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# Uses of Accelerometer Data Collected From a Wearable System

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**ORIGINAL ARTICLE**

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# Uses of accelerometer data collected from a wearable system

**Abstract** This paper presents work, assessing the use of accelerometers in wearable systems for a number of applications. It discusses and demonstrates how body mounted accelerometers can be used in context aware computing systems and for measuring aspects of human performance, which may be used for teaching and demonstrating skill acquisition, coaching sporting activities, sports and human movement research, and teaching subjects such as physics and physical education. Analysis is restricted to considerations as to how raw data can be used, and how simple calculations of quantities of data in the time domain, can be used. The limitations of the use of such data are discussed.

**Keywords** Accelerometer · Wearable computer · Context aware · Human movement · Sports performance · Match analysis · Teaching

## 1 Introduction

In recent years accelerometers have become an attractive tool for use in wearable computer systems for detecting and measuring aspects of human movement. Such devices are typically very small, even with the requisite processor and power units, one can fit the device into a housing considerably smaller than a matchbox, or for surface mount units, the size of a coin.

Accelerometers incorporate a mass mounted on a cantilever beam or spring, which is attached to the accelerometer housing. As the housing accelerates, because of its inertia, the mass lags behind deforming the beam. This deformation is measured by using strain

gauges, where the greater the acceleration the greater the deformation and the accelerometer output. Strain gauge accelerometers are gravity sensitive. This means that their orientation affects their output. If they are orientated with the active element perpendicular to the axis of gravity, they will register the effect of gravity on the mass mounted on the beam and so give an accelerometer reading of 1G or 9.81 m/s/s. If the accelerometer is rotated 90°, the axis of gravity will run parallel to the mass and so it will not deform the beam on which it is mounted. In this case the accelerometer will give an output reading of 0G or 0 m/s/s.

The accelerometer output then represents the vector sum of the gravity and kinematic accelerations. Both these phenomena, of the accelerometer output being affected by kinematic acceleration and gravity, have been used in our studies using accelerometers mounted on the body. The output that represents kinematic acceleration has been used in assessing dynamic human movement activities. The output that represents gravitational acceleration has been used to detect changes in posture. The following sections present studies where we have investigated the use of body worn accelerometers for a number of applications. The work presented does not involve any analysis in the frequency domain. Instead, analysis is restricted to considerations as to how raw can be used, and how simple calculations of quantities of data in the time domain, can be used.

## 2 Teaching

### 2.1 Physics teaching

In UK education, for the requirements of Key Stage 4 (age 14–16 years) Double Science, pupils need to understand that acceleration is change in velocity per unit time and that only unbalanced forces can alter the acceleration of the moving object (since balanced forces do not alter the velocity of a moving object). Students should be able to distinguish between positive and

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negative velocity, and explain how changes in direction would be shown in graphical representations. In addition, science teaching requires involving the students in scientific inquiry, where the student is encouraged to generate hypotheses and test them by collecting and interpreting empirical data.

Within the context of teaching the mechanical variables of displacement, velocity and acceleration, students are often introduced to abstract examples, such as the description of a car's journey, an act for which they will have previous participatory experience (as a passenger), but will not be able to gain direct active experience and be able to collect data from. By using body-mounted accelerometers however, it may be possible to relate issues of kinematics to personal physical activity that can be performed by the students themselves. By doing so, this may reinforce the student's relationships between representations of the activity and the activity itself, and facilitate the transition from the abstract concepts of the curriculum to tangible activities of real life.

To determine the efficacy of using body worn accelerometers in physics teaching a small-scale study was undertaken. In the study, Key stage 4 students undertook an exercise aimed at teaching them physical concepts regarding classical mechanics, specifically the relationship between acceleration and velocity.

### 2.1.1 Method

The participants of the study were 24 students aged 14–16 years. The students worked in pairs, and were divided into three condition groups. In the first condition, from each pair, one student was designated the role of the Actor the other student the role of the Observer. The Actor wore a wrist-mounted accelerometer that measured acceleration in a direction perpendicular to the long axis of the forearm. The role of the actor was to throw a tennis ball using a darts style throw. In this action, the upper arm is flexed towards the horizontal and the forearm vertical, the throwing action is achieved by extending the arm at the elbow. In this way, there is minimal movement at the shoulder, and movement takes place primarily in the sagittal plane. As such, the throwing action is as linear as possible, in an attempt to reduce rotation of the accelerometer and the gravitational effect on the readings. While throwing the ball, accelerometer data was sampled at 20 Hz and presented as an acceleration–time graph on a PC for both the actor and observer to see and discuss.

