Review Article

A Review of Emerging Analytical Techniques for Objective Physical Activity Measurement in Humans.

Cain C. T. Clark,[1,3] Claire M. Barnes,[2,3] Gareth Stratton,[1,3] Melitta A. McNarry,[1,3] Kelly A. Mackintosh,[1,3] and Huw D. Summers,[2,3]

[1]Applied Sports Technology, Exercise and Medicine (A-STEM) Research centre, College of Engineering, Swansea University, Singleton Park, Swansea, Wales, SA2 8PP

[2]Centre for Nanohealth, College of Engineering, Swansea University, Singleton Park, Swansea, Wales, SA2 8PP

[3]Engineering Behaviour Analytics in Sport and Exercise (E-BASE) Research group, College of Engineering, Swansea University, Singleton Park, Swansea, Wales, SA2 8PP

Corresponding author; Cain C. T. Clark. C.CLARK.801344@swansea.ac.uk

Key Points

• The diversification of techniques for assessing physical activity has grown. Therefore, the aim of this review was to draw together the current evidence base of novel (i.e. post-2010) analytical techniques used for physical activity measurement to assess their accuracy and limitations.

• Although physical activity measurement is the primary aim of many studies, the available techniques are diverse and characterized by different stages of refinement, levels of accuracy and limitations.

• This review highlights that although diverse and sensitive data may be assessed through the use of novel techniques, there is a need for further refinement and establishment of an acceptable level of accuracy for measuring physical activity with each technique.

Abstract

BACKGROUND

Physical inactivity is one of the most prevalent risk factors for non-communicable diseases in the world. A fundamental barrier to enhancing physical activity levels and decreasing sedentary behaviour is limited by our understanding of associated measurement and analytical techniques. The number of analytical techniques for physical activity measurement has grown significantly, and although emerging techniques may advance analyses, little consensus is presently available and further synthesis is therefore required.

OBJECTIVE

The objective of this review was to identify the accuracy of emerging analytical techniques used for physical activity measurement in humans.

METHODS

A search of electronic databases was conducted using Web of Science, PubMed and Google Scholar. This review included studies written in the English language, published between January 2010 and December 2014 that assessed physical activity using emerging analytical techniques and reported technique accuracy.

RESULTS

A total of 2,064 papers were initially retrieved from three databases. After duplicates were removed and remaining articles screened, 50 full-text articles were reviewed, resulting in the inclusion of 11 articles that met the eligibility criteria.

CONCLUSION

Despite the diverse nature, and the range in accuracy associated with some of the techniques analytics used, the rapid development of analytics has demonstrated that more sensitive information about physical activity may be attained. However, further refinement of these techniques is needed.

1 Introduction

Physical inactivity is one of the most prevalent risk factors for non-communicable diseases worldwide [1], resulting in a significant body of research investigating population physical activity levels [2, 3]. However, despite recognition of the importance of physical activity, our understanding surrounding the appropriate measurement and analytical techniques are currently limited, and further, the diversity of outputs from physical activity analyses has grown.

In general, accelerometers work using the same principles, and whilst the number of planes in which acceleration is detected can range from uni- to triaxial, they are considered to be the *de facto* standard device for objective physical activity monitoring [4, 5]. The most widely used accelerometers in research (e.g. ActiGraph, Movisens) use a piezoelectric lever to detect acceleration ranging from ~0.25 to 2.5g. In traditional physical activity analyses, participants typically, although not exclusively, wear the accelerometer on the right hip (near to the centre of mass). Any full body movement results in displacement of the accelerometer causing the piezoelectric lever to bend. As a result a signal is generated in proportion to the amount of acceleration, which subsequently generates intensity of movement output and the signal is sampled at a user specified value otherwise known as an 'epoch' [5-7]. Accelerometers are also used to provide velocity and displacement data [8], as well as inclination data that could be used to classify body orientation, and are widely used to assess physical activity [5].

