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Direct measurement of human movement by accelerometry

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Abstract

Human movement has been the subject of investigation since the fifth century when early scientists and researchers attempted to model the human musculoskeletal system. The anatomical complexities of the human body have made it a constant source of research to this day with many anatomical, physiological, mechanical, environmental, sociological and psychological studies undertaken to define its key elements.

These studies have utilised modern day techniques to assess human movement in many illnesses. One such modern technique has been *direct measurement by accelerometry*, which was first suggested in the 1970s but has only been refined and perfected during the last 10–15 years.

Direct measurement by accelerometry has seen the introduction of the successful implementation of low power, low cost electronic sensors that have been employed in clinical and home environments for the constant monitoring of patients (and their controls). The qualitative and quantitative data provided by these sensors make it possible for engineers, clinicians and physicians to work together to be able to help their patients in overcoming their physical disability. This paper presents the underlying biomechanical elements necessary to understand and study human movement. It also reflects on the sociological elements of human movement and why it is important in patient life and well being. Finally the concept of direct measurement by accelerometry is presented with past studies and modern techniques used for data analysis.

Keywords: Accelerometer; Human motion; Review; Motion sensors

1. Human motion—introduction

Analysis of human motion originates as far back as the fifth century BC, when Aristotle and his colleagues developed a model of the human musculoskeletal system involving levers, forces and a centre of gravity [1]. Human movement or motion according to Hamill and Knutzen [2], involves a change by the person in place, position or posture relative to some point in the environment. For simplicity this seems to be a strong enough definition that satisfies all necessary conditions. However, Brooke and Whiting [3] expanded on this definition by saying that movement is not uniform, that it is deeply stratified and requires that its many layers be analysed and clearly identified. They also stated that human movement, as a concept, cannot be restricted to the purely physical and that the concept of human movement requires that one recognizes the total 'context' or 'form of life' of which human movement is a part; sociological, environmental, psychological, mechanical, physiological and anatomical are all factors must be built into one's concept of movement [3,4].

2. The importance of human motion

The physical dimensions of life that includes health, physical function and energy and vitality contribute in a very significant way to quality of life [5]. The sociological factors of movement may be considered as to how one interacts with one's local and greater community. Developing interpersonal health means learning good communication skills,

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satisfying relationships, determining how one interacts with others and how one cultivates a support network of friends and family members through social interaction [6].

The environment in which one surrounds oneself will have a large impact on the manner in which one moves or the type/amount of movement performed. Whether urban or rural dwelling, the layout of one's dwelling, whether living with others or alone, the type of work, receiving home help, etc. can all contribute to defining ones movement pattern.

The psychological factors of cognitive and emotional function reflect everyone's desire to maintain productivity, independence and an active interaction (movement) within their environment. Life satisfaction and a feeling of well-being represent emotional control and good mental health [5].

Within these areas it is necessary to identify the skills a person requires to perform the activities of daily living and the way in which they try to undertake these activities [4]. With this acquired pool of knowledge it is possible to consider how certain tasks might be made more efficient or how a person with a disability might be helped towards greater independence [4]. Subject specific problems can be identified, goals set and a realistic program designed. The subjects progress will need to be regularly evaluated and goals altered when necessary. Systematically approaching each individual's movement problem in this way, will lead to better development of clinical judgment and clinical practice can become more effective [4].

Fig. 1 [5] is a good representation of the efforts of impaired or reduced movement and may be associated with all types of movement and highlight why it is important to maintain a health mobile lifestyle. We can see from this figure that many of the efforts are inter-related. Once one of these efforts is presented in a subject's life, it can cause a devastating knock-on effects that form a vicious circle (Fig. 2).

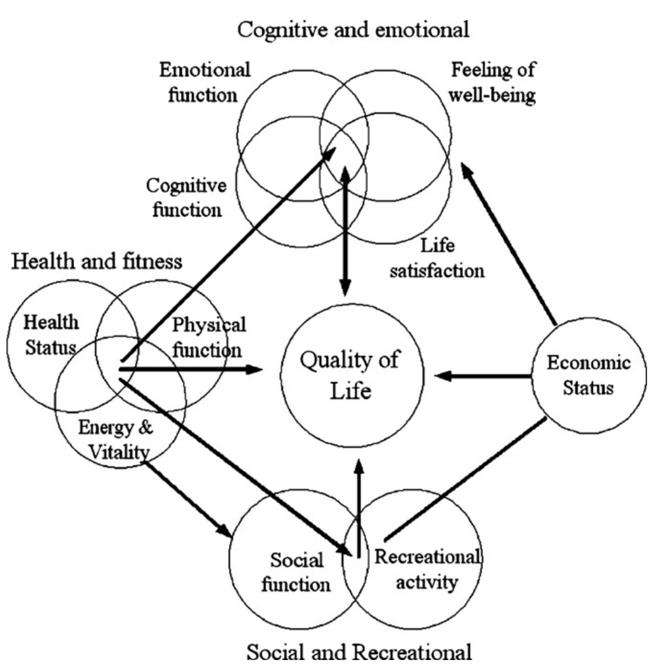

Fig. 1. Factors affecting the quality of life [5].

2.1. Medical assessment of human movement

As discussed, human movement is a complex phenomenon with many contributing factors: physiology, mechanics, psychology, etc. An ability to assess the quality or quantity of movement has the potential to provide an invaluable source of knowledge to clinicians to accurately diagnose and treat a variety of medical conditions.

Human movement has been researched in relation to many disorders. Many of these have been directly related to mobility-impaired or mobility reducing disorders such as osteoarthritis, obesity, stroke, chronic pulmonary disease, multiple sclerosis and Parkinson's disease [7–18]. In chronic pulmonary disease, for example, dyspnea (shortness of breath) and deconditioning prohibit physical activity (PA) and are known to produce spiraling losses in global functioning and quality of life [15]. One of the requirements for pulmonary rehabilitation is general exercise to improve physical functioning and quality of life. It is thought that the most beneficial outcomes of rehabilitation come through program-related improvements in the ability to carry out daily PA and to undertake periods of extended walking [15].

Brandes et al. [12] assessed quality of life in relation to quality versus quantity of gait in osteoarthritis patients. Gait analysis under controlled laboratory settings is a useful tool in detecting underlying causes of gait abnormalities. However, this does not reveal functional subject variability in everyday activity patterns. Brandes et al. concluded that a patient's level of mobility cannot be reliably estimated from the quality of gait, or life. Instead measures should be chosen to measure the quantity of gait in daily life [12].

Human movement has also been examined in other areas such as the activity patterns of the young, the elderly, those with back and neck pain, the mentally ill, those with coronary related illnesses, circadian rhythms and sleep, autism, chronic pain, arterial disease and even nutrition behaviour of adolescents [19–30]. Pan [29] examined the PA and social engagement in children with autism spectrum disorders (ASDs). Children who suffer from ASD, withdraw from physical activity mainly due to the negative social and behavioural outcomes associated with this symptom. Pan stated that PA and social engagement behaviours of children with ASD might be more affected by social and environmental constraints than the actual impairment. Pan also found that children who had frequent social engagement with adults displayed higher levels of PA. Such favorable interactions not only result in improved social skills but also physical fitness [29].

These research findings show the importance of human movement. They highlight how necessary it is for the promotion of PA for healthy living and general well-being. The studies highlighted such as those relating to stroke,