Following a number of throws to different distances, the students took part in semi-structured interviews with the researcher, and discussed the characteristics of the accelerometer graph. Subsequently, a velocity–time graph was generated by integrating an accelerometer-time graph using Microsoft® Excel 2000 (Fig. 1), which the students also discussed with the researcher. In particular, they were encouraged to consider the relationships between the hand moving, positive and negative acceleration, and positive and negative velocities. By throwing
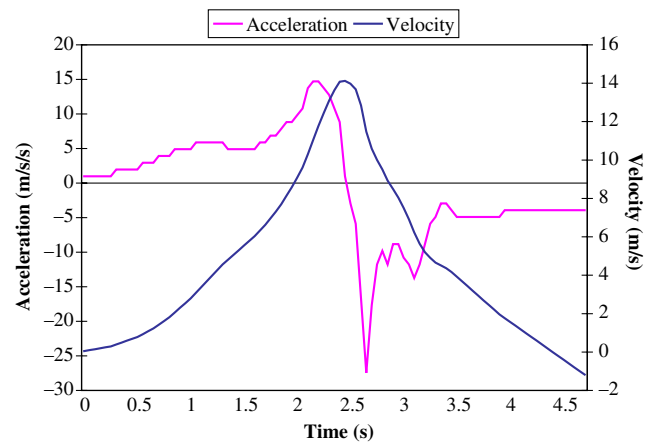


**Fig. 1** Graphical example of a throwing movement

the ball to different distances, the aim was to encourage the students to distinguish between graphical representations of movements with different accelerations.

In the second condition, an actor and an observer followed the same protocol as in the first condition. However, in this condition, accelerometer data was not collected. Instead, after throwing the ball a number of times, both students were interviewed and discussed accelerometer and velocity graphs generated from idealised data.

In the third condition, neither of the students acted out the role of throwing a ball. Instead, they solely discussed accelerometer–time and velocity–time graphs generated from idealised data, during the interview with the researcher.

Following the interviews with the researcher, the students were asked to complete a short test, based on the relationships between displacement, velocity, acceleration, and time, specific for attaining Key stage 4 requirements.

### 2.1.2 Discussion of results

Analysis of the test scores showed that there were no apparent or significant differences ($p > 0.05$) between the three conditions. However, analysis of the semi-structured interviews suggested that there were improvements in the understanding of the pictorial representations of displacement, velocity and acceleration, when using the accelerometers.

The interviews suggested that the idea of using their own hand instead of an external object to study movement and its graphical representation was attractive to the students. This relates to Papert's [1] body syntonic learning, where students have a more direct way to perceive the links between reality and pictorial representations, as they are able to manipulate the symbols with their own actions, which makes symbols directly related to them and thus makes them personal.

In this case, students were able to repeat the movement and see how their movement affect the different

shown the heart-rate data referred to the prior knowledge that heart-rate rises with exercise intensity, thus defeating the object of a student learning in practical sessions through experience and observation alone. The group that were shown the body accelerometer data on the other hand, were able to visually correlate the two sets of data to show that an increase in movement activity resulted in an increase in heart-rate. The addition of body movement data thus had the benefit over heart-rate data alone in that it was used to confirm when the player was active, and his relative level of activity. As such, the phenomena of the anticipatory rise, the relationship between exercise intensity and heart-rate, and the responses of the heart during recovery could be clearly demonstrated, rather than simply inferred using the heart-rate data alone and recalling body movement activities to make best guess interpretations.

## 3 Context awareness

Context has been defined as "[t]he circumstances in which an event occurs" [4] and as "[t]hat which surrounds, and gives meaning, to something else" [5]. A more detailed definition has been provided by Dey et al. [6] who defined context as "[a]ny information that can be used to characterize the situation of an entity, where an entity can be a person, place, or physical or computational object" (p21). This definition is attractive to designers and developers of computer systems, as it suggests that as context is information, if this information can be gathered, the context can be determined and context-aware computer systems can be developed. The aim for these systems is to adapt to the user's situation, and have been defined by Dey et al. [6] as being context-aware, if they use context to provide relevant information and/or services to the user, where relevancy depends on the user's task.

An example of the use of a context aware system is the amount or type of information that might be shown on a computer display. When sat at a screen, a user may be able to attend to a relatively high degree of complex visual information. However, if the user is in motion, i.e. walking while wearing a head mounted display, he or she may not be able to attend to the same level of information. A context aware system would then modify the amount of information displayed on the screen, depending on the user's situation. This example highlights that contextual awareness is of considerable interest to developers of wearable computer systems. In these situations as the user is highly mobile he or she is potentially exposed to different situations for which a technology that can detect and respond appropriately to changes in context would be highly useful.

### 3.1 Measuring movement and posture for context

In a series of studies that categorised daily activities and determined features inherent in the activities that defined its context [7], we found that aspects associated with posture and movement were the most prevalent features used in describing the activity. Posture and movement accounted for 24.25% of the features identified and as such was rated the most important context identifier in a derived list of 15 context identifiers [8]. The next highest ranked identifiers were: location (14.75%), object (14.50%), people (8.00%), and time (7.50%).

Schmidt et al. [9] noted in a list of different ways of sensing different aspects of context that motion could be sensed using accelerometers. Van Laerhoven et al. [10] used the outputs of 30 accelerometers to train a neural network to recognise particular postures and movements. Though giving a detailed picture of whole body movement, this perhaps exceeds the criterion of Rhodes [11] who asserted that it is important to keep sensors to a minimum and as resource-friendly as possible.

Other systems have used fewer numbers of accelerometers. For example, Kern et al. [12] used seven, tri-axial accelerometers over the whole body to measure posture and movement to annotate meetings.

Lee and Mase [13] used a single bi-axial accelerometer, located in the user's trouser pocket to measure the forward and upward acceleration of the user's thigh, and a separate gyroscope to measure thigh angle to recognise and classify sitting, standing and walking.