Signal processing of accelerometer data has moved beyond the descriptive approach of simply quantifying overall activity using time spent in thresholds or counts per minute. There have been two reviews in the area that are unanimous that there are more substantive insights that will take the accelerometer data past the descriptive stage that characterises the data, allowing both quantity and quality to be reported [8, 9]. Chen et al. [8] found in their review that sensor type and data processing may directly impact the results of the outcome measurement. Further, that multisite assessment and combining accelerometers with other sensors and new analytics may offer additional advantages. Yang et al. [9] found that the application and sensor placement is expanding beyond hip mounting. The review noted applications to fall prevention, posture identification and gait characteristics are growing. Both,
Chen et al. [8] and Yang et al. [9] highlighted issues with traditional analyses, such as device reliability, insensitive energy expenditure algorithms, epoch length affecting overall physical activity and inability to detect intermittent activities. Future technological improvements will necessitate examining raw acceleration signals and developing advanced models for accurate energy expenditure prediction and activity classification [8-10].

Recently, emerging approaches to physical activity measurement have focused on prevention of falls, postural movement, energy expenditure and analysing raw accelerometry traces [11, 12]. One example is pattern recognition, which is an analytical technique used to classify activity behaviours (such as jumping, walking or running) and can make use of data from several sensors placed on the body. This process involves gathering data from participants carrying out a protocol of structured activities and then processing the signal for common features. Once processed, it is possible to program a computer to detect these features in the data collected from participants carrying out defined activities, otherwise known as machine learning. The algorithms used to do this depend largely on the features used for classification of activities and subsequent variants of these. In addition to machine learning and pattern recognition, mathematical modelling has resulted in improved energy expenditure estimations, by incorporating accelerometry, heart rate monitors, indirect calorimetry (IC) and anthropometric data. Further the utilisation of more sophisticated techniques, such as artificial neural networks, can feed data information through the network, and then compute to better predict energy expenditure or movement [13].

Clearly, the diversification of analytical techniques to characterise physical activity is accelerating, and with the increase in analytics, multiple, diverse platforms on which to assess and report physical activity have come to the fore, and therefore an updated synthesis of the current evidence base is warranted. Further, consideration of accuracy and associated limitations is also needed to indicate the current suitability of different techniques. Therefore, the aim of the current review was to identify the accuracy of emerging analytical techniques reported in physical activity measurement.

2 Methods

2.1 Literature search

For the purpose of this review, a computerised search was conducted using the following databases; Web of Science, PubMed and Google Scholar. A combination of the following key words was used to locate studies for review, between the dates of January 2010 and December 2014; 'physical activity', 'pattern recognition', 'wearable motion sensor', 'artificial neural network', 'energy expenditure', 'sensor', 'multi sensor', 'monitor', 'motion sensor', 'accelerometer', 'accelerometry', 'regression', 'hidden Markov model' and 'machine learning'. Terms were combined such that every search included one term related to; 'physical activity' and one term related to type; 'measurement' or 'classification'. Figure 1 shows the results of the literature search and article selection process.

2.2 Study characteristics

Multiple searches were then made in each of the selected databases and additional searches for relevant references and citations linked to the studies obtained during this primary search were conducted. The selection process sought to identify studies that assessed physical activity using emerging analytical techniques, of varying study design, conducted human-based investigations, assessed the accuracy of analytical technique and were published in the English language from January 2010 to December 2014. This cut-off date was used because physical activity measurement and analytical techniques pre-2010 have already been well reviewed [8, 10]. All titles and abstracts and all full-text assessments were conducted by two authors, and decisions to accept or reject a paper were agreed between the first and second authors, and in instances where the first and second author could not agree, a third, independent, reviewer helped achieve consensus.