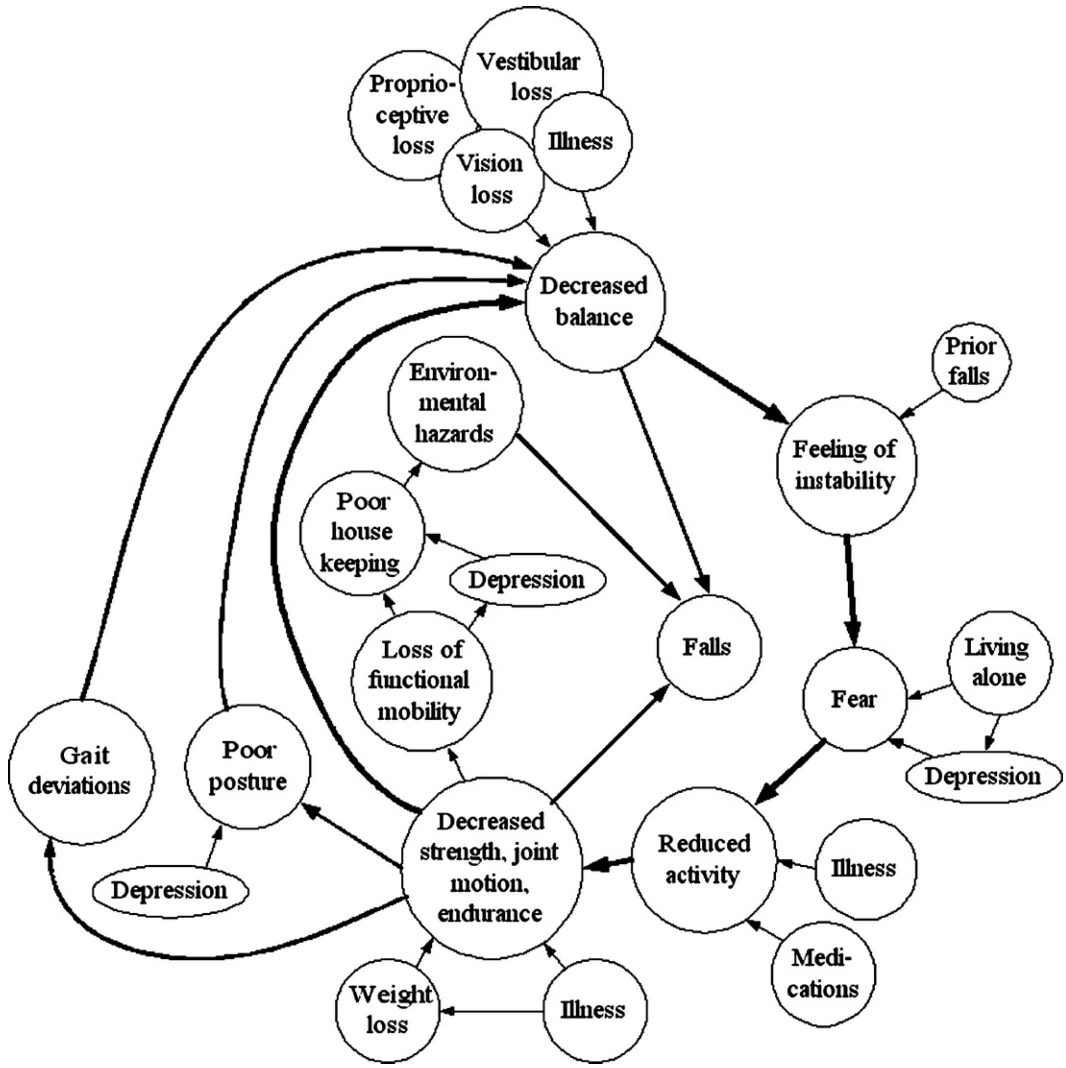

Fig. 2. The importance of movement leading to a 'vicious circle' [5].

osteoarthritis, multiple sclerosis, etc., are complex neuromuscular disorders. These disorders have many biomechanical related connections and as the primary motor functions of the human body become impaired it becomes necessary to understand the various components they affect. Therefore, we next consider the physical aspects of human movement and their various components, that of the change of position of the human body or its parts as defined by Sweigard [31] to be: the neuro-musculo-skeletal events; mechanical, physiological and anatomical. These can be described using the two branches of science: kinesiology and biomechanics.

3. The physical components of human motion

The following section details the primary but key components of physical human motion. The study of these biomechanics and kinesiology components are necessary for the successful physiological understanding and subsequent treatment of disabilitating illnesses and disorders relating to the human movement.

3.1. Kinesiology and biomechanics

Kinesiology is the title given to a program of study relating to the sciences associated with the anatomical, mechanical, physiological (or psychological) basis of human movement [2,32]. It can also describe the content of a class in which human movement is evaluated by examining its source and characteristics, such as the movements occurring in each phase of activity and hence define a qualitative approach to human movement [2]. The second term of biomechanics is defined as the area of study where the knowledge and methods of mechanics are applied to the structure and function of the living system [32]. Biomechanics has been used to incorporate qualitative components but with a more specific quantitative approach [2]. The components of a biomechanical and kinesiologic movement analysis are shown in Fig. 3.

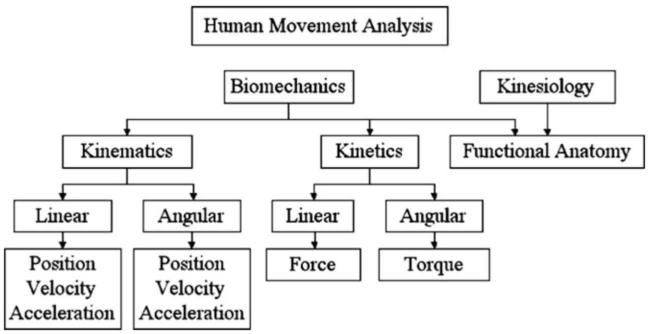

Fig. 3. Types of movement analysis [2].

Biomechanics is divided into two categories: *statics*, the study related to non-moving systems and *dynamics*, the study of factors associated with systems in motion. Dynamics can then be further divided into kinematics, the study of time and spatial factors of motion acting on a system, and kinetics the study of forces acting on a body that influence its movement [32], Fig. 3.

3.2. Kinematics and kinetics

Kinematics is mainly concerned with motion characteristics of a subject and examines this from a spatial and temporal perspective without reference to the forces causing the motion [32]. An analysis of this type, details the description of movement to determine how fast an object moves and how high or how far it travels. As a result, position, velocity and acceleration are of particular interest in kinematics [2]. This displacement data can be taken from any anatomical position such as the center of gravity of body segments, centers of rotation or extremities of limb segments [33].

Kinetics examines the forces that act upon a system such as the human body causing it to move. A kinetic analysis can provide information about how the movement is produced or how a position is maintained. This analysis is more difficult to evaluate because some forces cannot be seen with only their effects being observed, such as those forces resulting internal muscle structure [2,33].

3.3. Static's and dynamics

Static's is a branch of mechanics that looks at systems that are stationery or those that are moving at constant velocity. These systems are considered to be in equilibrium meaning that they are in a balanced state. This results in no acceleration because the forces causing a person to begin moving, speed up, or to slow down are negated by opposite forces, thus canceling them out [2]. As a result of these factors, kinetic techniques are used to identify the forces involved for maintaining a posture, position or constant speed. Although kinematics may be used to confirm there is equilibrium by the absence of acceleration [2].

Dynamics refers to the action of movement of the body as it undergoes acceleration and deceleration. Dynamics utilizes both kinematics and kinetics to analyse movement. Dynamic analysis was derived from Newton's Second Law of Motion and expanded by the Swiss mathematician Leonhard Euler [2].

3.4. Linear and angular motion

There are two main types of motion present in human movement. Firstly there is *linear motion* that is movement along a straight line (rectilinear) or curved pathway (curvilinear) in which all points on the body move the same distance in the same amount of time [2,32]. The center of mass of a body is usually the point monitored in a linear analysis system. This is the point at which the mass of the body is concentrated and it represents the point at which the total effect of gravity acts on the body [2].

The second type of motion is *angular motion* that involves movement around a point (axis of rotation) so that different regions of the same body do not move through the same distance in a given amount of time [2]. The change in orientation of a rotating body is called its angular displacement, typically denoted by the Greek letter theta, θ [32].

3.5. Qualitative and quantitative movement analysis

Two approaches can be used when studying the various aspects of movement. These are a *qualitative* approach and a *quantitative* approach. The qualitative approach can be described as a nonnumeric evaluation of movement that will produce a description of the movement [2,32]. Qualitative evaluations of movement should be based on the analyst's (or equipments) ability to recognize the vital aspects of the movement. Subjective conclusions based on this particular type of analysis can be accepted or rejected on the basis of subsequent quantitative data [32].

The quantitative approach on the other hand, is a numeric evaluation of the movement or motion based on data acquired during analysis [2,32]. This approach can eliminate subjective descriptions as numbers/data collected can describe or explain the physical situation [32].

3.6. Body and segmental plane names and terms

The regions of the human body can be divided into 11 functional segments: head and neck, thorax, lumbar region, pelvis, thigh, leg, foot, shoulder girdle, arm, forearm and hand [32]. The head, neck and trunk are the segments that comprise the main part of the body and are termed the *axial* portion of the body. The upper and lower extremities such as the arms and legs are called the *appendicular* portions [2].

The term *medial* refers to a position close to the midline of the body or movement that moves towards the midline. The opposite of medial is *lateral* and describes a position far from the midline or a movement away from the midline

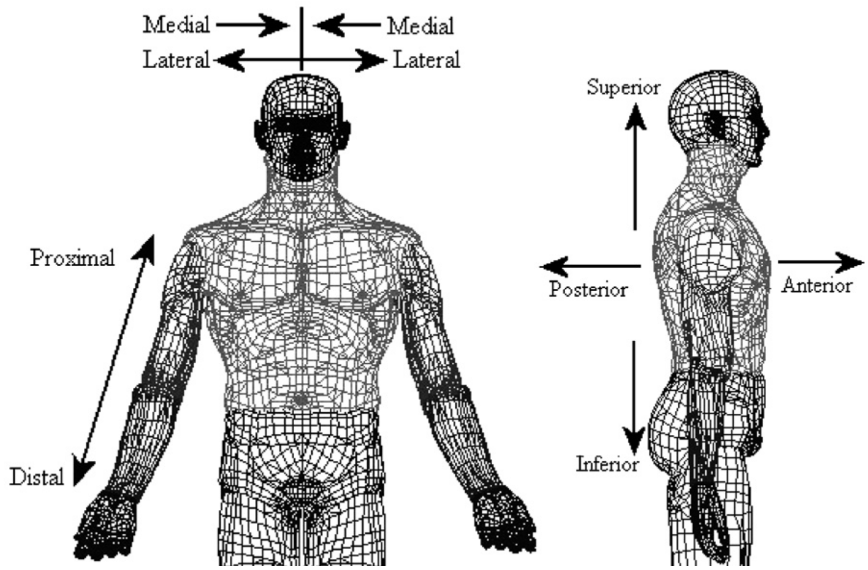

Fig. 4. Anatomical terms used to describe position or direction.

[2]. *Proximal* and *distal* describe position with respect to a predefined reference point, with proximal defining a position closer to the reference point and distal being further away [2] (Fig. 4).