For our context aware wearable computer ($\chi^3$) we use a single bi-axial accelerometer (ADXL210E). This is attached to the lateral side of the right leg with an elastic strap. In this position, the $x$-axis runs parallel to the longitudinal axis of the leg and the $y$-axis runs parallel to the sagittal axis of the leg. Details of the wearable system can be found in [7].

The $\chi^3$ system uses the accelerometer data to determine if the wearer is in one of three states: standing, sitting or walking. To ascertain which state the wearer is in, data from the accelerometers are sampled at 100 Hz and a root-mean-square (RMS) value over two seconds is calculated. This value is then compared to threshold values, known for each state, which were determined experimentally. These thresholds are shown in Table 1. Any given RMS-$x$ and RMS-$y$ value can then be used to determine the wearer's state. Trials have shown this system to be extremely accurate and highly reliable.

## 4 Detection of ambulatory mode

A number of fields of research have used body-mounted accelerometers to measure aspects of human movement.

Human movement scientists and exercise physiologists have used body-mounted accelerometers as activity

**Table 1** Threshold values for $\chi^3$ posture and movement determination

| State | RMS-$x$ value | RMS-$y$ value |
|---|---|---|
| Standing | $1.6 > x > 1$ | $y < 0.5$ |
| Sitting | $x < 0.5$ | $y > 1$ |
| Walking | $X > 1.6$ | Any value |

monitors. By correlating 'activity counts' (a measure of the magnitude of the accelerometer output) to traditional measures of activity, such as heart rate and oxygen consumption, estimations of energy expenditure can be made using accelerometers [14–16]. Although some concern has been raised as to their accuracy, due to the inability of such methods to detect increased energy cost from upper body movement, load carriage, or changes in surface or terrain [17, 18], these systems have been used in research to unobtrusively measure a person's daily level of physical activity. Considerable research, for example, has used accelerometer-based systems to assess school children, with concerns related to the lack of physical activity in their daily lives and health issues, such as fitness and obesity [19–22].

In the medical field, research has used accelerometers for gait analysis, specifically with interest in assessing patterns of pathological gait as a means of diagnosis and for determining changes over time [23–25]. Other pathological movement patterns have been measured using accelerometers, such as the involuntary movements and tics in Tourette's syndrome [26].

A number of studies have successfully used accelerometers to detect a range of movement patterns. Foerster and Fahrenberg, for example, have used combinations of accelerometers mounted on the sternum, wrist, thigh and lower leg [27], and three uni-axial accelerometers mounted on the sternum and on the thigh [28].

With this in mind, our next step was to use body mounted accelerometer to measure aspects of human movement, specifically we aimed to develop a system of determining different ambulatory movement patterns using a minimal number of accelerometers that could easily be interfaced with the $\chi^3$.

Initial trials established that differences in ambulatory mode patterns could not be determined consistently and easily, from a single biaxial accelerometer mounted on the thigh, as used in the $\chi^3$. Therefore a second biaxial accelerometer was added to the trunk. This position for a second accelerometer fitted in with other research work we were carrying out [3].

### 4.1 Data collection for determining ambulatory mode

The SensVest [3] is a device, designed and built at the University of Birmingham, to measure and collect physiological variables, such as heart rate and body temperature. In addition, the SensVest houses accelerometers to measure aspects of body acceleration; as such the SensVest was used in this study to measure and record the acceleration during the data collection exercise.

Six male participants took part in the data collection exercise (age 20 ± 3 years). The exercise required that each participant undertake six ambulatory modes; these were: walking, running, ascending stairs (8 flights of 11 steps, with a 180° left turn between flights), descending stairs, ascending a slope (12.3 m, 10°) and descending a slope. For each mode, the participants were requested to act as normal as possible, selecting their own pace.

The accelerometers used in the exercises were ± 10 g dual axis strain gauge accelerometers (ADXL210). They were attached to the right side of the chest and the right thigh. The placement of the accelerometers means that four accelerometer readings are given. Body-$X$ gives an acceleration reading from the accelerometer parallel to the longitudinal axis of the body; Body-$Y$ gives an acceleration reading from the accelerometer parallel to the sagittal axis of the body; Leg-$X$ gives an acceleration reading from the accelerometer parallel to the longitudinal axis of the leg; Leg-$Y$ gives an acceleration reading from the accelerometer parallel to the sagittal axis of the leg.

Recording at 10 Hz, the signals from the accelerometers were first sent to a Mitsubishi M16C processor worn on the upper right back of the SensVest, then via a serial port to a Libretto 70CT worn around the waist in a belt-bag. The data were fed in to LabVIEW™ 5.0 and saved as a text file. Subsequent data processing and analysis was carried out using Microsoft® Excel 2000.

### 4.2 Data analysis for determining ambulatory mode

The data were normalised by subtracting the accelerometer value when the participant was stood at rest (prior to movement) from the accelerometer data when the participant was in motion. To determine the magnitude of the amplitudes, a RMS value of a 10-s sample of the movement data was calculated. Mean values of RMS accelerometer (RMSA) data for the body and leg in the x and y directions, when performing the different types of ambulation, are shown in Fig. 3.

