All these novel emerging technologies have readily found application and have the breaking potential of priming a new era in the field of motor assessment. They certainly have the advantage of providing informative, quantitative data for the application of traditional approaches, reducing work load in terms of time, improving inter- and intra-rater reliability, enabling systematic analysis and objective evaluation of concurring factors, facilitating population classification, characterization and longitudinal monitoring; but they are also opening the path to novel perspectives in the objective assessment of motion, as for the evidence-based characterization of specific aspects of motor control and development.

As exciting as the potential provided by these innovative technological tools can appear, its effective deployment to applied research requires a certain level of critical awareness; specific advantages and the possible limitations have to be considered to support the informed selection of the most suitable solution for each specific application. Different technological solutions have become available for certain types of assessment, and, on the other hand, the same devices can be exploited for different applications using different computational approaches.

Far from aiming to be conclusive, this chapter is intended to provide a synthetic overview of the broad and developing landscape of novel technological solutions for the measurement and assessment of youth physical activity. Considering the continuous on-going advances in the field, the authors want to provide a schematic scope-oriented out-line of the possible solutions, the basic references supporting further specific in-depth analysis, highlighting key advantages and limitations.

A synthetic out-line of the state of the art: A brief overview of the literature

Given the number of technological solutions proposed and available for the quantitative assessment of motor activity, they have been organized in a scope-oriented schematic out-line in Table 1 and Table 2, to summarize and organize the key concepts and terms, and introduce basic references. In particular, Table 1 outlines solutions proposed for quantitative activity monitoring, considering both product and process-oriented approaches, while Table 2 refers to quantitative motion analysis, which is a detailed process-oriented description of specific motor tasks.

Table 1. Activity monitoring

Scope	**Target**	**Target variable**	**Technology**	**Computational Approach**
Activity monitoring	Product	Space parameters	Magnetometer (Barnes et al, 2018)	Dynamic time warping; cross-correlation (Barnes et al, 2018)
	Process	Space parameters; time parameters	Magnetometer (Barnes et al, 2018); Force sensitive resistor (Xiao and Menon, 2014)	Dynamic time warping (Barnes et al, 2018); contour mapping (Barnes et al, 2018); Extreme learning machine classifier (Xiao and Menon, 2014)
	Daily living	Visual; time parameters; space parameters	Electro-oculography (Bulling et al, 2011); gyroscope (Leutheuser et al, 2013); Radio frequency identification (RFID) (Spinney et al, 2015)	Support vector machine (Bulling et al, 2011; Leutheuser et al, 2013); *k*-Nearest Neighbor classifier (Leutheuser et al, 2013); classification and regression tree (Leutheuser et al, 2013); linear correction (Spinney et al, 2015)
	PA intensities	Visual; tangible; frequency parameters	Magnetometer (Crossley et al, 2018); 3-D printing (Khot et al, 2014); micro electromechanical system (Clark et al, 2016; 2017)	Vector of dynamic body acceleration (Crossley et al, 2018); visual inspection (Crossley et al, 2018); arithmetic mean (Khot et al, 2014), spectral density (Clark et al, 2016; 2017), Fourier transformation (Clark et al, 2016; 2017).
	PA type/characterisation	Time parameters; space parameters; visual	Heart rate + calorimeter (Duncan et al, 2011); video sensor (Zhang et al, 2011; Loveday et al, 2016); force sensitive resistor (Fulk and Sazonov, 2011); inclinometer (Crouter et al, 2018)	Feature extraction (Duncan et al, 2011); Machine learning (Duncan et al, 2011); Good features detector (Zhang et al, 2011); binary coding (Loveday et al, 2016); Support vector machine (Fulk and Sazonov, 2011); feature extraction (Crouter et al, 2018)
	Global position	Space parameters	WiFi Real-time locating system (Loveday et al, 2016); Global positioning system (Holliday et al, 2017); WiFi + accelerometer (Kjaergaard et al, 2012)	Proximity (Loveday et al, 2016); location features detector (Holliday et al, 2017); hierarchical cluster analysis (Kjaergaard et al, 2012).

Definitions. *Magnetometer*: a device measuring the direction, strength, or relative change of a magnetic field at a given location; terrestrial magnetic field is usually assumed as reference. *Force sensitive resistor*: a material whose resistance changes when a force, pressure or mechanical stress is applied. *Electro-oculography*: a device for measuring the corneo-retinal standing potential that exists between the front and the back of the human eye. *Gyroscope*: a device used for measuring or maintaining orientation and angular velocity. *Radio frequency identification*: the use of electromagnetic fields to automatically identify and track tags attached to objects. *3D printing*: is where material is joined or solidified under computer control to create a three-dimensional object. *Micro electromechanical system*: microscopic devices merged at the nano-scale. *Calorimeter*: an object or device used for calorimetry, or the process of measuring the heat of chemical reactions or physical changes as well as heat capacity. *Inclinometer*: an instrument used for measuring angles of slope, elevation, or depression of an object with respect to gravity's direction. *WiFi Real-time locating system*: uses a wireless network to automatically identify and track the location of objects or people in real time, usually within a building or other contained area. *Global positioning system*: a system that uses satellites to provide autonomous geo-spatial positioning. *Accelerometer*: a device which measures the acceleration of a body in its own instantaneous rest frame.