The terms *superior* and *inferior* relate to the position on the body an object may lie. If an object is located on the superior aspect of the body it is above a reference point and closer to the head while inferior places it below the same reference point and closer to the feet. *Anterior* (*ventral surface*) and *posterior* (*dorsal surface*) define a position located on the front or back, respectively [2], Fig. 4.

Three imaginary planes of motion are used to describe human movement. These planes are positioned through the body at right angles and they intersect at the center of mass of the body and are called the *principal* or *cardinal planes* [2,32]. The *sagittal plane* (SP) divides the body into left and right halves and movement in this plane occurs about a *mediolateral axis* (MA) [32]. The *frontal* (*coronal*) *plane* (FP) divides the body into front and back halves, with movement occurring in the *anteroposterior axis* (AA). Movement about this particular plane is not as common as movements in the other planes [2]. The *transverse* (*horizontal*) *plane* (TP) divides the body into upper and lower halves with movement on the *longitudinal axis* (LA) [32] (Fig. 5).

So how can one successfully monitor and record movement? One such means of movement measurement is through direct measurement by accelerometry.

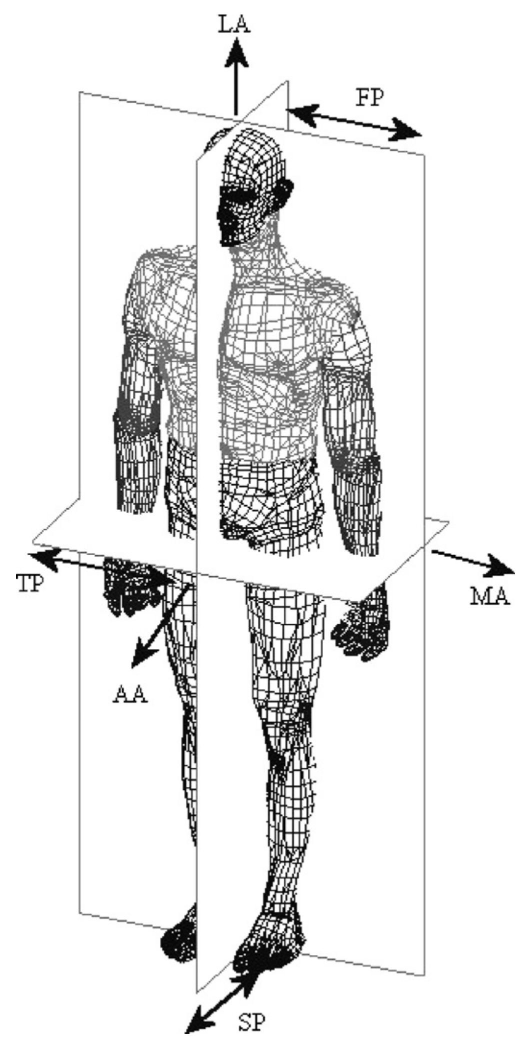

Fig. 5. Planes and axes on the human body.

4. Direct measurement by accelerometry

Many techniques are used to assess human movement some of these include observation, physical science technologies (foot switches, gait mats, force plates, optical motion analysis), diaries and questionnaires. Many of these techniques have clear disadvantages for continuous analysis such as the physical science technologies, which are primarily laboratory based [34]. Thus, accelerometers have become the preferred choice for continuous, unobtrusive and reliable method in human movement detection and monitoring.

Accelerometers were first conceived to monitor the motion of human movement as early as the 1950s [35] but due to their expensive and bulky state were deemed unsuitable for this purpose [34]. With advances in science and technology, the topic of accelerometry in human motion again resurfaced in the 1970s [36]. Morris suggested that the use of accelerometry as a quantitative measure to completely define the movement of a body in space had many advantages over the commonly used kinephotography and electrogoniometry. Morris incorporated the use of multiple cantilever type accelerometers with semiconductor strain gage elements to define the movement of a segment of a body (the shank). The data were recorded to a portable recorder that was attached to the waist and connected via a lightweight cable.

Accelerometers are devices that measure applied acceleration acting along a sensitive axis which can be used to measure the rate and intensity of body movement in up to three planes (anterior–posterior, mediolateral and vertical, Fig. 5) [37]. As they respond to both the frequency and intensity of movement they are superior to actometers or pedometers, which are attenuated by impact or tilt [38]. Accelerometers can also be used to measure tilt (body posture) making them superior to those devices that have no ability to measure static characteristics [38,39].

Advances in integrated microelectromechanical systems (iMEMSs) have enabled the size and cost of the accelerometer device to be greatly reduced while ensuring the fabrication of these devices are maintained at a high quality and reliability as required by industrial standards [34].

Advantages of accelerometer devices include their small size, ability to record data continuously for periods of days, weeks and even months. This continuous recording capability is due to the relatively low current draw of modern accelerometer devices (iMEMS, 0.18–0.7 mA[1]) in contrast to gyroscope (iMEMS, 3.5–6.0 mA (see foot note 1)). Models with internal real-time clocks also help differentiate activity patterns over this recording period [37]. Accelerometers also have high resolution at typical sampling frequencies used for ambulatory detection (2 mg at 60 Hz, ADXL322 (see foot note 1)). Their bandwidth may also be set by the simple attachment of coupling filter capacitors to outputs of the accelerometer device. This allows the accelerometer device to be easily matched to the frequency response of the activities performed by human motion, where typically the information for gait patterns corresponds to 0.6–5.0 Hz [40]. Eq. (1) is a simple means of calculating the correct value capacitor at the 3 db bandwidth, where C_X and C_Y are the capacitor values to be determined:

$$F_{-3\,\mathrm{db}} = \frac{1}{2\pi(32\,\mathrm{k}\Omega) \times C_{(X,Y)}} \tag{1}$$

Eq. (1): calculation of filter capacitor values for correct bandwidth in ADL.

4.1. Accelerometers

Accelerometers included for kinematic studies include piezoelectric, piezeresistive, differential capacitor, all of which implement the same basic principle of the spring mass system [38,41].

4.1.1. Piezoelectric accelerometers

Piezoelectric accelerometers consist of a piezoelectric element with a seismic mass. When the sensors undergo acceleration, the seismic mass causes the piezoelectric element to bend. This change causes a displacement charge to build up on one side of the sensor, which results in a variable output voltage signal that is proportional to the applied acceleration. Piezoelectric accelerometers have high outputs for small strains and the potential of a large dynamic range [41].

4.1.2. Piezoresistive accelerometers

These accelerometers are typically manufactured from a surface micromachined polysilicon structure. On this sits polysilicon springs (arranged in a Wheatstone configuration) whose electrical resistance changes as the acceleration forces are applied. The acceleration is again proportional to the resulting voltage [38]. These accelerometers are useful for acquiring vibration information at low frequencies.

4.1.3. Differentiable capacitor accelerometers

These operate on the principle of change of capacitance is proportional to applied acceleration. They use a differentiable capacitor with central plates attached to the moving mass and fixed external plates. The applied acceleration unbalances the capacitor. This results in the output wave for the accelerometer.

4.2. Accelerometer placement

The location at which an accelerometer is placed on the body is an important consideration in the measurement of body movement, with it normally attached to the part of the body whose movement is being studied [38]. For example, accelerometers attached to the ankle and shin, are used to study leg movement during walking and accelerometers attached to the wrist have been used in the study of Parkinsonian tremor. In many circumstances it is necessary to study ‘whole body’ movements. This is best represented by placement of a sensor as close as possible to the center of mass of the body, such as the sternum, under arm or waist [42].

[1] Analog Devices, Inc. www.analog.com.

The exact location of the accelerometer – even if placed on some rigid segment – might influence the accuracy of measurement. For example, if the sensor is attached too close to a center of rotation, the amplitude of the resulting measured signal might be attenuated. In addition to this, using walking assistive devices (cane or Zimmer frame/walker) might affect the pattern of the measured signals. This may result in a general attenuation in amplitude of the signal during step impact and also increase the jerkiness of movement during ambulatory movement.

4.3. Acquiring the correct accelerometer data

The output of an accelerometer worn on the body is dependant on four factors as listed as follows [38]:

1. Position at which it is placed,
2. Its orientation at this location,
3. The posture of the subject and
4. The activity being performed by the subject.

Modern fabrication techniques provide researchers with uni-axial devices (accelerometers that can record acceleration in a single direction), bi-axial and tri-axial devices (that can act along two/three orthogonal axes and so can thus provide a representation of acceleration in two to three dimensions).

If the subject or patient is at rest the output of the accelerometer, is determined by its inclination relative to the gravitational vector. If the orientation of the accelerometer relative to the person is known, then the resulting accelerometer recordings can be used to determine the posture of the subject relative to the vertical or gravitational direction. For a multiple accelerometer configuration Lyons et al. [39] showed that the subjects posture could be determined under static conditions by using the arc-cos transform of Eq. (2), where 'a' is the acceleration output, 'g' is equal to 9.81 ms^{-2} and θ is the resulting angle for the subjects posture. If the subject is moving (dynamic response) the resulting signal is a combination of the subjects orientation and movements [38]:

$$\theta_{\text{degrees}} = \frac{180}{\pi}\cos^{-1}\left(\frac{a}{g}\right) \tag{2}$$

Eq. (2): The arc-cos transform for posture detection [39].

The main acceleration components are due to the movement of the body. The body-generated linear, centripetal and coreolis accelerations are the main factors that constitute both the translational and rotational body movements. Other spurious resulting accelerations, such as artifact due to soft tissue movement or external vibrations may also be present in the accelerometer signal, but can be minimized through careful instrument placement and signal filtering [38].