Figure 3 indicates that there is variation in the levels of RMSA between the ambulatory modes. Statistical analysis using one way repeated measures ANOVAs showed that the level of variance was significant for the different measures [Body-$X$ ($F(5,25) = 59.285$, $p < 0.001$), Body-$Y$ ($F(5,25) = 125.791$, $p < 0.001$), Leg-$X$ ($F(5,25) = 25.617$, $p < 0.001$) and Leg-$Y$ ($F(5,25) = 12.831$, $p < 0.001$)]. Such variation implies that using RMSA data from the accelerometers could determine the ambulatory mode performed.

### 4.3 Accelerometer data to determine ambulatory mode

The variation between the RMSA for the different ambulatory modes described in Sect. 4.2 suggested that using RMSA data from the accelerometers could be used to determine what ambulatory mode someone was performing.

Using the mean and standard deviation from the data collected above, a "determining ambulatory mode model" (DAMM) was developed. DAMM detects the ambulatory mode by scoring how close the RMS of a 10 s sample of data is to the mean data calculated for the six modes of ambulation. DAMM scores 3 if the RMSA from the sampled data is within one standard deviation

**Fig. 3** RMS accelerometer (*RMSA*) for the body and leg during different ambulatory modes
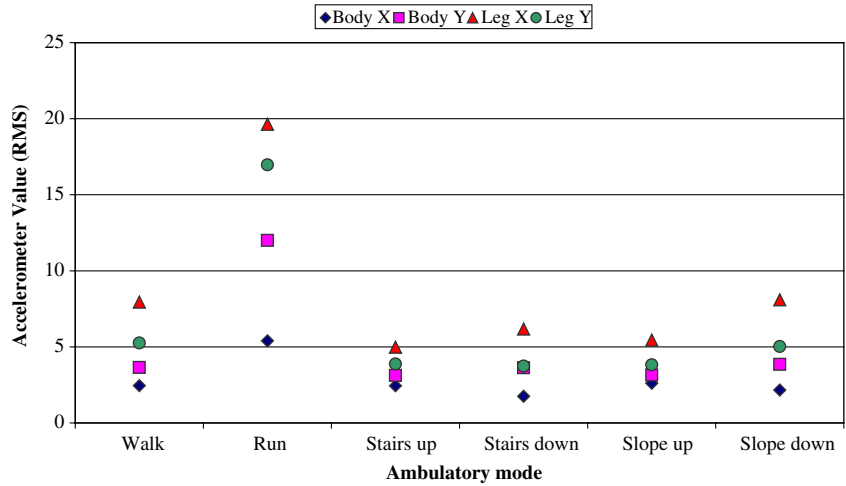


of the mean, 2 if it is within two standard deviation of the mean and 1 if it is within three standard deviation of the mean. As such, the closer the match, the higher the score. The RMSA ranges for the two axes of the two accelerometers for the six ambulatory modes are shown in Table 2. By adding up the scores for the two axes of the two accelerometers, a total score (within the range of 0–12) is given.

The simplest method, of using the DAMM score to determine which ambulatory mode was in operation, is to select the mode with the highest score. For example, Table 3 shows that a Body-$X$ RMSA of 2.92, Body-$Y$ RMSA of 2.96, Leg-$X$ of 8.25 RMSA and Leg-$Y$ of 5.16

gives a score for walking of 10, running 4, stairs up 7, stairs down 5, slope up 6, and slope down 9. By generating the highest score, the example suggests that 'Walk' is the ambulatory mode from which the RMSA data was sampled.

To test the model, six male students (age 19 ± 3 years) participated in a further data collection exercise. The participants followed the exact same protocol as those used to collect data to produce the DAMM. RMS data from 10 s samples, recorded from the six participants, were fed in to the DAMM. The results showed that that 29/36 (80.6%) of the ambulatory modes were successfully detected using the