Activity monitoring

Process-oriented assessment is considered an important tool in the development of children's physical activity programmes, motor competence and indeed physical development. Problematically, traditional assessments of child motor competence and physical activity have been conducted with either direct observation, or accelerometers, in the case of the latter. Technological development has progressed to a point where multi-disciplinary teams are utilising engineering-based tools or analyses, applied to human movement, and whilst in its infancy, promising developments have prompted novel perspectives. In Barnes et al (2018), a magnetometer, which measures magnetism—either the magnetization of a magnetic material like a ferromagnet, or the direction, strength, or relative change of a magnetic field at a given location, affixed to the dominant wrist on children (10-12y), was worn during a motor competence assessment. The raw signal output was treated with novel analytical techniques, namely Dynamic time warping (DTW), which enables two signals to be artificially matched, (i.e., where children complete identical tasks but over a shorter or longer time-frame), facilitating direct comparison between signals, or, in this case, children, removing time-based discrepancies. Pairwise comparison across a cohort produces a similarity matrix of all child to child correlations. Visualisation of the relative performance in 3-dimensions, using multi-dimensional scaling of the similarity matrix, shows a 'performance sphere' (Barnes et al, 2018) in which children sit on concentric shells of increasing radius as performance deteriorates. The relative distance between children within the multi-dimensional scaling can then be used to create an automated sensor-based rank scoring. This technique was also shown to provide "product" assessments, by reducing the dimensionality, removing process measures, product can be efficaciously plotted against time (Barnes et al, 2018). Further work highlighting our potential to assess process-oriented measures was demonstrated by Xiao, et al. (2014), who utilised a force sensitive resistor, and applied it to the upper extremities to analyse force myographic signals of the forearm. The authors were able to accurately identify upper extremity movements during a controlled drinking task (92% accuracy). Xiao, et al. (2014) also utilised a form of machine learning to learn and classify the data, an extreme learning machine (ELM) classifier, where a training approach was taken, where the ELM classifier was 'taught' or 'trained' to model the force myography trace.

Daily living

Developments have not only ensued for short-term, acute bouts of activity. Technological advancement and integration have facilitated novel perspectives into daily free-living activities. Bulling, et al. (2011) reported an accuracy of 76% when identifying activities such as text copying, reading a printed paper, taking hand-written notes, watching a video, and browsing the web. The authors assert that recording the movements of human eyes, otherwise termed *'electrooculography'*, can successfully be used to identify certain activities and may be feasible in wider applications, such as accurately identifying non-traditional activities (e.g., rock climbing), which would inherently be missed by common sensing modalities. However, whilst promising, further investigations to corroborate the effectiveness of this technique are required in order to up-scale this technology. The application of cameras, in different forms, to characterise activity has demonstrated variable success when complemented with novel analyses. Leutheuser, et al. (2013) utilised machine learning, in combination with feature extraction, on gyroscopic data and could correctly identify basic free-living physical activities with up to 89.6% accuracy. The use of machine learning with gyroscopic signals appears to allow identification of specific movements with high accuracy. However, at present activity classification using this method appears to only be able to identify basic movements. Notwithstanding potential drawbacks, when integrated with more traditional sensor-based devices, (e.g., accelerometers), the limitations of this approach are somewhat ameliorated (Leutheuser et al, 2013). Further evidence exists, not only in the form of wearables, but rather, 'nearables'; Spinney et al (2015) used Radio-frequency identification (RFID) to successfully demonstrate patterns of physical activity, standing, and sitting by office workers. This study highlighted the relationship between location, light physical activity and sitting, across multiple office environments, and although preliminary, the explanatory power of the technique is promising.