4.4. Past accelerometer-based laboratory mobility research

Table 1 offers a summary of some of the laboratory and clinical studies, using accelerometers for movement and mobility analysis. The primary aim of the researcher is to develop an appropriate means of movement and mobility detection from body mounted accelerometer-based sensors by means of multiple or single locations. As discussed by Mathie et al. [38], there are a number of key considerations when selecting a sensor configuration. Mathie highlights the design tradeoffs between the number of accelerometer-based sensors that are used, the cost, the usability and the transferability of the monitoring system. The design choices will be determined by the purpose, duration of the monitoring and the type of subjects to be monitored. In long-term unsupervised monitoring environments, subject compliance is essential if the system is to be used, with the monitor being as comfortable and unobtrusive as possible [38].

Multiple sensors increase the complexity of the monitoring system. The use of one sensor attached at a single location on the body is a more straightforward approach. This significantly simplifies the design and use of the monitor but also reduces the quantity of information that is obtained about the movements [38].

Table 1 also summarises the various techniques that have been used since the early 1990s for human movement analysis. Large heavy equipment with multiple body mounted sensor configurations, have been replaced by smaller and lighter sensors of singular body placement. To account for this reduction in the number of sensor locations, more complex signal-processing approaches have also been introduced. This is because with the minimum number of sensors applied to the body, the maximum processing return on recorded data must be acquired.

5. Translating accelerometry data for clinical purposes

As can be seen from Table 1 the basic interpretations of accelerometry data include simple mathematical operators such as means and standard deviations. These methods have been used in conjunction with thresholds to define the basic motoric activities such as sitting, lying (supine, prone, left and right), standing and walking where the orientation of the accelerometer is rotated about the range of 0 g to −1 g [39].

The basic technique for determining PA due to motion sensors are based upon the raw output from the accelerometer, known as 'counts'. Chen and Bassett [41] describe the process of sampling, digitisation, thresholding and subsequent techniques of applying detective algorithms for PA. The following are some typical techniques that have been applied to accelerometer signals.

Table 1
This table highlights some of the laboratory and clinical studies done using accelerometers. *N* refers to the number of subjects recruited for the testing protocol. Length (days) is the time spent monitoring.

Year	Author	*N*	Length (days)	# Sensor/placement	Size (cm^3)	Mass (g)	Detection success	Motivation and activity recognition	Algorithm and signal processing
1991	Meijer et al. [43]	4 (2M, 2F)	<1	1 waist (lower back)	>1 cm^2, 192 cm^3	20 g + 350 g	80%	PA: bench test of accelerometers, instrument variation	Counts/min, mean (for test–retest)
1993	Veltink et al. [44]	5	<1	1 trunk, 1 upper leg	0.96 cm^3 + logger	3 g + Vitaportlogger	Not reported but visual detection	To detect posture and movement: standing, sitting, lying, moving	Applied thresholds
1995	Tamura et al. [45]	10 (F)	<1	1 waist, 1 wrist and 1 ankle	344 cm^3 (logger)	1.5 g + 200 g	Not reported but visual detection	Activity levels in the elderly (recorded with ECG)	Frequency and amplitude of acceleration over time
1996	Veltink et al. [46]	10 (M)	<1	1 sternum*, 1 shoulder, 1 thigh*, 1 shank (*used)	0.96 cm^3 + logger	1.5 g + recorder	Visual detection (errors—20% some cases)	PA: static/dynamic activities, stand, sit, lying supine, walking, cycling, ascending/descending stairs, speed of activity	Thresholds, mean values, signal morphology (correlations), cycle times, standard deviations of cycles
1997	Bouten et al. [42]	13 (M)	<1	1 waist, lower back	1.6 cm^3 + 270 cm^3	0.9 g + 250 g	Correlations (r = 0.77 and 0.89) for IMA_{tot} and EE_{act},	PA: bench test of device, correlation of activities of daily living (dressing, walk, lie, desk work, etc.) in respiration chamber to monitor output	Time integrals from separate measurement direction (IMA_{tot}) versus physical activity (EE_{act}, chamber), mean, std deviation, FFTs
1998	Bussmann et al. [47]	3 (M)	<1 (twice)	2 upper legs, 2 sternum, HR	1.5 cm^3 + Vitaport1 logger	1.5 g + recorder	88% spontaneous, 96% standard (video to monitor)	Psychophysiological study in the young: static/dynamic activities, 40 activity protocols (sit, lie, stand, walk + variations etc.), ECG	Thresholds, video analysis, 1 second resolutions, Psychophysiological effects of benzodiazepines
1999	Foerster et al. [48]	24 (M)	<1	1 sternum, 1 wrist, 1 upper thigh, 1 lower leg, HR	0.8 cm^3 + Vitaport2 logger	4 g + 700 g	95.8% posture, 67% ambulation	Ambulatory monitoring: retests, 9 postures (lab ref of sit, lie, walk, stairs, etc.), recordings in real world v. observer, speech activity and heart rate	Measured v. observed readings (L_1 distances, standard deviations), resolutions of >20s and >40s
2000	Yoshidai et al. [49]	3	<1	1 centre of abdomen	0.05 cm^3 + 35.1 cm^2	1 g + 15 g	Visual detection	PA: 11 postures (inc. lying left, right, supine and prone)	Addition of integrated outputs for I minute resolution
2000	Najafi et al. [50]	11 (6F, 5M)	<1	1 chest	0.05 cm^3	1 g + logger	99% postural trans, >90% lie/walk	Postures, posture transitions (gyroscope), walking periods	Wavelet transform (DWT), optical reference system (Vicon^{TM})
2003	Mathie MJ, et al. [51]	26 (7F, 19M)	<1	1 front of waist	63.9 cm^3	50 g	Sensitivity 0.98, specificity 0.88-0.94	ADL: 11 discrete dynamic activities (sit-to-stand, stand-to-sit, walk), 12 distinct rest periods (stand, sit)	Various length of median filter, window widths and thresholds, mean, energy expenditure (integral area)
2003	Lee et al. [52]	24 (4F, 20M)	<1	1 back	Sensor + sampling equipment and micro-controller	–	Average success rate of 95.1%	PA: 5 static activities (stand, sit, lower head, sit down & lean against, lie supine & prone) and 4 dynamic activities (walk, run up/down stairs)	Thresholds to DC (static), thresholds to AC analysis (dynamics), video analysis

Table 1 (*Continued*)

Year	Author	*N*	Length (days)	# Sensor/placement	Size (cm^3)	Mass (g)	Detection success	Motivation and activity recognition	Algorithm and signal processing
2003	Najafi et al. [40]	44 (11 + 24 + 9) (3 studies)	<1	1 chest	$9.4\,cm^3$ + Physilog® logger	–	PT 99%, average sens. and spec. 94%, 95%	Sitting, stand, lying, walking, postural transitions PT (gyroscope)	Wavelet transform, DWT, thresholds, visual observation
2004	Bao et al. [53]	20	<1	1 wrist, 1 waist, 1 upper arm, 1 thigh, 1 leg	$0.05\,cm^3$	–	Ranging from 41.42% to 97.49%	Walking, sit and relax, stand, watch television, run, stretch, scrubbing, fold laundry, brush teeth, ride elevator, walk + carry, read, cycle, climb stairs, vacuuming, lie down, strength training, etc	Mean, energy, frequency domain entropy, correlation of acceleration data, classifiers: C4.5 decision tree, decision table, naïve Bayes classifier, instance based learning (IBL)
2004	Luinge et al. [54]	2 (repeated trials)	<1	1 upper back, 1 pelvis	$41\,cm^3$ + $1140\,cm^3$	40 g + 900 g	98%	Posture: inclination of trunk and pelvis	Kalman filtering, optical reference system (Vicon™)
2004	Lyons et al. [39]	1 (repeated over several days)	<1	1 sternum, 1 upper thigh	$0.05\,cm^3$ + $75.6\,cm^3$	2 g + 192 g	*Sit 93%, stand 95%, lying 84%	Posture and movement detection: Static and dynamic activities, Posture (sit, lie, stand)	*Best-estimate/mid-point thresholds, mean, std. dev., observed comparison (1 minute resolution)
2004	Baek et al. [55]	1	<1	1 waist	Sensor + sampling equipment	–	97.5%	Activity: retest, standing, sitting, lying back/on, walking, running, upstairs, downstairs	Mean, standard deviation, skewness, kurtosis, eccentricity, histograms, neural network (NN)
2004	Noury et al. [56]	5 (health, older)	<1	1 chest*, 1 wrist, 1 thigh, I ankle (*used)	Constructed cube kinemeter	–	Visual detection	PA young and old: Walking, postural transitions (accelerometers + magnetometers), orientation angles	Frequency spectrum analysis
2004	Culhane et al. [17]	5 (3F, 2M)	4 (6 h per day)	1 chest, I thigh	$0.05\,cm^3$ + $75.6\,cm^3$	2 g + 192 g	>92%	Mobility monitoring of elderly in clinical environment (stoke patients); sit, stand, lying, postures	Means and standard deviations, thresholding (best estimate and mid-point), comparison with manual recordings of patient activity
2005	Barralon et al. [57]	–	<1	1 chest (under armpit)	Constructed device	–	Walk 76%, postures 80%	Postural states, walking, postural transitions	Angles/inclinations, Frequency analysis (FFT), thresholds, video analysis
2006	Barralon et al. [58]	20 (18F, 2M)	<1	1 under left arm pit	Constructed device	–	DWT* 78.5% sensitivity, 67.6% specificity	Six methods for walking periods,	Video analysis, thresholds applied/not to: short time fourier transform ($StFT_T$, $StFT_{T/Tb}$), discrete wavelet transform (DWT, DWT*), continuous wavelet transform (CWT, CWT*) (*less coefficients)
2006	NiScanaill et al. [59]	–	Long-term potential	1 trunk, 1 thigh	$4.9\,cm^3$ + transmitter at waist	–	–	Remote sensor for home care: Sit, stand, lie, walk	Means, thresholds, SMS message on GSM network
2006	Hester et al. [60]	15	<1	1 wrist, 1 ankle, 1 walking stick	Sensors + transmitter	–	Sensitivity 95%, specificity >95%	Stroke patients: Motor tasks at home-assessment of mobility assistive devices (cane) (accelerometers + gyroscopes)	Dominant frequencies, energy aspects, cross-correlations, auto-covariance’s, NN, threshold, wireless transmission