**Table 2** RMSA ranges based on ± 1SD, ± 2SD, ± 3SD for different ambulatory modes

| | 1 SD | | 2 SD | | 3 SD | |
|---|---|---|---|---|---|---|
| | − | + | − | + | − | + |
| **Body $X$** | | | | | | |
| Walk | 2.17 | 2.73 | 1.90 | 3.00 | 1.62 | 3.28 |
| Run | 4.59 | 6.21 | 3.79 | 7.02 | 2.98 | 7.82 |
| Stairs up | 1.98 | 2.90 | 1.52 | 3.36 | 1.06 | 3.82 |
| Stairs down | 1.28 | 2.22 | 0.81 | 2.69 | 0.34 | 3.15 |
| Slope up | 2.42 | 2.80 | 2.23 | 2.99 | 2.04 | 3.18 |
| Slope down | 1.79 | 2.53 | 1.41 | 2.91 | 1.04 | 3.28 |
| **Body $Y$** | | | | | | |
| Walk | 3.12 | 4.17 | 2.60 | 4.69 | 2.07 | 5.22 |
| Run | 10.47 | 13.54 | 8.94 | 15.07 | 7.41 | 16.60 |
| Stairs up | 2.29 | 3.95 | 1.46 | 4.78 | 0.63 | 5.61 |
| Stairs down | 3.08 | 4.17 | 2.54 | 4.71 | 2.00 | 5.25 |
| Slope up | 2.81 | 3.50 | 2.47 | 3.84 | 2.12 | 4.19 |
| Slope down | 3.02 | 4.68 | 2.19 | 5.51 | 1.37 | 6.33 |
| **Leg $X$** | | | | | | |
| Walk | 6.68 | 9.21 | 5.41 | 10.47 | 4.15 | 11.73 |
| Run | 13.29 | 25.99 | 6.94 | 32.34 | 0.59 | 38.69 |
| Stairs up | 4.34 | 5.62 | 3.70 | 6.26 | 3.06 | 6.90 |
| Stairs down | 5.51 | 6.84 | 4.84 | 7.50 | 4.18 | 8.17 |
| Slope up | 4.70 | 6.19 | 3.96 | 6.94 | 3.22 | 7.68 |
| Slope down | 6.68 | 9.51 | 5.27 | 10.92 | 3.86 | 12.34 |
| **Leg $Y$** | | | | | | |
| Walk | 4.62 | 5.89 | 3.99 | 6.53 | 3.35 | 7.16 |
| Run | 7.97 | 25.96 | -1.02 | 34.96 | -10.02 | 43.95 |
| Stairs up | 2.81 | 4.94 | 1.75 | 6.00 | 0.69 | 7.07 |
| Stairs down | 2.91 | 4.56 | 2.09 | 5.39 | 1.26 | 6.22 |
| Slope up | 3.27 | 4.37 | 2.72 | 4.92 | 2.17 | 5.47 |
| Slope down | 4.24 | 5.82 | 3.44 | 6.62 | 2.65 | 7.41 |

**Table 3** Example of points scoring. Body $X$ = 2.92, Body $Y$ = 2.96, Leg $X$ = 8.25, Leg $Y$ = 5.16

| Ambulation mode | Body $X$ | Body $Y$ | Leg $X$ | Leg $Y$ | Total |
|---|---|---|---|---|---|
| Walk | 2 | 2 | 3 | 3 | 10 |
| Run | 0 | 0 | 2 | 2 | 4 |
| Stairs up | 2 | 3 | 0 | 2 | 7 |
| Stairs down | 1 | 2 | 0 | 2 | 5 |
| Slope up | 2 | 3 | 0 | 1 | 6 |
| Slope down | 1 | 2 | 3 | 3 | 9 |

DAMM. However, there were occasions where the highest score was shared by two or three ambulatory modes (see Table 4), which would result in the DAMM detecting two or three modes at the same time.

For all but one occasion, a shared highest score involved the slope up or slope down mode. In most situations slope walking is not a common occurrence so removing it from the model is not unreasonable. This would greatly improve the accuracy of the DAMM.

### 4.4 Uses of the DAMM

The $\chi^3$ (mentioned above) successfully establishes, a persons location, using (GPS), and whether the person is sat, stood or walking. It then uses this information, to determine what information is shown on a head mounted display, as users have navigated around a real world environment [7, 8]. At present, the $\chi^3$ can only determine whether a person is moving (walking) as opposed to being static (sat or stood) using accelerometers, it does not determine how they are moving. However, by adding the DAMM, the $\chi^3$ could detect when someone is walking, running, ascending stairs or descending stairs. With this knowledge $\chi^3$ could alter the quantity, quality and character of information presented to the wearer. The different ambulatory modes each have their own demands on attention. Walking down stairs or running requires more care than walking on level ground. Therefore, given the changes in capacity for shifting attention from the outside world to the computer driven

**Table 4** Accuracy of detecting ambulatory mode

| Actual mode | Detected mode | | | | | |
|---|---|---|---|---|---|---|
| | Walk | Run | Stairs up | Stairs down | Slope up | Slope down |
| Walk | 4(2) | – | – | – | – | 4(2) |
| Run | – | 6 | – | – | – | – |
| Stairs up | – | – | 5(1) | – | (1) | 1 |
| Stairs down | – | – | (1) | 5(1) | – | 1 |
| Slope up | – | – | 5(3) | (1) | 4(3) | – |
| Slope down | – | – | (1) | (1) | (1) | 5 |

NB 1. Number in cell indicates the total number of times (out of six) the highest prediction points was given including times when shared with another ambulatory mode
NB 2. Number in brackets is the number of times the high score was shared with another ambulatory mode

environment DAMM on a context aware wearable computer could determine whether it is appropriate to attract the attention of a user.

The DAMM (or similar methods) may also be useful in other applications. For example in health sciences, it has been noted that Tritrack (used for predicting energy expenditure using a triaxial accelerometer) underestimates the energy expended when stair walking [29]. DAMM could be used to determine stair walking so that appropriate adjustments to the energy expenditure calculation could be made.

## 5 Assessments of performance

The previous sections considered using accelerometers to determine what activity a person is performing to develop a context aware system. The next section considers the use of accelerometers to measure specific actions or to break down an activity into its constituent parts.