Physical activity intensities

Magnetometers have not only been applied in the assessment of process-based metrics, but preliminary studies in children have shown them to be useful in the assessment of turning, or altering direction (Crossley et al, 2018). Recently, it has been suggested that turning is power intensive; and given the sporadic and irregular movement patterns of children, may be an important consideration for physical activity assessment. Crossley et al (2018), firstly highlighted significantly higher energy expenditure when the angle and speed of turn was increased, then demonstrated that magnetometry can be used to highlight where and when such turns take place. By incorporating accelerometry with novel technology (i.e., magnetometry), the additional energy expenditure as a result of turning can be taken into consideration. Additional wearable-based technology, in the form of micro-electromechanical systems devices (MEMS), which are microscopic fabrications such as accelerometers or magnetometers, has shown promise in the assessment of physical activity intensities. MEMS devices were applied in either a controlled fitness test (Clark et al, 2016), or in free-play (Clark et al, 2017), in children aged 3-11 y. The novel, microscopic technology was complemented with novel analytical procedures, where Fourier transformations facilitated the use of the frequency domain (as opposed to traditional time-space), in addition to hierarchical clustering of metrics. The resultant technology-analytics combination demonstrated that frequency-based metrics cluster with motor competence and physical activity levels (Clark et al, 2017), are indicative, and potentially predictive, of physical fitness (Clark et al, 2016). Novel wearable technology has been showcased to provide novel insights, however, 'tangible' technology has been shown to not only to measure and enhance physical activity, but also improve knowledge and understanding of personal activity levels (Khot et al, 2014; Crossley et al, 2019), where the Precaution Adoption Process Model (Weinstein, 1988), from the Stages of Change (Procahska and DiClemente, 1992), suggests that an individual is unlikely to proceed to the contemplation stage unless they become aware that their behaviours are inadequate. Khot et al (2014) advocate a novel approach of representing physical activity in the form of material, 3-D printed, artefacts, where a 3-D printing device was located in households, and manufactured three-dimensional "print-outs" of corresponding heart rate data. This novel contribution of this work is the first to highlight a conceptual understanding of the relationship between material representations and physical activity, and is promising, given the suitability of being located across households, rather than research labs, potentially reducing participant burden. Further work, by Crossley et al (2019), has also reported that, when supplied with 3-D representations of physical activity, the majority of children and adolescents are able to identify whether they did or did not meet, or how close they were to meeting, PA guidelines, and encouraged a healthier, more active lifestyle.

Physical activity characterisation/type

A further example of instruments used when attempting to characterise human movement with novel analytics is force sensitive resistors, which contains a material whose resistance changes when a force, pressure or mechanical stress is applied. Fulk and Sazonov (2011), for example, mounted the device in the footwear of participants to measure plantar pressure and record the acceleration signal, thereby inferring postural activity in stroke victims. The raw signal from the device was analysed using a support vector machine, which is a supervised machine learning technique that can use training examples to learn the dependencies in the data. The computer was taught how the signals from the sensors can predict postural activities, and the learned model was then applied to the recognition of previously unseen data (Fulk and Sazonov, 2011). Across all participants, accuracy in identifying postural activity of 99-100% was found, indicating that with a modest sample size, and applying the combination of acceleration and pressure traces, postures may confidently be assessed.

Conversely, when focussing more broadly on inferring activity type, and not specifically falls or basic movement, Duncan, et al. (2011) achieved 97% accuracy in the assessment of walking and running in the laboratory and 84% accuracy in the field, using feature recognition. This particular method appears to be increasingly successful when energy expenditure assessment in combined, in order to infer activity type, rather than the accelerometer signal alone. However, once in field testing was performed, the accuracy falls by 13 percentage points, indicating reliability issues outside of a controlled setting, and highlights the need for more robust machine learning techniques to be developed for free-living activity.

So far, novel technology has been showcased in the form of MEMS, 3-D printing, force sensitive resistors, RFID, gyroscopes and magnetometers. A further novel technology being pioneered in the assessment of physical activity in children is inclinometers, which measure angles of slope, elevation, or depression of an object with respect to gravity's direction. Crouter et al (2018) demonstrated, in a comprehensive evaluation of time spent in sedentary behaviours, utilising inclinometers, accelerometers and indirect calorimetry, that inclinometers can facilitate precise estimates of sedentary behaviour during free-living activity in youth.

Global position

Up to this point in the chapter, it is clear that refining and developing emerging technologies should remain a strong focus, so that adequate levels of accuracy and confidence may be established and further improved upon. Moreover, it is clear that the technologies and techniques by which physical activity can be measured will continue to proliferate. Cluster analysis has been utilised for the assessment of frequency-based metrics for microscopic technology (Clark et al, 2016; 2017). This analytical technique involves the use of algorithms to separate a population into clusters or groups based on various parameters, such as activity behaviours. Kjaergaard et al (2012) employed the same analytical protocol, yet focussed on group activity, rather than individual activity, using ‘flock detection’ (i.e., multiple persons forming a cohesive whole) and Wi-Fi signals to identify and track pedestrian flocks with 87% accuracy. Whilst the novel application of this technology is promising, problems emerged regarding flock proximity (i.e., the ability of the cluster analysis to successfully differentiate between flocks was encumbered when various groups become entwined or proximity was too high). This indicates that the mathematical modelling process applied to the novel technology requires further refinement.

The importance of location-based information, to better inform physical activity, has recently come to the fore, whether that be restricted to specific locations, such as an office, or wider. Holliday et al (2017) sought to highlight necessary wear time for global positioning system devices. They demonstrated that in general, minutes of all physical activity intensities spent in a given location could be measured with over 80% reliability, including fitness facilities, schools, and footpaths (Holliday et al, 2017). However, in order to accurately monitor location-based activity in parks and roads, a wear time minimum of 5 days is required, and PA assessment in homes and commercial areas necessitates over 19 days of monitoring to yield accurate results (Holliday et al, 2017). Furthermore, this approach for the assessment of free-living PA in youth is likely feasible as current, global surveillance practices already utilise multi-day accelerometry, such as the National Health and Nutrition Examination Survey (NHANES) in the USA (Freedson and John, 2013), Brazilian birth cohorts (da Silva et al., 2014), the Growing up in Australia Checkpoint (Wake et al., 2014), and Biobank investigations in the UK (http://www.ukbiobank.ac.uk/about-biobank-uk/). Moreover, numerous accelerometers include global positioning attachments, compatibility or in-built functionality, which represents the opportunity for a relatively straightforward adoption.