2006	Pärkkä et al. [61]	16	<1	1 wrist, 1 chest	12000 cm^3 (rucksack)	5 kg	CDT 82%, ADT 86%, NN 82%	Lie, row, cycling, sit/stand, run, nordic walk, walk (includes HR, EKG, SaO2, skin temperature, skin resistance, light intensity, compass, audio, GPS and altitude sensors)	Mean, variance, median, skewness, kurtosis, percentiles, spectral centroid/spread, peak frequencies, power, power in frequency bands, decision trees (custom/auto, CDT/ADT) (NN)
2006	Karantonis et al. [62]	6	<1	1 waist	62.5 cm^3	50 g	Overall 90.8% (posture 94.1%, walk 83.3%, possible falls 95.6%)	Ambulatory monitoring: Activity (12 tasks), rest, posture, walking, falls, estimation of metabolic energy	FFT, normalised signal magnitude area (SMA), signal magnitude vector (SMV), threshold

5.1. Common analytical and mathematical techniques

The earliest forms of algorithmic techniques applied to accelerometer signals were the adoption of *thresholds* [46,63,64]. Veltink et al. examined the *mean* and *standard deviation* of the accelerometer signal to determine periods of static and dynamic activity. Thresholds were applied to these two properties and if the activity was detected as static, the type of static activity could be identified from the orientation of the body segments, relative to the gravitational field. In the case of dynamic activity, the positions and orientations of the segments varied with time [46]. Beak et al. [55] used further mathematical operands and statistical features such as *skewness*, *kurtosis*, and *eccentricity* of the accelerometer signal as further features for discrimination in PA such as walking up and down stairs.

Bouten et al. [65] used simple integration methods to determine the relationship between the integral of absolute accelerometer output ($\mathrm{IAA_{tot}}$) and EE. Here it was found that EE could be determined by body accelerations in 3 planes (a_x, a_y and a_z) using a tri-axial accelerometer. This method has since has been adopted and improved in similar subsequent studies [51,62,66–68]:

$$\mathrm{IAA}_{tot} = \int_{t=0}^{T} |a_x|\mathrm{d}t + \int_{t=0}^{T} |a_y|\mathrm{d}t + \int_{t=0}^{T} |a_z|\mathrm{d}t \tag{3}$$

Eq. (3): estimation of EE from a tri-axial accelerometer.

Bourke et al. [69] in his study of fall detection examined the integrated resultant signal from a tri-axial accelerometer. The resultant or root sum of squares (RSS, or signal magnitude vector, SMV) of the tri-axial accelerometer output resulted in 100% detection of 240 falls from normal ADL. Bourke et al. [70] also examined the vertical velocity to investigate pre-impact detection of falls. The vertical velocity vector was calculated through numerical integration of the vertical acceleration, a_v, during stages of quasi-static and dynamic activity:

$$\mathrm{RSS} = \sqrt{a_x^2 + a_y^2 + a_z} \tag{4}$$

Eq. (4): the resultant from a tri-axial accelerometer.

5.1.1. Frequency spectrum analysis

More recent accelerometer data analysis has involved the use of frequency spectrum analysis and the examination of dominant frequencies using the fast Fourier transforms (FFT) [56,57,60]. These traditional spectral analysis methods tell us about the frequency components of a signal. Fourier analysis is a global tool providing a description of the overall regularity of a signal and copes superbly with naturally occurring sinusoidal behaviour [40,71]. In the Fourier transform, the original waveform is compared to a whole family of sine functions at harmonically related frequencies (sine functions are popular as they contain energy at only one specific frequency). This is performed by multiplying the waveform with the sinusoidal functions and averaging (using integration in continuous domain, or summation in the discrete domain) [72].

However, the Fourier transform does not provide the time at which these frequency components occurred. Thus, a more comprehensive tool is required that can analyse the accelerometer signal in more detail (in both time and frequency). Time–frequency analysis is important in analysing non-stationary signals, i.e. where the frequency content changes over time. An example of a non-stationary signal includes the acceleration pattern during human movement, where varied accelerations with sharp high-frequency transients are present at certain time instances and frequencies [40].

5.1.2. Multi-resolution analysis

Multi-resolution analysis (MRA) aims to overcome the shortfalls of frequency analysis. As its name suggests, MRA analyses the signal at different frequencies with different resolutions. MRA is designed to give good time resolution and poor frequency resolution at high frequencies but good frequency resolution and poor time resolution at low frequencies. As human movement is generally associated with low frequencies (approximately 2.5 Hz for walking), MRA can be considered to be ideally suited for translating accelerometer data into comprehensive clinical terms (quantitative and qualitative data). Wavelet analysis with the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT) are two such MRA techniques.

5.1.3. Wavelets

Wavelets are used extensively in many varied technical fields and can actually be understood in terms of simple comparisons or correlations with the signal one is analysing [73]. Like Fourier analysis, however, wavelet analysis uses an algorithm to decompose a signal into simpler elements and is far more efficient than Fourier analysis whenever a signal is dominated by transient behaviour or discontinuities such as human movement [40,71].

So what is a wavelet? A wavelet is a waveform of effectively limited duration that has an average value of zero and they come in many different shapes and sizes (Fig. 6). Unlike sinusoids that extend from minus to plus infinity, wavelets have a beginning and an end. Sinusoids are smooth and predictable and are good at describing constant frequency (stationary) signals while wavelets are irregular, have limited duration and are often non-symmetrical. Wavelets are thus better at describing anomalies, pulses and other transient events that start and stop within a signal [73].

Wavelet analysis uses many different probing (wavelet) functions divided into families (different orders) but they always consist of enlarged or compressed (scales, pseudo frequency) versions of the same basic function, as well as translations [72]. Wavelet and wavelet families such as Daubechies, Morlet and Coiflet etc are shown in Fig. 7.

5.1.4. The continuous wavelet transform (CWT)

In wavelet analysis a variety of different probing functions (wavelets) are used to evaluate some particular behaviour or characteristic of the waveform. This leads to the defining of the continuous wavelet transform (CWT) in Eq. (5):

$$W(a,b)=\frac{1}{\sqrt{|a|}}\int_{-\infty}^{\infty}x(t)\psi*\left(\frac{t-b}{a}\right)\,\mathrm{d}t \tag{5}$$

Eq. (5): the continuous wavelet transform (CWT) [72].

The transformed signal is a function of two variables b and a, which are the translation and scale parameters, respectively. The transforming (wavelet) function ($\psi(t)$) is defined as the 'mother wavelet'. If a (scale—high scale correspond to low frequencies and low scale correspond to high frequencies) is greater than one the wavelet function is stretched along the time axis, while b, translates the function across $x(t)$. The resulting wavelet coefficients, $W(a,b)$, describe the correlation between the waveform and the wavelet at various translations and scales. The coefficients may also be understood to be the amplitudes of a series of wavelets, over a range of scales and translations, which would needed to be added together to reconstruct the original signal. However, reconstruction of the original signal is rarely performed using the CWT because of the redundancy of the transform [72]. This is due to the fact that the CWT provides an oversampling of the original waveform, i.e. more coefficients are generated than are needed to uniquely specify the signal [72]. This is not a problem in analysis applications so when reconstruction of the original signal is required, the discrete wavelet transform is used.

5.1.5. The discrete wavelet transform (DWT)

The discrete wavelet transform (DWT) provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time compared to the CWT. The DWT is often given in terms of

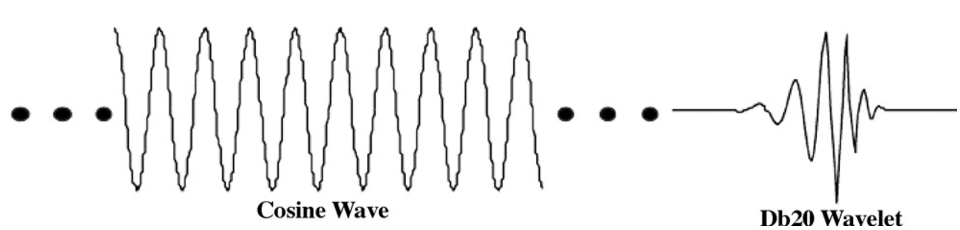

Fig. 6. A selection of an infinitely long sinusoid and a finite length wavelet [73].