Accelerometers mounted on the body enable the measurement of body segments and overall body movement. Usually, body movement analysis is carried out using vision based systems such as digitising video or cine film, or automatic opto-electronic tracking systems (e.g. ELITE, CODA, Selspot). These systems are expensive and require that the wearer remain in a specific calibrated volume. Accelerometers on the other hand are relatively cheap and can be used anywhere. However, there are limitations, which must be considered when using them for assessing movement [3]. For consideration here, the main limitations are that accelerometers give no indication of a segments initial conditions, and as previously mentioned they are gravity sensitive and so are affected by orientation. To derive accurate acceleration data additional information regarding segment orientation is needed. Alternatively, the user must either assume that the movement was linear so that the gravitational component can be subtracted from a resting value, or that the gravity component is negligible. Other limitations include the relative movement of the accelerometer against the body and any signal drift over time. Ultimately, the value of the data depends on the required accuracy.

### 5.1 Activity analysis

For activity analysis, we have used accelerometers primarily to give a pictorial representation of the movement, where the accelerometer trace can be used to show the timing and patterns in movement, using relative changes in acceleration, rather than using it to give absolute values.

In Osmington, Dorset, UK, 3D-Education and Adventure run classes with school children where heart rate is recorded as students ascend a tower and then abseil down it. The aim of this exercise is to demonstrate heart rate responses due to changes in physical activity and psychological stress (i.e. anxiety).

After recording a sample of heart rate from an abseil trial, a graph is produced, which the students then discuss with their teacher or instructor at the site. From the graph the students consider cardiac responses to climbing the abseil tower, standing at the top of the tower, and descending the tower. Unfortunately, no record of timing of these activities is recorded, which means that interpretation of the graph relies on the students and their teacher assuming that specific activities take place at a given time, usually because of the responses of the heart on the graph, e.g. an increase in heart rate must indicate that the student is climbing the tower (i.e. physical response) or descending the tower (anxiety response). On many occasions though, there is no clear change in cardiac response, for example the heart rate may rise when ascending the tower but may remain elevated so it is not clear when the student began descending the tower.

As such, the aim here then was to determine if using a body mounted accelerometer could clearly indicate when the specific actions of the abseiling activity commence and terminate. This data could then be used to supplement the heart rate data and aid its interpretation.

Figure 4 shows data collected during an abseil from an accelerometer mounted on the chest. During the abseiling activity, the participant climbed a tower up three ladders. This is demonstrated by the increased activity on the trace. At the top of the tower the abseiling equipment is attached to the user, and as the user is static there is little activity. The tower is designed so that during decent there is an initial slope at approximately 60° (first lean back), which then goes out to a vertical 90° (second lean back), after a slight readjustment between the two slopes. As the user leans out from the tower, the accelerometer value drops. This is in response to the gravitational effect on the accelerometer as acceleration drops from 1G (when the user is vertical) towards 0G (when the user is horizontal). The final stage involves jumping down the tower during which there is a gravitational effect as the user tends towards a vertical upright posture and a dynamic effect due to the increased body acceleration as the user kicks off and collides with the tower. Finally, as the user lands on the ground there is a large amount of body accelerometer action, with a return of the baseline value of 1G (10 m/s/s) as the user is fully upright.

The trace demonstrates that accelerometer data can be used to highlight when specific actions are performed in the abseiling activity at Osmington. Indeed, this exercise demonstrates that accelerometer data can be used for activity analysis where the activity can be broken up into its constituent parts, the timings and sequencing of actions within an activity can be determined, key moments can be highlighted and determining the physical activity that a person is carrying out at a specific time during the activity can be assisted.

## 5.2 Match analysis

Match analysis data from sports performance is of great importance to coaches, players and sports scientists, and of great interest to commentators and spectators. Virtually all broadcast sport, these days relay to the viewer aspects of a team's or player's performance, by using match analysis (e.g. time in opponents half, time in possession of the ball, passes attempted/completed, number of pitches, strikes, penalties, free-kicks, etc). For the spectators this is intended to enhance their enjoyment of the game, for the coach this may dictate strategy.

One aspect of match analysis that is of great interest to coaches and sports scientists is that of estimating a player's work rate, i.e., the amount of energy they are expending to meet the demands of the game. This data is useful for designing specific training programs for individuals. For example, if a player performs a high number of short sprints during play then short sprints are incorporated into his training, and emphasis may be placed in hastening recovery between intense passages of play. Alternatively if he performs few short sprints but spends the majority of time jogging, then sprint training