Finally, global position work in the form of WiFi real-time locating systems, showcased in Loveday at al (2016), can be used to enable remote assessment of intervention adherence. The proximity-based assessment indicated that office workers may spend a proportion of working hours outside of their office. This, evidently, has implications for assessing the efficacy of office based environmental interventions; and could be extended to children’s time spent in classrooms, and adherence to location-based interventions. This novel technology may provide more robust means of assessing intervention efficacy, as opposed to comparatively time consumptive, participant burdensome, and inaccurate self-report measures. Although refinement and development are clearly necessary, the adoption of novel technologies will provide researchers with a more complete understanding of physical activity behaviours than has previously been available.

Video based

Whilst actigraphy-based sensors have become the *de facto* tool for the objective assessment of physical activity, the use of other sensors (i.e., cameras, force sensitive resistors, electrooculography) to achieve the same, or advancing outcomes has grown. It is evident that the aim of many emerging analytical technologies and techniques has been to aid in better detecting the quality and type of activity that a person is undertaking. Zhang, et al. (2011) incorporated motion cameras to automatically recognise patterns of movement, albeit in young adults, and demonstrated that basic motor movements could be recognised with 85% accuracy. Notwithstanding this promising accuracy, Zhang, et al. (2011) assert that this upper limit of accuracy could be an artefact of the device, as acquired images are often blurry and ineffective in capturing feature points, which may be an inherent limitation of cameras. Furthermore, contemporary work has also demonstrated that wearable cameras can be used to assess children’s physical activity and behaviour recall (Everson et al, 2019). However, particularly with respect of children and adolescents, wearable cameras carry some ethical and technical challenges, as Everson et al (2019) highlight, parents and children reported that wearable cameras are burdensome and invade privacy.

Further vison-based approaches for the assessment of physical activities has been showcased by Loveday et al (2016). Whilst there is a plethora of reasons for the prevalence of sedentary behaviours, a possible contributing factor to our lack of intervention success is the current lack of behavioural context offered by accelerometers and posture sensors. Utilising concurrent electrical energy monitoring and wearable cameras as measures of television viewing, Loveday (2016) found that, on average, televisions were switched on for 202 minutes per day, yet only visible in just 90 minutes of wearable camera images with a further ~50 minutes where the participant is in their living room, but the television is not visible in the image. The authors highlight that the high number of un-codeable images from the wearable cameras (deployed on a lanyard or fixed to clothing) may therefore not be conducive to a reliable measure of television viewing. In order to counteract this limitation, the method of camera affixation, and therefore resultant field of view, must be acutely considered, but remains a promising novel technology in the assessment of physical activities.

Within the same study, Loveday (2016) utilised indoor monitoring with the same video monitors, to assess where individuals accumulated their sedentary time. Utilising this novel technology and approach, quantifying time spent in specific rooms, or communal areas becomes a realistic accomplishment. Given the potential, it would be advantageous to investigate the utility of this technology in settings which may offer more location possibilities with populations such as children and adolescents, who are likely to spend their time in varied locations.

Table 2. Motion analysis

Scope	Task	Target	Target variables	Technology	Computational Approach
Motion analysis	Gait	Gait events (foot contact and toe-off) and temporal parameters (stride, step, stance, swing time)	Acceleration; angular velocity; plantar pressure	*Wearable:* accelerometers (Caldas, Mundt, Potthast, Buarque de Lima Neto, & Markert, 2017; Pacini Panebianco, Bisi, Stagni, & Fantozzi, 2018; Taborri, Palermo, Rossi, & Cappa, 2016); gyroscopes (Caldas et al., 2017; Pacini Panebianco et al., 2018; Taborri et al., 2016); Foot switches (Taborri et al., 2016); foot pressure insoles (Taborri et al., 2016) *Non wearable:* Markerless 2D video camera (Castelli, Paolini, Cereatti, & Della Croce, 2015; Verlekar, Soares, & Correia, 2018); Kinect (Latorre, Llorens, Colomer, & Alcañiz, 2018)	*Wearable:* Peak identification (Pacini Panebianco et al., 2018); threshold identification(Pacini Panebianco et al., 2018; Taborri et al., 2016); artificial intelligence (Caldas et al., 2017); machine-learning (Taborri et al., 2016) *Non wearable:* 2D markerless technique(Castelli et al., 2015); Kinect-based methods (Latorre et al., 2018)
		Kinematics	Joint angles	*Wearable:* IMUs (Caldas et al., 2017; Picerno, 2017; Teufl, Miezal, Taetz, Fröhlich, & Bleser, 2018) *Non wearable:* Markerless 2D video cameras (Colyer, Evans, Cosker, & Salo, 2018) Depth-sensing cameras (narrow-baseline binocular-stereo camera systems or active cameras) (Colyer et al., 2018)	*Wearable:* artificial intelligence (Caldas et al., 2017); sensor fusion (Teufl et al., 2018) *Non wearable:* Machine learning; Generative or discriminative algorithms (Colyer et al., 2018)
		Motor control performance	Variability structure of trunk/limb kinematics	*Wearable:* IMUs (Stergiou, 2016) *Non wearable:* Markerless 2D video camera (Verlekar et al., 2018)	*Wearable:* Non-linear measures of human motion (Stergiou, 2016) *Non wearable:* Markerless 2D video camera (Verlekar et al., 2018)
	Posture	Postural sway parameters	Trunk sway (acceleration and displacement)	Accelerometer (Mancini et al., 2012; Palmerini, Rocchi, Mellone, Valzania, & Chiari, 2011)	Frequency domain and time domain analysis (Mancini et al., 2012; Palmerini et al., 2011)
	Other tasks of daily living	Space-time parameters; joint kinematics; body segment kinematics	Joint angles; foot contacts; time events	IMUs (Bergmann, Mayagoitia, & Smith, 2010; Bergmann, Mayagoitia, & Smith, 2009; Camomilla, Bergamini, Fantozzi, & Vannozzi, 2018; El-Gohary et al., 2013; Filippeschi et al., 2017; Fino, Frames, & Lockhart, 2015)	Computational approaches applied to the different gait target variables