2.3 Study selection

Coding of papers only allowed for studies that adopted emerging analytical techniques for physical activity measurement, including; pattern recognition, artificial neural networks, hidden Markov models, machine learning and regression, and assessed technique accuracy. Studies of varying designs were acceptable for the purposes of this review; however, technical reports, review articles, non-human based studies, or studies which did not measure activity or report technique accuracy were not considered further. Following the selection of appropriate articles, study design, aims, population, analytical technique, overall accuracy and limitations were reviewed in table I.

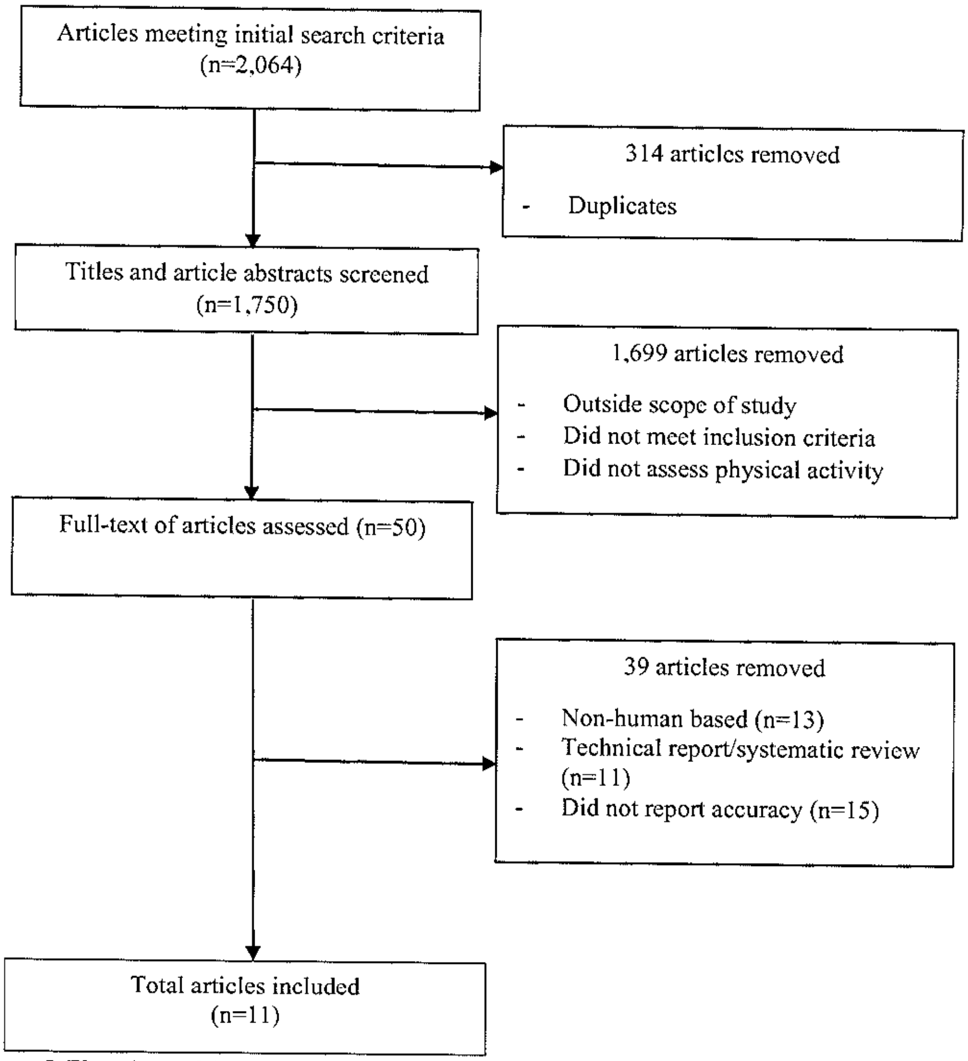

Figure I. Flowchart of the search and selection process.