**Fig. 4** Accelerometer trace of abseiling
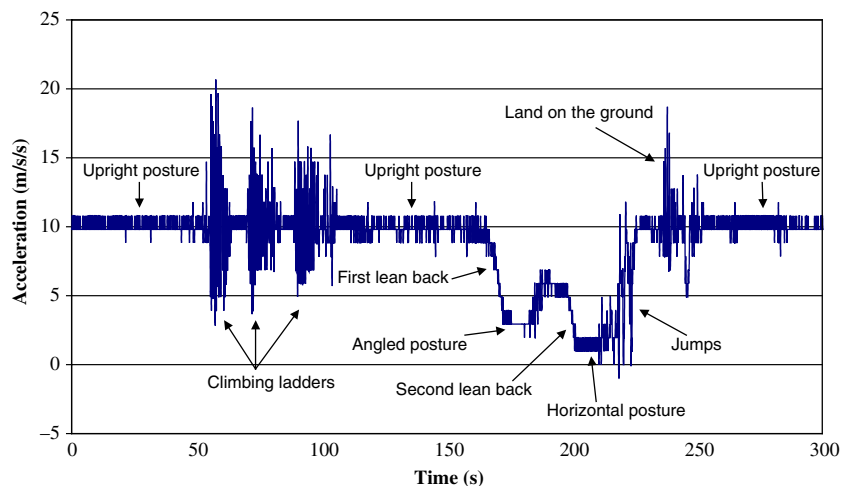
may be reduced or removed in favour of low-intensity endurance training, etc. In the past, assessing a player's work rate during a game was achieved by structured commentary of a player's movements, validated by film analysis [30, 31]. More sophisticated methods employ a number of cameras spotted around a pitch so that synchronised observations can be made of all the players on the pitch. These systems, although yielding vast amounts of data, are expensive to employ and time consuming. In carrying out a player's work rate analysis, his distance covered during a game, and the frequency and duration he performs bouts of exercise at different intensities, are estimated. This often involves tallying up the number of times, and timing how long a player spends, walking, jogging, running or sprinting [31].

Section 4 demonstrated that accelerometers could be used to determine when a person is walking and running. The next aim was to determine if a wearable accelerometer system could be used to determine other speeds of ambulation (e.g. jogging and sprinting) and as such be used to carry out a work rate assessment for an individual as part of a match analysis.

To get data for each ambulation speed, accelerometer data was sampled from an individual as he performed four different intensities of ambulation: walking, jogging, running and sprinting. Data was sampled at 100 Hz from an accelerometer strapped to the side of the chest, orientated vertically (parallel to the longitudinal axis of the body) and an accelerometer strapped to the side of the right thigh, just above the knee, orientated horizontally (parallel to the sagittal axis of the leg). An average value of accelerometer data was calculated as the mean of the RMS, which was applied to the data with a sliding window over 100 data points (i.e. 1 s).

Figure 5 shows that, for both the body and leg mounted accelerometers, there was a linear relationship between the RMS accelerometer data and the speed at which the subject was moving.

To test how well this data could be used to distinguish between walking, jogging, running and sprinting during a match analysis, the subject performed a mock game activity, where he shifted between different walking and running speeds.

Root mean square data of the game activity is shown in Fig. 6, similar looking data was generated from the body-mounted accelerometer. In Fig. 6, the cut off levels between the different modes of moving (i.e. walking, jogging, running and sprinting) were determined from the data used in Fig. 5, as being mid point between the highest and lowest RMS values between the adjacent modes (i.e. between walking–jogging, jogging–running, and running–sprinting). More accurate assessments of types of mode and cut-offs between them could be achieved by collecting data from a greater range of speeds.

Using Fig. 6, an activity analysis can easily be carried out. For example, the player performed four clear bouts of sprinting and six bouts of walking, with transitions down from sprinting to walking, which usually involved a period of jogging. Further analysis of this data could be used to determine ratios of time spent in each mode. It turns out that in this case the player spent 48% of the time walking, 24% jogging, 15% running and 13% sprinting. As such, a training program specific for this activity should incorporate similar ratios.

These results show that body worn accelerometers can be used to determine different movement speeds for aspects of estimating energy expenditure in match analysis. However, they may also be used for different aspects of match analysis. For example in racket sports, such as tennis and badminton, a tally of shots in a rally is often calculated [32]. Again, this usually requires counting the shots in real time or reviewing the rally on video. Figure 7 shows accelerometer data collected from an accelerometer mounted on the body and the arm during a tennis rally. The graph indicates when a shot has been played as a large negative spike in the arm acceleration trace, as such a tally of shots per rally can easily be calculated. In addition, the combination of body accelerometer data with wrist accelerometer data may offer insights in to the technique of the player. For example, is the body in motion or static during the shot?.

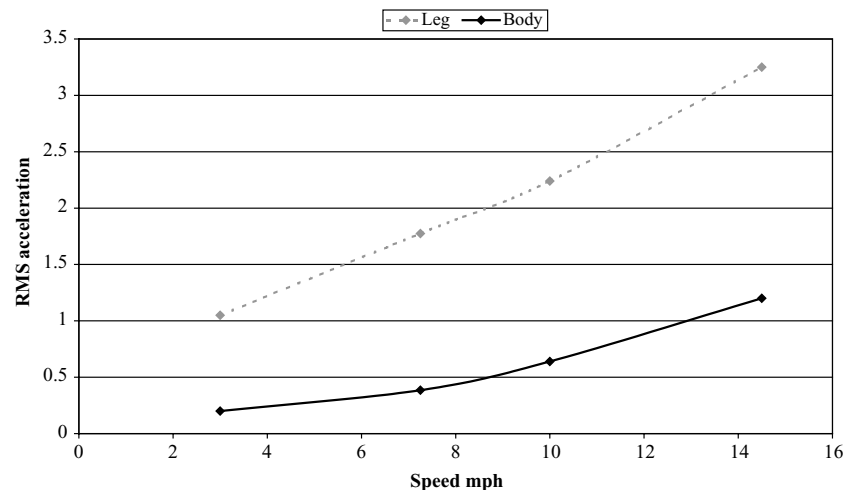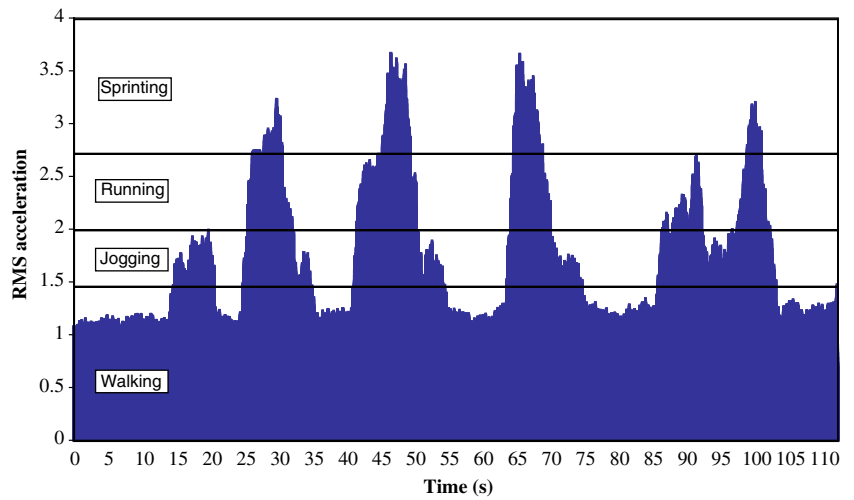**Fig. 5** Changes in RMS accelerometer data with speed