Definitions – *Footswitch*: a pressure sensor used to detect on-off of ground contact of specific points under the foot. *IMU*: Inertial measurement unit, a device integrating a 3D accelerometer and a 3D gyroscope.

Motion analysis

Human motion analysis, with particular reference to the evaluation of gait, was traditionally process oriented, aiming at the quantitative assessment of joint kinematics and kinetics in time, to be compared with reference normality patterns for biomechanical analysis, diagnosis and/or follow-up evaluation. Gait analysis is extensively used for the quantitative assessment of motor function in basic research as well as clinical and sport applications. The traditional implementation of motion analysis relies on laboratory instrumentation, stereophotogrammetry and force platforms being just the basic laboratory set-up, but the availability of inertial measurement units (IMU) rapidly gained a primary role for the ecological assessment out of the lab. Wearable, cheap and self-contained, IMUs are now extensively exploited for the ambulatory evaluation of gait, as described through spatio-temporal parameters, joint kinematics, as well as newly proposed metrics for characterization of the underlying motor control (e.g., variability, stability, complexity, automaticity).

Spatio-temporal parameters (IMUs)

Gait timing is considered of primary importance for the characterization of gait alterations. The quantification of gait temporal parameters (GTP) (i.e., step and stance times) requires, first of all, to identify gait events (GE) (i.e., heel strike and toe off). GE can be estimated from measurements obtained using various portable sensing technologies, such as foot-switches, pressure insoles (in both cases identifying when the contact pressure under a specific area of the foot crosses a certain threshold), as well as IMUs. In particular, segment angular velocity and acceleration as quantified by IMUs led to the need for appropriate gait segmentation methods (Taborri et al., 2016) and to the development of a number of algorithms. These were proposed and applied in different conditions, exploiting different sensor positions, analysing different variables, with different computational approaches. A recent work (Pacini Panebianco et al., 2018) analysed all these different implementation characteristics, highlighting how all these factors affect GE and GTP estimation. No proposed algorithm is generally preferred over the others, and specific characteristics have to be taken into account based on the experimental conditions (e.g., number/type/placement of sensors) and research questions (e.g., mean/variability of the selected gait variable).

Kinematics (IMUs)

Body-worn IMUs were also proposed for the estimation of segment orientation and joint angular kinematics (Picerno, 2017; Teufl et al., 2018). Using sensor fusion algorithms (e.g., variations of the Kalman filter or optimization based methods (Teufl et al., 2018), or artificial intelligence methods (Caldas et al., 2017)), it is possible to estimate the IMU's orientation in reference to a global coordinate system (Picerno, 2017; Teufl et al., 2018). Combining more IMUs attached to linked body segments, it is possible to estimate the joint kinematics of the specified segments. Commercially available solutions usually provide a 3D sensor's orientation or even protocols for estimating 3D joint kinematics during gait. In this case, the user must be aware of the issues related to ferromagnetic disturbances, to sensor-to-segment alignment and to the proprietary sensor fusion algorithm's accuracy when estimating the 3D sensor's orientation.

The drawbacks concerning IMU systems when measuring human motion are mainly that IMU-based orientation estimation suffers from drift due to the integration of noisy gyroscope measurements, and that the incorporation of magnetometer measurements is typically based on the assumption of a homogeneous magnetic field, which is often violated (Teufl et al., 2018). The main approaches (Picerno, 2017) proposed in literature for drift correction are (1) kinematical reset or sensor fusion), (2) by using a mixed approach of the two previous methodologies, and (3) by using neural network prediction. These approaches have been proven efficient in particular for the evaluation of low-frequency cycling gestures like walking. For the second limitation, there are efforts to develop methods for handling magnetic disturbances or completely omit magnetometer data but still no gold standard method has been identified because environmental settings are unpredictable and not very standardisable from this point of view.