3 Results

The electronic search identified 2,064 potentially relevant articles. Following screening and detailed assessment, 11 studies were deemed suitable for review. Of the 11 studies included, one study utilised linear discriminant analysis, four utilised feature extraction and machine learning, two utilised a support vector machine classifier, one utilised dynamic time warping, one utilised hierarchical clustering, one utilised an extreme learning machine, and one utilised a hidden Markov model. Table I summarises; study aims, participant characteristics, study outcomes, overall accuracy and study limitations.

Table I. Emerging technique accuracy (including falls, activity type, behaviour, prediction).

Study	Aim	Population[a]	Instrument/technique	Overall accuracy	Conclusion	Limitations
Aziz et al. [14]	To develop and evaluate the accuracy of wearable sensor systems for determining the cause of falls.	Nine males and three females (20-35y)	Accelerometer (MicroStrain), linear discriminant analysis.	89%	These results establish a basis for the development of sensor-based fall monitoring systems that provide information on the cause and circumstances of falls, to direct fall prevention strategies at a patient or population level.	All falls were performed under controlled laboratory conditions by healthy individuals between the ages of 20 and 35, who fell on soft gymnasium mats. So application to real world setting needs to be investigated. Small sample and biased towards males.
Bulling et al. [15]	To investigate eye movement analysis as a new sensing modality for activity recognition	Six males and two females (23-31y)	Electrooculography (Mobi8), feature extraction and machine learning, SVM.	76.1%	Activity recognition using eye movement analysis can be used to successfully recognise five office based activities and has future potential	Some subjects had to be excluded due to poor signal quality. Any pathologic eye disorder (such as nystagmus) can significantly affect activity recognition
Duncan et al. [16]	To examine the accuracy of a MSB that infers activity types (sitting, standing, walking, stair climbing, and running) and estimates EE	25 males and 37 females (39.2±13.5y)	MSB, accelerometer (Actical), stationary calorimetry (TrueMax), HR monitor (Polar), feature extraction.	97% (laboratory) and 84% (field).	The MSB provides accurate measures of activity type in laboratory and energy expenditure during treadmill walking and running.	Device underestimates EE when used in the field. Device estimates EE based on walking speed and does not factor in events such as carrying loads.
Fulk et al. [17]	To determine the ability of a novel shoe-based sensor that uses accelerometers, pressure sensors, and pattern recognition with a SVM to accurately identify sitting, standing, and walking postures in people with stroke.	Two males and six females (60.1±9.9y) who suffered a cortical CVA 51.7±45.1 months prior	Force sensitive resistors (Interlink), SVM.	99.1% to 100% individual models. 76.9% to 100% group models.	The combination of accelerometer and pressure sensors built into the shoe was able to accurately identify postures	There was no attempt to examine the ability of the sensors to detect transitions such as sit to/from stand position or ascend/ descend stairs
Goncalves et al. [18]	To determine stereotypical motor movements for application to individuals with ASD	Two participants	Xbox Kinect sensor, dynamic time warping algorithm	100%	Results were promising, some aspects need to be improved, i.e. noise of the depth image that can lead to false-positives in the identification, and improve the accuracy of the application when the user sits too far from or too close to the Kinect sensor.	Subjects used did not suffer from ASD. No participant information. Hand flapping was the only movement. Did not correctly identify duration of movement.