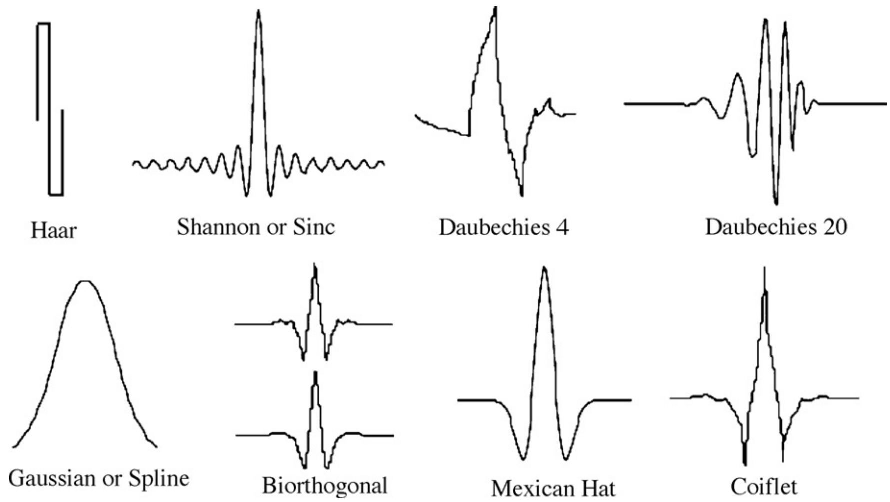

Fig. 7. An example of wavelets for CWT and DWT applications [73].

its recovery transform:

$$x(t) = \sum_{k=-\infty}^{\infty} \sum_{\ell=-\infty}^{\infty} d(k, \ell) 2^{-k/2} \psi(2^{-k}t - \ell) \quad (6)$$

Eq. (6): the discrete wavelet transform (DWT) [72].

The purpose of the DWT is similar to that of the CWT, a time–frequency representation of a signal. However, where the CWT compared a wavelet function to generate coefficients per translation the DWT owes its functionality to the fast pyramid algorithm, as developed by Mallat and Meyer [71,72]. The pyramid algorithm has both forward and backward (inverse) algorithms to compute the wavelet transform. The backward algorithm reconstructs the original signal from the component wavelets [71].

The discrete transform process high and low pass filters the original signal to split the signal into high-scale components (low-frequency) called the approximation and low-scale (high-frequency) called the detail at various scales. This use of a group of filters to divide up a signal into various spectral components is called 'subband coding'. The filters are based upon the coefficients of the wavelet used. This has important implications when reconstruction of the original signal is necessary, as in the case for quantitative (time) activity determination such as sitting, lying, etc.

Reconstruction of the original signal can be performed by the addition of the approximations and details and this is done so mathematically by the use of quadrature mirror filters, Fig. 8 (synthesis filter banks). Multilevel decomposition of the original signal and reconstruction of the approximations have previously been used for the quantitative activity determination of the elderly [40,50]. Reconstruction of the evaluated approximation was necessary in order to have the same number of samples as the original signal to accurately determine times per activity of the ADL.

The forward algorithm process also combines the filtering process with down sampling operations. This eliminates every other sample at each operation, which halves the data each time. This feature results in the fast computational speed of the algorithm because the down sampling reduces the computations at each iteration geometrically [71]. The backward pyramid algorithm inverts the process, it combines a series of up sampling operators by a factor of two with linear filter operations. The up sampling inserts a zero between the data values, doubling the data at each iteration.

5.2. *Activity determination—classifiers*

Once the necessary information has been extracted from the accelerometer signals due to simple or more complex arithmetic operands, it is becoming more commonplace to use artificial intelligent-based systems. This approach not only recognises the basic parameters of ADL such as sitting, lying, standing, etc., but can also highlights extended periods of ambulatory behaviour such as performing random chores involved during housework [53,61,74].

Duda et al. [75] describe a pattern recognition process such as one highlighted in Fig. 9. There are many pattern recognition processes that available for potential use within systems such as these. The following are some examples of these that have been used in human recognition patterns to date:

5.2.1. *Decision trees—classification and regression tree (CART)*

The most simple and straight forward of these methods is a classification and regression trees (CART), which have been adopted for pattern recognition involving human movement based upon activity performed during ADL [53,61].

CART tree classify a pattern through a sequence of questions in which the next question asked depends on the answer to the current question. This approach is useful for non-parametric data, because all of the questions can be asked

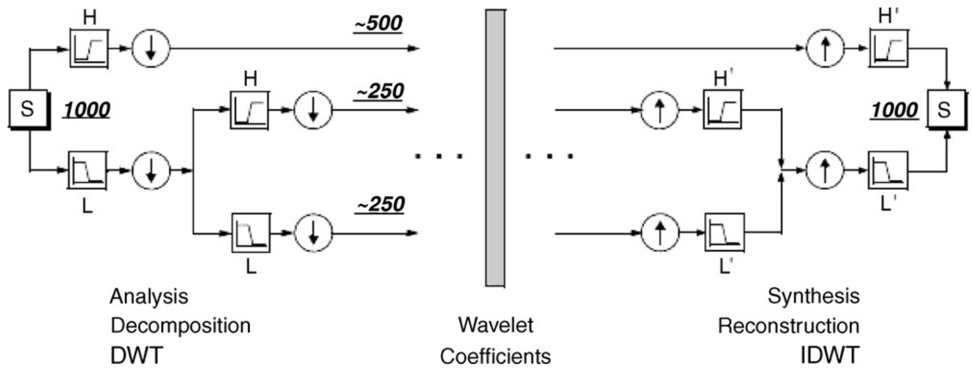

Fig. 8. Quadrature mirror filter structure for multi-level decomposition and reconstruction, of the original signal (s), during the DWT [153].

in a 'yes/no' style that does not require any notion of metric [75].

These questions can be displayed in a classification tree, shown in Fig. 10, where the first or 'root node' is displayed at the top. This primary node is connected by successive links (branches) to other nodes and the classification tree terminates at the leaf nodes. The classification of a pattern always begins at the root node, which asks for a value of a property to be given. The links to subsequent nodes correspond to different possible values. Based on the answer, one follows the appropriate link to the next node (descendant node) [75].

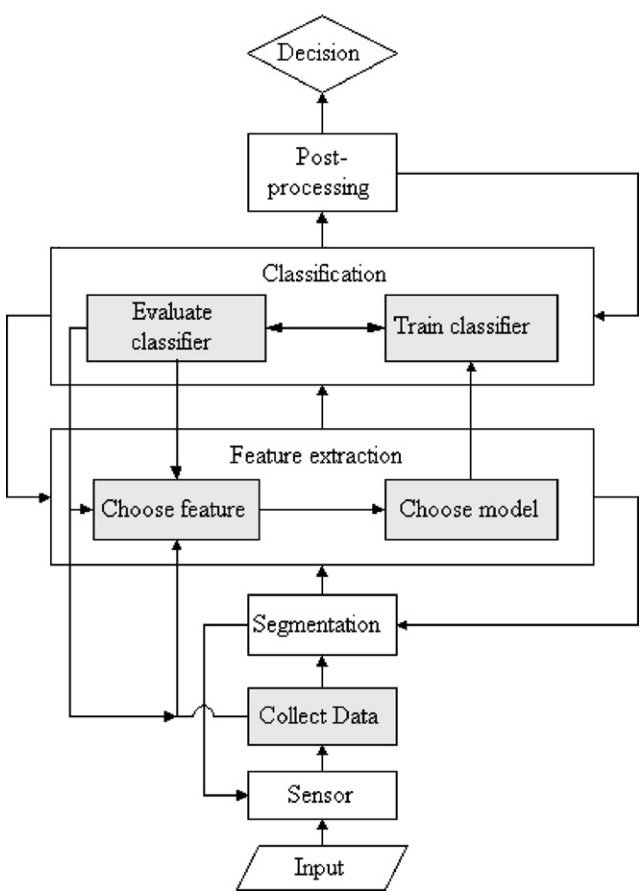

Fig. 9. Classification system flow design, pattern recognition system and the design cycle (shaded).

5.2.2. Decision trees—ID3

This tree algorithm is for use with nominal or unordered inputs. This algorithm works by binning its real valued variables into intervals, with every interval treated as an unordered nominal attribute. Every split of the tree has a branching factor B_j, where B_j is the number of discrete attribute bins of the variable j chosen for splitting [75]. The defining characteristic of these trees is that each node has as many children nodes as the number of categories of the (nominal) feature at that node, i.e. the number of levels in the tree, are equal to the number of input variables [75,76]. The main problem with the ID3 algorithm is lost information when continuous-valued variables are discretized into categories [76].