Other tasks

Similarly, wearable sensing supports the quantitative assessment of other non-gait human daily tasks (e.g. posture, stairs, turns), with the aim of assessing and defining the functional status of a person. Quantitative measures of (process) task performance, mainly proposed and used for clinical purposes (El-Gohary et al., 2013; Fino et al., 2015; Mancini et al., 2012; Palmerini et al., 2011) can be applied in several different contexts (e.g., for monitoring how personal postural oscillations vary during the day, after sports, and in relation to tiredness). For example, if static posture is accurately recognized during daily activities, a number of quantitative measures could characterize the quality of the postural oscillations, by means of one accelerometer positioned on the trunk. These measures allows quantification of postural displacement, acceleration and, if of interest, tremor (e.g., in participants with Parkinson disease (Mancini et al., 2012; Palmerini et al., 2011)).

Continuous monitoring of turning, in terms of anatomical joint angles (El-Gohary et al., 2013), and type of turns (turning on the ipsilateral or on the contralateral turn, respectively) (Fino et al., 2015) during spontaneous daily activities were proposed to help clinicians and patients determining who is at risk of falls and could benefit from preventative intervention. A similar approach have been proposed for assessing the quality of stair ascent, allowing the identification of gait events (initial contacts) (Bergmann et al., 2010) and lower limb joint angles (Bergmann et al., 2009). Last but not least, it is possible to focus on upper limb movement, in order to track and assess the quality of upper limb joint kinematics during the day (Filippeschi et al., 2017).

The above tasks are only some of the possible examples. By extracting classic biomechanical parameters (Camomilla et al., 2018), or developing specific algorithms for assessing limbs coordination (Bisi, Pacini Panebianco, Polman, & Stagni, 2017) based on body segment acceleration/angular velocities, an automatic evaluation of subjective performance during physical activity and/or specific motor tasks is possible (e.g,. for children motor competence assessment (Bisi, Tamburini, Pacini Panebianco, & Stagni, 2018; Grimpampi, Masci, Pesce, & Vannozzi, 2016; Masci et al., 2013; Masci, Vannozzi, Getchell, & Cappozzo, 2012)).

Video based motion analysis

Recently, vision-based motion analysis methods within sports and rehabilitation applications have evolved substantially thanks to innovative (markerless) techniques developed primarily for entertainment purposes. This allowed biomechanical research to contribute a vast amount of meaningful information in sports and rehabilitation applications (Colyer et al., 2018). Literature shows that some of these systems are capable of measuring sagittal plane angles to within 2°–3° during walking gait (Colyer et al., 2018). However, accuracy requirements vary across different scenarios and the validity of markerless systems has yet to be fully established across different movements in varying environments.

The four major components of a markerless motion capture system are (1) the camera systems that are used, (2) the representation of the human body (the body model), (3) the image features used and, (4) the algorithms used to determine the parameters (shape, pose, location) of the body model (Colyer et al., 2018). Body pose on a given image is inferred by algorithms, which can be classified as 'generative' or 'discriminative': Generative algorithms use model parameters to generate a hypothesis that is evaluated against image data and then iteratively refined to determine a best possible fit; discriminative algorithms start from image data to directly infer model parameters (Colyer et al., 2018).

Each of these components have limitations and, depending on the specific implementation choice, influence the final accuracy and validity of the reconstructed motion data. Accuracy evaluation, performed by comparing kinematic output variables obtained by markerless system and by marker-based optoelectronic ones was mostly evaluated on slow movements (typically walking gait), highlighting that transverse plane rotations are currently difficult to extract accurately and reliably by markerless technologies. To verify the utility of these approaches in physical activity applications, much quicker movements need still to be thoroughly assessed.

Key and Emerging Issues

Activity monitoring

Research into physical activity is expanding to incorporate a multitude of different technologies and analytical techniques, and within each approach exists a series of constraints that must be considered. This chapter has identified an array of technological developments, showcasing high accuracies across physical activity measurement, with success in activity classification, success in identifying global position, success in quantifying intensity of movements, and even daily living; all whilst using various wearable, nearable or tangible technology.

Notwithstanding, the application of such novel technology remains in its infancy; many of the studies were exploratory, under-powered or require further development to establish reliable, accurate measures across larger samples, and this raises a number of key and emerging issues. Based on the findings highlighted in Table 1, four key issues were emergent, with reference to activity monitoring: (1) developing performance, reliability and constraints, (2) scaling up of datasets/sample size, (3) utilisation of interventionist study designs, and (4) integration of technologies.

Firstly, an important consideration when classifying data is that large datasets obtained through novel sensing units will result in multiple features, which necessitates time-consuming data analysis, and may significantly impact the classification methods. In fact, large feature sets may need huge datasets for training computational methods that could be unavailable (the *so-called* curse of dimensionality) and, notwithstanding, would slow down the development of the classification system. This issue of developing the performance, reliability and constraints from novel technology is exacerbated by the relatively small sample sizes currently recruited, given that a number of participants' data is often 'withheld' to 'train' appropriate analytical frameworks.