Kjaergaard [19]	To identify multiple human movement (flocking) derived from multiple sensors.	16 participants	WiFi, accelerometer, compass, hierarchical clustering.	87%	Hierarchical clustering improves flock recognition and multiple sensors improve recognition compared to uni-model approaches	No participant information was provided.
Leutheuser et al. [12]	To generate a publicly available benchmark dataset for the classification of daily life activities, comparing multisensor based classification to state-of-the-art algorithms	13 males and 10 females (27±7y)	Wearable sensor (SHIMMER; 3axial accelerometer and 3axial gyroscope combination), feature extraction and machine learning.	89.6%	The comparison showed that the proposed data fusion of accelerometer and gyroscope provided a useful tool to distinguish between complex activities like ascending stairs.	Inconsistent sensor placement and numbers used for different algorithms.
Mannini et al. [20]	To investigate machine learning methods for classifying human PA	20 participants	Accelerometer. HMM	92.2 to 98.5%.	The use of HMM with pattern recognition is a promising approach for the future.	Only basic motions captured. No sex or age information.
Trost et al. [21]	To develop and test ANNs to predict PA type and EE from processed accelerometer data	100 participants (11.0±2.7y)	IC (Oxycon), accelerometer (Actigraph), ANN	81.3% to 88.4%.	ANNs can be used to predict both PA type and EE in children and adolescents using count data from a single waist mounted accelerometer	Authors noted that EE can be predicted accurately from a limited number of activities. ANNs developed from laboratory controlled activities not PA or free living conditions. No sex information provided.
Xiao et al. [22]	To develop a wearable feedback system for monitoring the activities of the upper-extremities	6 participants (29.7±4.4)	FSR, ELM classifier	92%	Results support the use of this system for providing instant feedback during functional rehabilitation exercises.	Only discrete postures were used. No sex information provided.
Zhang et al. [23]	To extract and evaluate PA patterns from image sequences captured by a wearable camera	One participant	Wearable camera, good features detector	>85%	Many types of PA can be recognized from field acquired real-world video	Extremely low sample size, camera position was not securely fixed. No participant information reported.

Table I definitions; ANN: Artificial neural network, ASD: autism spectrum disorder, CVA: cerebro-vascular attack, EE: energy expenditure, ELM: extreme learning machine, FSR: force sensor resistor, HMM: hidden Markov model, HR: heart rate, IC: indirect calorimetry, MSB: multi-sensor board, PA: physical activity, SVM: support vector machine. [a] Age data are mean ± SD, or range.

4 Discussion

The aim of the current review was to identify the accuracy of emerging analytical techniques reported in physical activity measurement. In accord with the aim of this review, 11 studies that evaluated support vector machines, dynamic time warping, hierarchical clustering, extreme learning machines or hidden Markov modelling were reviewed

4.1 Accelerometry based studies

Within this review, a number of studies applied emerging analytical techniques with accelerometry in order to assess physical activity, with a range of accuracies and limitations (see Table I). Measuring human physical activity using wearable monitors [11, 12] demonstrates promising results. Physical activities, including walking, running, cycling and rope jumping, have been accurately (up to 100% accuracy in certain circumstances) classified using sensors with multiple inputs (for example accelerometers or gyroscopes) [12, 17]. Aziz et al. [14] successfully measured physical activity and sedentary behaviour using accelerometers in older adults or those with impaired ambulation using linear discriminant analysis, which is a type of machine learning, with overall accuracy of up to 89% in classifying fall type. Further, computed values were highly correlated to walking speed prediction (R=0.98). However, problems arose when using the same approach in highly transitory activities and when detecting falls that were a result of syncope. Leutheuser et al. [12] also utilised machine learning, in combination with feature extraction, and was able to correctly identify basic daily life physical activities with 89.6% accuracy. The use of machine learning with accelerometry 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. Conversely, when focussing more broadly on inferring activity type, and not specifically falls or basic movement, Duncan et al. [24] achieved 97% accuracy during walking and running in the laboratory and 84% accuracy in the field (performing scripted activities including walking up and down stairs, walking around and picking up a 20 pound object), using feature recognition. This particular method appears to be successful due to the incorporation of EE 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. Trost et al. [21] advocated the use of a different form of machine learning, ANN, and reported high accuracy (88.4%) in activity classification. This type of machine learning has been applied to multiple settings with high levels of accuracy and reliability and relies on a computational model inspired by natural neurons to process and link inputted data [25]. Trost et al. [21] was the only study to have utilised a substantial sample size, giving strength and reliability to their findings. Although accelerometers can be combined with novel analyses for the same or similar outcomes, there are a number of mathematical processes and models that can be applied under the umbrella of machine learning, i.e. ANN, feature detection, linear discriminant analysis, all of which demonstrate comparable level of accuracy. In addition to machine learning approaches, pattern recognition in combination with accelerometry has demonstrated very good reliability. Mannini et al. [20] reported that very high accuracy (92.0 – 98.5%) could be achieved when classifying postural (sitting, lying and standing) and basic motor movements (stair climbing, walking, running and cycling) when applying a HMM to characterise an accelerometer signal. This indicates that when pursuing activity classification, machine learning and pattern recognition represent two very promising techniques. At present, these techniques are limited to classifying only simple or basic movements and as such, further work is required to extend these models to be applicable in a more generalised setting. Further, a confounding limitation of emerging analytics in conjunction with accelerometry is that the number of participants used in studies has been small (Fulk et al. [17], Leutheuser et al. [12]). It is evident that studies have addressed varying problems, ranging from pedestrian flocking, to falls, or more predominantly, inferring activity and the relative accuracies of these techniques has been shown to be very high.