5.2.3. Decision trees—C4.5

The C4.5 algorithm is the most popular construction method in a series of 'classification' tree methods [75]. This method overcomes the problem of discretization (as described with the ID3 algorithm) by using continuous valued variables like CART, and the nominal variables

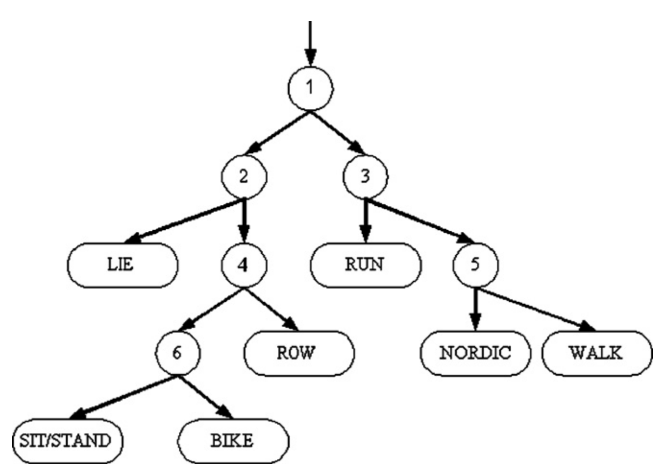

Fig. 10. A classification tree example [61] (IEEE© 2006).

like ID3 [76]. C4.5 is superior to the CART process as it can classify patterns with missing features [75]. Bao and Intille used this algorithm with an overall recognition accuracy of 84% for the detection of 20 daily activities [53].

5.2.4. The Naive Bayes classifier

The Naïve Bayesian classifier has good computational efficiency and relative performance and has been used in the detection of falls and ADL [77,78]. It assumes conditional independence among all attributes given the class variable. It learns from training data the conditional probability of each attribute given its label class [79].

5.2.5. Neural networks

Artificial neural networks consist of inputs and outputs with a processing layer or hidden layer in between. Statistically, the inputs are the independent variables while the outputs are the dependant variables [80]. The internal hidden layer(s) can be adjusted through optimization (learning) algorithms, such as the resilient backpropagation (RPROP), scale-conjugate (SCG) and Brodyen–Fletcher–Goldfarb–Shannon (BFGS) algorithms. For example, with supervised learning algorithms, the inputs with its required outputs are applied to the network, which iteratively self-adjusts. This learning process terminates when a prediction error falls below a set threshold [80].

Artificial neural networks have been used for the detection of ADL (walking up and down stairs, standing, etc.) and even some sports [55,74,81]. These networks have adopted techniques such as the *multilayer perceptron* (MLP) and *feed-forward* (FF) neural network methods. The MLP method has also been used in the study of fall risk, the detection of voluntary movement from levodopa-induced dyskinesia, the classification of human tremor signals (with the use of back-propagation) and human locomotion (feed-forward and back-propagation) [82–85].

The laboratory and clinical based studies as outlined above involve complex analytical and engineering-based procedures. The successful outcomes from these trials determine suitable algorithms and methods that may then be applied to a broader spectrum of human related movement disorders. Non-engineering researchers through the use of commercial accelerometer-based devices can also apply application of these methods. These commercial devices are equipped with their own computer analysis software, which makes understanding the raw data easier and more user friendly.

6. Current commercial technologies

There are many commercially available PA monitors on the market for academic research and individual health care monitoring that incorporate accelerometers. A recent study by de Vries et al. [86] reviewed the quality of motion sensors in children and adolescents (2–18 years). In this study a 20-item checklist was developed to evaluate and compare the published evidence on the *clinimetric* quality of the identified motion sensors selected from a computerised bibliographic database. (The outcomes from some of this study are highlighted later in this section.)

The study by de Vries et al. [86] highlights the necessary characteristics when choosing an effective motion sensor within a study. These factors include:

(a) Reproducibility; this is the extent to which the sensor is free of measurement error and includes two concepts
   - a.1 Intra-instrument reliability, i.e. test–retest reliability. This assesses the variability of a motion sensor over time and reflects measurement error and real change in the observer behaviour. The most suitable measure for this concept is the calculation of the intra-class correlation coefficient (ICC), with an ICC $\geq$ 0.70 considered as “good”.
   - a.2 Inter-instrument reliability. This quantifies measurement error and detects systemic differences between two measurements. The inter-instrument reliability is best measured with the 95% limits of agreement, kappa coefficient, standard error and coefficient of variation [86].

(b) Validity, referred to the appropriateness, meaningfulness and usefulness of the specific outcome measure, i.e. does the sensor measure what it is supposed to measure. The validity of a sensor can be measured by sensitivity, specificity, correlation coefficients, *t*-test, etc. Validity can also be considered under the following types:
   - b.1 Criterion validity. This measures the motion sensor against the gold standard or criterion standard.
   - b.2 Convergent validity. The extent to which the measurements made by the sensor are associated with those made with other assessment methods that intend to measure the same or similar aspects [86].

(c) Sensitivity,
(d) Feasibility referring to the cost (including software), expertise and acceptability (comfort, tolerance, refusal, and amount of missing data due to malfunctioning of the device) [86],
(e) Cost.

The following is a summary of some of the commercially available monitors that are attached to the waist, thighs and lower limbs for various applications. All monitors presented here have been used in clinical trials involving independent validation of the device and its application to a particular study group (obese, elderly/young, those with back pain, etc.) to determine their levels of activity. As with any study the correct choice of monitor is important for a successful outcome.

Fig. 11. The RT3 Tri-axial Research Tracker Kit (image published with permission).

6.1. RT3 tri-axial research tracker kit

This RT3[2] has replaced the much validated and tested Tritrac R3D [87–97]. The two devices differ in the number of accelerometers incorporated. The original R3D activity device used 3 one-dimensional accelerometers while the RT3 uses one integrated three-dimensional accelerometer [86]. The RT3 is a waist-mounted device that has been used extensively for calorie tracking in humans due to physical activity (Table 2). The RT3 provides tri-axial vector data in activity units, metabolic activity units or kilocalories. Its software displays performance graphs and activity unit data that can be used to assess and track subjects in ongoing comparative studies (Fig. 11).

The earlier R3D model was used successfully in numerous clinical studies that have included energy expenditure estimation among adult men and women and also young children [87,90,91,93,97–99]. This monitor was validated against various devices and methods including indirect calorimetry, the gold standard for energy expenditure and achieved satisfactory accuracy results for a range of age groups [86,87,100]. The newer RT3 device has been validated in young children (7–12 years) and young men (18–22 years) and deemed a good (valid) measure of physical activity [101,102]. (Reproducibility of the RT3 in assessing PA has not been reported). Recently the device has been used in some clinical activity studies involving adults with and without some neurological dysfunction (stroke, Parkinson disease, multiple sclerosis and controls), fatigue and postoperative recovery in the elderly, the mentally ill and those suffering from schizophrenia [26,103–105].

[2] Stayhealthy Inc., Monrovia, CA, USA.

Fig. 12. The activPAL™ Professional activity monitor (image published with permission).

6.2. activPAL™ Professional

The activPAL™ Professional from PAL Technologies[3] is a new compact monitoring device incorporating a uni-axial piezoresistive accelerometer. The activPAL™ generates timing results in three categories of sitting/lying, standing and stepping. It also provides the cadence and number of steps of the user. The breakdown can be given per hour (in increments of 15 s) or over the course of a day or week (Fig. 12).

The activPAL™ monitor has been validated for the amount of time-spent sit/lying, etc. and also shown to be highly accurate for step number and cadence [106,107]. The monitor also provides data for energy expenditure (MET.hours, Physical Activity Level (PAL), kCAL) that is derived from the activity parameters; however, these have not been independently validated. The activPAL™ has been used for various clinical studies involving prosthetics and lower limb amputees [108–110], back pain [111], osteoporosis [112], cerebral palsy [113], the elderly [114–116], cardiology [117], venous ulceration [118], stroke [119] and motoric subtyping of delirium [27].

6.3. ActiGraph GT1M

The ActiGraph[4] was previously known as the ‘Computer Science and Applications’ (CSA) monitor and also as the ‘Manufacturing Technology Inc.’ (MTI) monitor. ActiGraph have produced a number of models such as the 7164,

[3] PAL Technologies Ltd., 141 St. James Road, Glasgow G4 0LT, United Kingdom.

[4] Actigraph, LLC, Fort Walton Beach, FL, USA.

Fig. 13. The Actigrpah GT1M (Photo Courtesy of ActiGraph).

AM7164, GT256 and GT1M. There is no clear distinction as to which monitor is the most popular among these choices but the collective ActiGraph motion sensor are the most widely used motion sensors (especially in children and adolescents). These use a single axis piezoelectric accelerometer which can be programmed to turn itself on at a specific time and date [86] (Fig. 13).

The device can accurately measure activity counts, steps counts, calories and activity levels across a range of ages and clinical groups and test conditions [86,120–126]. The ActiGraph is also used for sleep pattern studies to measure sleep/wake cycles, sleep latency and sleep efficiency (general circadian rhythms) [127–129]. The ActiGraph is the most studied motion sensor in children and adolescents due to its good reproducibility, validity and feasibility within these groups [86].

6.4. Cyma StepWatch3

The StepWatch3[5] (StepWatch) was previously known as the Step Activity Monitor, SAM. The device is programmed through a PC, which has the capability of adjusting the sensitivity of the StepWatch by adjusting its characteristics to suit that of its user. The standard mode permits users to program the StepWatch3 by entering the subject's height and answering simple questions that describe the subject's gait for more accurate recordings. The StepWatch is a microprocessor controlled step counter that has the capability of recording the number of steps performed by its wearer for up to 2 months (Fig. 14).

The StepWatch is also a validated activity monitor for use on the healthy, obese, amputees, stroke, spinal injury, the young and old [130–137]. The StepWatch has also been validated against a number of devices (including the TriTrac-R3D) on nursing home residents with dimentia. Here the StepWatch yielded data from the highest proportion of observations, explained the most variance and was also acceptable to nursing staff [138]. The StepWatch has also been directly compared to the Dynastreams AMP331 pod. It was found from this study that while the StepWatch was more prone to 'fidgeting' it did give higher estimates of steps per day (>18%) than the AMP because it detected a greater percentage (approx 99% accuracy) of actual steps taken at slow walking speeds when compared to observational recordings [139].