Given that usage of some technology for PA assessment is in its infancy, it is unsurprising that there exists an over-propensity of cross-sectional study designs, and a dearth of interventionist studies. This is likely an artefact of the stage of development and refinement. In order to progress the application and acceptance of novel technology for PA assessment, the performance and reliability of the technology and data output must be affirmed in response to interventions, to elucidate whether such novel outputs can be positively (or negatively) impacted, and likewise, to detect change and normative values over time, through the course of motor development, thereby highlighting the constraints novel technology operates within.

A further, emergent issue, manifest in the activity monitoring literature is one of technology integration. Some studies utilised novel technology in isolation, yet a number of groups have advocated the combination of technology of different types, to better measure physical activity (Table 1). Novel technological approaches to PA measurement may be tentatively demarcated into wearable – specific to body-worn technology such as inclinometers or magnetometers, nearable – technology located 'near' participants, usually, to define position or proximity, and tangible – a physical output that the participant can feel and touch, where the physical form of the output is defined by preceding activities or intensities of movement. Whilst integration of these technology types is pragmatic and attractive, the integration of multiple inputs and outputs brings difficulties, including time-alignment of sensor outputs, harmonization of different data, the pairing of data measured in different space, (e.g., time vs frequency domain), and indeed, time taken to process multiple data sources. Notwithstanding the self-evident challenges, the integration of such technology is intertwined with the development of performance, reliability and constraints, which must remain a strong focus.

Motion analysis

As presented in the previous section, IMUs are a promising wearable solution for the characterization of different motor tasks out of the laboratory and during daily living activities. Among the analysed tasks, gait is surely the most widely investigated in literature and, thus, is an example of the current and crucial issues with respect to motion analysis.

First, most of the developed algorithms for the estimation of (gait) space-temporal parameters were validated for healthy subjects in controlled environments. Thus, before effective widespread use of these methods, there are still some relevant question to answer. For example, to what extent are the developed solutions ecological valid (Pacini Panebianco et al., 2018)?; How does their performance (in terms of sensitivity, specificity, accuracy, repeatability) change when used by people with an altered (gait) pattern (e.g, children, older adults, etc) (Pacini Panebianco et al., 2018)?. Recently, researchers started addressing these questions, suggesting that there is no 'perfect' algorithm fitting for all conditions, but probably compromises are necessary depending on the specific goal. Clearly, further investigation is still needed in this area.

With respect to the estimation of segment orientation and joint angle kinematics, the main limitations concerning IMU systems are the drift affecting the numerical integration of the gyro-based segment's orientation and ferromagnetic disturbances. Sensor fusion methods and kinematical resets (Picerno, 2017) are the two main approaches used to efficiently handle the drift, especially during low-frequency cycling gestures like walking. On the other hand, compensation for ferromagnetic disturbances remains the biggest issue, because any alteration of the local magnetic field may introduce errors in the estimation. The unpredictability of ecological environment for a continuous activity monitoring remain an unsolved issue, that cannot be handled using sensor fusion algorithms. The best solution thus far seems to be, when possible to avoid using magnetometers at all, but by settling for a two-plane approach rather than 3D joint kinematics in order to have a significant signal-to-noise ratio (Picerno, 2017).

Beside kinematic analysis, in the last few years, IMUs have also been proposed for estimating ground reaction forces (GRFs) during movement, paving the way to kinetic analysis and sport performance testing outside of labs (Ancillao, Tedesco, Barton, & O'Flynn, 2018). This aspect in considered 'emerging' and not presented in the previous section given the major open issues that still need to be addressed. As outlined in the review by Ancillao et al (Ancillao et al., 2018), the literature demonstrates the possibility of predicting GRFs from IMU data by using biomechanical models in conjunction with Newton's second law of motion, or machine learning approaches. These methods have been proposed for several motor tasks like walking, running, jumping, squatting.

The most critical aspects in estimating GRF from kinematic data were synthetized as follows (Ancillao et al., 2018):

(1) The number of sensors/body segments required for the biomechanical modelling

(2) Knowledge of the inertial properties of each body segment

(3) Determining the antero-posterior and medio-lateral components of GRF

(4) Determining the GRF acting on each foot in double support conditions and evaluating loading asymmetry

(5) Even if a correlation between predicted and directly measured GRF exists, it is difficult to estimate.

Clearly, despite the above-mentioned open issues, the design of a small non-invasive wearable system or sensor network to estimate GRF represents a significant research challenge for physical activity assessment. Such a device would enable smart monitoring of training and of injuries or fatigue related to repeated loads on the lower limbs.