4.2 Other sensor based studies

There have been a number of approaches used to classify characteristics in physical activity data, for example pattern recognition, machine learning, principal component analysis (PCA) [20]. When analysing a raw accelerometry trace, it is very difficult to deduce what action has been performed without any other input or prior knowledge about the actions. In such cases, a pattern recognition technique, such as a HMM, may be applied, where observations are available (the raw accelerometry trace) but the states giving rise to those observations are 'hidden' (prior knowledge of any activities or movement). Therefore, HMM is an approach used to classify features in a dataset. Other statistical modelling approaches can be used where the probability data derived from a 'training set' of data are used to classify some features into various motion and physical activities. An important consideration when classifying data is that large datasets will result in multiple features and characteristics, which results in time consuming data analysis and collection. Artificial neural networks, in addition to decision trees, have also been used to good effect [26, 27]. Further, pre-processing and reclassifying data can help reduce the dimensionality of large data sets [20], and using novel analytics can help to compute the meaningful basis in a data set by filtering out noise which results in improved accuracy [20]. However, a consistent feature associated with many pattern recognition analytics is that many data need to be gathered in order for patterns to be recognised. This can be time-consuming and expensive and requires significant computer memory and power [20]. Further, whilst accelerometry has become the *de facto* device for objectively assessing physical activity, the use of other sensors (i.e. cameras, force sensitive resistors, electroocculography) to achieve the same outcome has grown. It is evident that the aim of many emerging analytical techniques has been to aid in better detecting the quality and type of activity that a person is undertaking. Zhang et al. [23] incorporated motion cameras in order to recognise patterns of movement and concluded that basic motor movements could be recognised with 85% accuracy. The accuracy reported by Zhang et al. [23], using a pattern recognition approach, was lower than Mannini et al. [20]. This could be an artefact of the device, as acquired images are often blurry and ineffective in capturing feature points. However, this approach attained similar levels of accuracy to Trost et al. [21]. Goncalves et al. [18] utilised an Xbox Kinect camera in conjunction with a pattern recognition approach, dynamic time warping, where the similarity between patterns which may vary with time of different durations is measured [18]. The authors reported success in application of the technique, however, the gesture sensing algorithm was only applied to two participants and one action, hand flapping. So, although the accuracy reported was absolute, there is still much development needed in order to apply this to more movements. Bulling et al. [15] 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 contended that recording the movements of human eyes, 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 be missed by common sensing modalities. However, further investigations would be required to corroborate the effectiveness of this technique.