Fig. 14. The StepWatch3 (Photo Courtesy of OrthoCare Innovations).

6.5. Dynastream AMP331

The AMP311 from Dynastream[6] is an ankle mounted activity monitor. The AMP331 pod houses two accelerometers (one uni-axial and one bi-axial). Data analysis is based on Dynastreams patented 'SpeedMax' technology which was customised for the recreational running market. Its multi-dimensional motion tracking ability gives a continuous method of measuring distance and velocity travelled for both runners and walkers. Data is downloaded to a PC via Dynastream's proprietary RF protocol and exported to Excel where further data analysis can be performed (Fig. 15).

The AMP331 device is a relatively new and unused device for clinical studies. It has been shown to be accurate for counting steps to within 3% at walking speeds of 67 m/min and faster but underestimates at slower walking speeds. The device also underestimated distance by a mean estimate of 11% for various speeds above 40 m/min. However, the device does not seem prone to spurious movement that may occur during daily activity [139].

[5] Cyma Corporation 6405 218th St. S.W., Suite 100, Mountlake Terrace, WA 98043-2180, USA.

[6] Dynastream Innovations Inc., 228 River Avenue, Cockrane, AB T4C 2C1, Canada.

Fig. 15. The AMP331 Pod and attachment sleeve from Dynastream (Photo Courtesy of Dynastream Innovations Inc.).

Fig. 16. The Ossur PAM: Prosthetic Activity Monitor™ (Photo Courtesy of Ossur Americas, www.ossur.com).

6.6. Ossur PAM: Prosthetic Activity Monitor™

The PAM[7,8] is a lower leg mounted device that is designed especially for the orthotic and prosthetic industry. It monitors the level of daily activity and walking patterns of lower amputee patients that incorporates one bi-axial and one uni-axial accelerometer. This device has been validated for this study group in comparison with visual observation, video and 3D motion analysis during treadmill testing but limitations exist for normal ADL and distance measured [140–142]. Also, calculation of step length by the PAM is calculated by dividing stride length by a factor of 2. This assumes the patient is walking symmetrically, for amputees this may not always be the case [141] (Fig. 16).

Fig. 17. The IDEEA: Intelligent Device for Energy Expenditure and physical Activity (Photo Courtesy of MiniSun LLC).

6.7. IDEEA: intelligent device for energy expenditure and physical activity®

The IDEEA[9] provides a physical activity assessment, portable gait analysis, energy expenditure analysis and functional capacity evaluation monitor. It can identify and differentiate more than 40 types of activities, including 15 different parameters of gait. It provides information on the onset, duration and frequency of each activity and computes the amount and intensity of these activities. However, IDEEA comprises multiple sensors located at numerous points on the upper and lower leg, wrist, sternum and foot via cables. This hinders its use for long-term ambulatory monitoring (Fig. 17).

The IDEEA has been validated for its ability to accurately detect gait parameters [143], EE [144] and PA (reduced accuracy for up/down stairs) [145,146]. The IDEEA has even been deployed in a field validation of the accuracy of the MTI ActiGraph [147].

From the work by de Vries et al. [86] a number of issues regarding clinimetric studies were also highlighted. Testing for reproducibility, validity and feasibility among accelerometer-based motion sensors is poor and should be improved. Previous studies have highlighted only one commercial monitor to be sufficiently and rigorously tested for a certain age range. Subsequently, sufficient testing on new modern 3D sensors has yet to be undertaken with these recommendations in mind.

[7] Ossur hf. Grjóthálsi 5, 110 Reykjavík, Iceland.

[8] Dynastream Innovations, Inc., 228 River Avenue, Cochrane, AB T4C 2C1, Canada.

[9] MiniSun LLC, 935 E. MillCreek Dr., Fresno, CA 93720, USA.

Table 2
Current accelerometer-based commercial technologies.

	RT3	activPAL	GT1M (Actigraph)	StepWatch3	AMP331	PAM	IDEEA
Range of accelerometers	–	>2 g	0.05–2.5 g	–	–	–	3–5 g
Sampling Freq	0.017–1 Hz	10 Hz	30 Hz	128 Hz	–	–	32 Hz
Axes	3	1	1	2	–	3	2
Memory capacity	21 days (1–60 s resolution)	4 megabytes (MB)	1 MB	32 kB	–	7 day data collection	200 MB
Battery life	30 days	>8 days	14 days	60 days (min sampling freq)	7–10 days	7 days	3 days
Method of data transmission	Docking station (RJ-11)	Docking station (USB)	USB	Docking station (USB)	Wireless RF or USB	–	USB or RS-232
Reported information	Vector Magnitude, EE, metabolic equivalent units (METs)	Steps (taken and interval), Sit/lying, standing, stepping, METs	Activity counts, EE, steps, activity levels, sleep wake, etc.	Steps, patterns of activity	EE, steps, distance, locomotion, activity	Activity, steps, step length, distance, speeds, impact	40 + activities and 15 parameters of gait, EE
Place of attachment	Waist	Upper thigh	Waist, wrist, Ankle	Ankle	Lower leg	Lower leg	Upper & lower leg, wrist, sternum, foot
Accuracy	97%	98–99%	99%	91-99%	97 – 99%	>96%	>98%
Size and weight	105 cm^3, 67 g	13 cm^3, 20 g	25.3 cm^3, 27 g	7.5 cm × 5.0 cm × 2.0 cm 38 g	7.1 cm × 2.4 cm × 38 cm 50 g	8.5 cm × 3.8 cm × 3.2 cm 50 g	7.0 cm × 6.5 cm × 1.7 cm – 59 g, 1.8 cm × 1.5 cm × 3.0 cm – 02 g × 5 + sensors
Research references	47	51	199	74	25	3	7

7. Discussion and conclusion

Human movement is an important neuro-musculo-skeletal event which incorporates mechanical, physiological, anatomical, sociological, environmental and psychological factors [3,4,31]. The physiological, mechanical and anatomical factors include many underlying elements such as planes of movement, kinematics, biomechanics, etc. that must be understood when quantifying and defining human movement.

Accelerometry has proven itself to be an appropriate and viable means of determining the movement of various groups. This has been made more readily possible due to its current state of a miniature low power device coupled with lightweight compact data acquisition instruments, off-line and real time data processing techniques. As a result of this, accelerometry has become a relatively non-intrusive means of assessing ambulatory movement, posture, postural transitions, energy expenditure, rate and intensity of movement.

Groups such as those suffering from back-pain, Parkinson's disease, obesity, those at risk of falling, venous insufficiency, stroke, etc. [17,22,69,92,118] have all been monitored by accelerometry in clinical and non-clinical-based studies. Many studies involving these groups have been accelerometry validation studies, i.e. studies that ensure accelerometry is a viable means to detect accurate mobility monitoring for that group [22,60,148,149]. Bourke et al. [69] assessed young healthy subjects in a controlled environment and elderly subjects performing ADL under free-living conditions for the development of a threshold-based fall detection algorithm. This method of short term activity defined monitoring examined peak acceleration profiles of fall events to normal activities of ADL. Bourke et al. showed that fall detection with a trunk mounted accelerometer was possible with a specificity of 100% [69].

Culhane et al. [17] performed a medium to long-term mobility monitoring study within a clinical environment on older adults for on average 6 h per day over 4 days for all patients. This study involved the attachment of 2 accelerometer-based sensors, one on the thigh and one on the sternum with a data-logging device attached to the waist via cables. Manual recordings validated the accuracy of this study within 92%.

The systems described above usually require a more complex arrangement for attachment to the patient to be monitored. Where this is not possible, commercial accelerometer-based devices have been used. Commercial devices also provide non-engineering researchers with an opportunity to perform clinical studies with accelerometry. Commercial accelerometer-based devices such as the RT3, SeptWatch3, ActiGraph, activPAL™, etc. have broadened the field of human movement research to include such areas as metal illness and delirium [26,27], circadian rhythms and sleep disorders [24,25], autism [29], arterial diseases [30], nutrition [150] and anorexia [151]. The benefits that commercial devices offer to non-engineering researchers are their ease of use, accompanying software and their compact, lightweight and discrete nature. Clarke-Moloney et al. [118] performed a long-term study involving venous leg ulceration patients and their healthy aged match controls. Here the activPAL™ physical activity monitor recorded the patient's activity of sitting/lying, standing, stepping and number of steps continuously over a 7-day period.

Current accelerometer-based techniques have been reasonably well defined for PA monitoring of adolescents but there are still reliability and accuracy issues concerning older adults, where the validation of both laboratory and commercial devices in the young is not applicable to this group. Accelerometer patterns for older adults are more susceptible to noise as the fluidity of movement becomes impaired with increasing age. More advanced signal processing, perhaps incorporating multi-resolution analysis techniques, or the development of more suitable biomechanical models of human motion would help improve the accuracy. Algorithms should also be validated in the elderly to account for slow and erratic movement.

Multiple accelerometer arrangements enable the researcher to define more daily activities. However, these sensor arrangements are impractical for long-term monitoring and commercial use as it involves numerous cables running across the joints and along the body. Incorporation of wireless limb attachment sensors would make this multiple arrangement possible.

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Conflict of interest

None.

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