Beside the standard methods of movement analysis (kinematic and kinetic analysis of movement), a growing number of novel approaches have been proposed aiming at revealing intriguing properties of the motor control system and introduce new ways of thinking about variability, adaptability, health, and motor learning. These methods, often referred to as Nonlinear Analysis Methods for Human Movement Variability (Stergiou, 2016), have been proposed as descriptors of specific features characterizing the motor control underlying said realization of motor pattern. Examples of such Nonlinear assessments include; pattern regularity (recurrence quantification analysis, RQA (Sylos Labini, Meli, Ivanenko, & Tufarelli, 2012)), motor complexity (entropy-based measures (Bisi & Stagni, 2016; Costa, Peng, Goldberger, & Hausdorff, 2003)), gait stability (short Lyapunov exponents,(Rosenstein, Collins, & De Luca, 1993)), and rhythmicity or symmetry (harmonic ratio (Menz, Lord, & Fitzpatrick, 2003)). They have been often applied on trunk acceleration data, collected by a single IMU, for the investigation of postural control, gait, motor control, and motor development, in healthy adult populations (e.g., evaluating the influence of environmental conditions (Tamburini et al., 2017)), in developing children (Bisi & Stagni, s.d.; Bisi et al., 2018), and in elderly and pathologic patients (Stergiou, 2016), offering new insights about how conditions/development/age/pathology influence motor performance.

However, despite the promising and intriguing results that these measures are revealing in several contexts, further research is needed to assess the influence of experimental implementation parameters on the estimated measures, in order to ensure their reliability and, to understand their physiological correlates.

Wearable systems research to date has focused more on analysis and less on intervention as only a low number of works focused wearable feedback. While wearable sensing enables gait assessment, wearable feedback can facilitate intervention. Wearable feedback has been proposed to facilitate gait changes in foot progression or joint loading, to improve postural stability for the elderly, and to assist in a variety of human learning tasks such as drumming, snowboarding and jump landings (Shull, Jirattigalachote, Hunt, Cutkosky, & Delp, 2014).

Most studies of this type have been published in the last few years, and further research is needed to investigate on the effective advantages that this approach have in different context. However, it is plausible that the growth of wearable systems will extend into a diverse array of human movement applications (Shull et al., 2014).

When comparing wearable versus vision-based approaches, different advantages and/or limitations are present. Vision based methods have the advantage that the setup is usually less complex (the subject needs to only move in front of the camera without any wearable sensors). On the other hand, IMUs-based solutions allow an assessment without space restriction. Nowadays, IMUs-based sensor system showed a better performance and a higher reliability than vision systems for the estimation of space time parameters and joint angles (Kyrarini, Wang, & Gräser, 2015).

As introduced in the previous section, markerless techniques are evolving rapidly thanks to developments in computer vision methods, but it is not yet clear exactly what accuracy can be achieved and whether such systems can be effectively utilised in field-based and therefore, more externally valid settings. Accuracy requirements vary across different scenarios and the validity of markerless systems has yet to be fully established across different movements in varying environments. In particular, accuracy and validity of markerless approach has been investigated mainly on low speed movement (gait, stairs (Oh, Kuenze, Jacopetti, Signorile, & Eltoukhy, 2018), single leg stance (Asaeda, Kuwahara, Fujita, Yamasaki, & Adachi, 2018)) with results that are task specific and dependent on the variable of interest (e.g., joint angle, time parameters, etc). For physical activity and sports applications, much quicker movements need still to be thoroughly assessed.

Recommendations for research, researchers, and practice

Overall, the novel technology available in the field, acutely juxtaposed with the historical beginnings in the ancient Roman empire, presents researchers with hitherto unseen options in the assessment of physical activity. Yet, this availability and ubiquity comes with both positives and negatives. As evidenced in this chapter, novel technology, in the form of IMU’s, magnetometers, gyroscopes, foot switches, RFID, Wi-Fi, inclinometers, oculography, 3D printing and more, can be used to proffer new insights into how (well), why, where, and when we move, beyond that of current *de facto* standards. However, with novelty, often comes naivety, and there remains a number of outstanding issues to be resolved or improved upon, in order to advance assessment through novel technology. Following the presentation and discussion of key issues, above, there emerged three, broad recommendations for research, researchers and practice.

Firstly, given the innumerable technological and analytical options available, open source development, data and analytics are essential to facilitate global benchmarking of novel technology and incumbent data. Second, there exists an over-predominance of cross-sectional based empirical studies when novel technology is used. As such, a clear, realistic goal for research, researchers and, eventually, practice, is to conduct interventionist and longitudinal studies of data emergent from novel technology, in addition to advancing the application of such techniques from the lab, and into free-living environments. These study priorities will facilitate our understanding of the technology, and their eventual outputs. Third, the integration of technologies is both an attractive and powerful prospect, and if successfully operationalised, would facilitate a greater, clearer picture of physical activity, theoretically enabling objective assessment of how (well), where, why and when activity behaviours are performed (or not).

It is clear that the technology we use is a large piece of the ‘physical activity’ puzzle, however, concomitant to the technology, is the analytical approach undertaken, and as such, researchers must be acutely aware that any decision made in the analytical process will impact the outcome of any technological output, giving further credence to the assertion that open source and transparent reporting and development, and inter-disciplinary collaboration between sport and exercise scientists, computer scientists and engineers, among many others, is essential.

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