The application of cameras, in different forms, to characterise activity has demonstrated variable success when complemented with novel analyses. A further example of instruments used when attempting to characterise human movement with novel analytics is force sensitive resistors. Fulk et al. [17], 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 (in Fulk et al. [17], the computer learns how the signals from the sensors can predict postural activities) and apply the learned model to recognition of previously unseen data [17]. Across eight participants, accuracy in identifying postural activity of 99-100% was found, indicating that, using a modest sample size, the combination of acceleration and pressure traces, postures may confidently be assessed. Similar to Fulk et al. [17], Xiao et al. [22] utilised a force sensitive resistor, however 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. [22] also utilised a form of machine learning to learn and classify the data, an extreme learning machine classifier. As with previously mentioned studies, a training approach was taken, where the ELM classifier was 'taught' or 'trained' to model the force myography trace.

Although substantial gains have been made utilising emerging analytics to develop deeper insights into human physical activity data, the underlying algorithms require further development. It is evident that when simple postural changes or activities are quantified, there are a number of techniques and instruments that can be used to accurately determine them, which is not the case when complex or specific activity recognition is required. The main problem with the studies reviewed is that they are predominantly laboratory based, or have much lower accuracy in-field, use small sample sizes and are exploratory. Many of these studies also failed to account, or indeed, report, anthropometric and physiological metrics such as age, sex and fitness which could conceivably affect patterns of movement.

4.3 Cluster analysis

Whilst refining emerging techniques should remain a strong focus, so that adequate levels of accuracy and confidence may be established and improved upon, the techniques by which physical activity can be measured will continue to proliferate. Cluster analysis involves the use of algorithms to separate a population into clusters or groups based on various parameters, such as activity behaviours, and has been identified by Kjaergaard [19] to have high accuracy. Kjaergaard [19] focussed on group activity, rather than individual activity, using flock detection and found by incorporating accelerometry, Wi-Fi and cluster analysis that pedestrian flocks could be correctly identified and tracked with 87% accuracy. One problem encountered in this study was flock proximity, i.e. the ability of the cluster analysis to successfully differentiate between flocks was encumbered when different groups become entwined or were too close. This indicates that the mathematical modelling process needs further refinement. The cluster analysis approach relies upon an iterative process of interactive, multi-objective optimization and may be used in various ways depending on which parameters are applied. For example, cluster analysis can be used to determine friendship groups in the playground or could be used to determine trends and correlations between factors such as physical activity, age and socioeconomic status. Cluster analysis is versatile and has previously been used to study animal behaviours and movements theory [28] and in biology to identify and track cells [29]. Given the nature of human behaviour, cluster analysis could be of great use in advancing the analysis of physical activity indices.

5 Conclusion

The aim of the current review was to identify the accuracy of emerging analytical techniques reported in physical activity measurement. In accord with these aims, it was found that research into 'physical activity', is expanding to incorporate a multitude of different techniques, and within each approach exists a series of limitations that need addressing. This review identified that between 2010 and 2014, a range of emerging analytical techniques have reported high accuracy across physical activity measurement, with particular success in postural activity classification. However, many of the studies were exploratory or require further development to establish reliable, accurate measures across larger samples.

The field of physical activity measurement is rapidly developing, however, emerging analytical techniques have only achieved variable success in relatively small samples, and the degree of measurement accuracy across a range of activities has been inconsistent [47]. It is of importance to establish the degree of accuracy achieved by using these techniques in order for researchers to make an informed choice on analytical approach. Further, future studies should include more detailed participant characteristics, as many individual factors affecting gait and physical activity characterisation vary by age, sex and motor competence. Despite the different techniques undertaken, these problems were consistently found. Consequently, as methods develop, we recommend that analytical techniques be refined to account for participant differences, and an acceptable level of accuracy for measuring physical activity be established for each technique, and that 'qualities' of different activities, such as characteristics of gait, activity duration and idiosyncratic differences be further investigated. Finally, given the success in classifying postural activity, this should be incorporated into studies investigating physical activity to gain greater understanding of activity and movements.

Compliance with Ethical Standards

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Conflict of Interests

Cain C. T. Clark, Claire M. Barnes, Gareth Stratton, Melitta A. McNarry, Kelly A. Mackintosh and Huw D. Summers declare that they have no conflicts of interest relevant to the content of this review.

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