**Fig. 6** Match analysis using
RMS leg accelerometer data



## 5.3 Analysing quantity and quality of individual training

Coaches cannot always supervise an athlete's training. Endurance athletes, such as long distance runners and cyclists, spend the majority of their training as solitary performers and may only meet up to discuss their training, or indulge in a group training session with their coach, once or twice a week. In the absence of the direct observation of a coach, analysis of the quantity and quality of an athlete's training often uses retrospective questionnaires and diaries. These methods have several advantages: they are cheap and easy to administer, they can yield a considerable amount of information on every aspect of training over any time period, and they do not interfere with the athletes' training program [33]. Their main disadvantage is the subjective nature of the measures they provide. They are limited in only being able to record subjective information. Questions may be misunderstood; responses may be deliberately or accidentally distorted; or information may be forgotten [33]. As such, objective methods of assessing training are of great importance to a coach and his athlete.

GPS and accelerometer systems are ideal for measuring changes in speed and distance throughout a training session and with correlation with heart-rate monitor data can provide a high degree of information. For example, they are ideal for assessing fartleking sessions, where endurance athletes perform periods of faster (high-intensity) running interspersed within running at their normal pace. The responses of the heart during these sessions are of great interest to the coach, especially assessing the recovery period when the athlete returns to their normal pace. We believe however, that wearable accelerometer system could provide more information than just a break down of speed and distance. Accelerometers could be used to assess changes in the runners gait pattern. Gait analysis is an aspect of biomechanical assessment beneficial for improving technique, which can increase running efficiency and reduce the risk of injury [34].

In a good running posture the athlete maintains an upright upper body. This ensures that the chest and abdomen are not restricted so breathing can be deep and regular and less strain is placed on the lower back. During efficient running there is high knee lift, this

**Fig. 7** Arm and body
accelerometer data during a
tennis rally
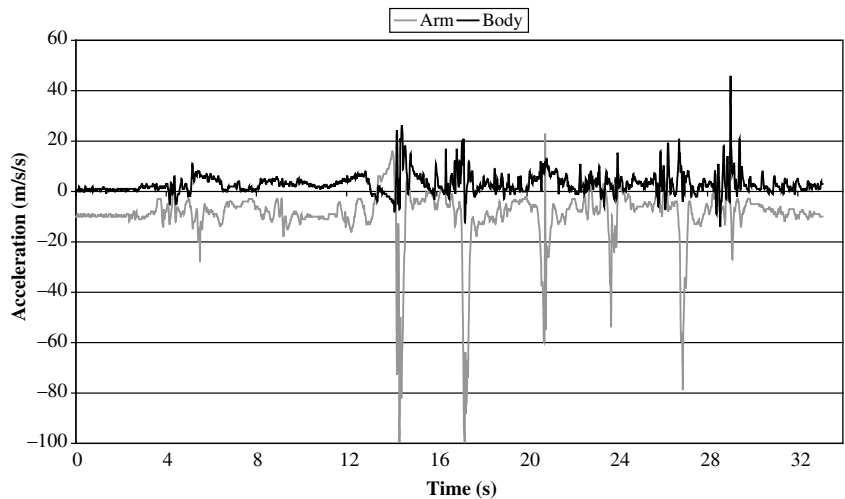
enables the runner to generate elastic energy when the foot strikes the ground and use it to propel the body forward as the foot pushes off the ground [35]. During poor running posture, the body leans forward cramping the chest and abdomen and the knees drop so that there is more of a shuffling action, which is highly inefficient.

As mentioned in Sect. 1, strain gauge accelerometers are gravity sensitive and as such can be used to show changes in angle. Using this phenomenon we aimed to ascertain whether a wearable accelerometer system could be used to show changes in running technique, specifically a shift to a forward body lean and lowered knee lift.

While wearing accelerometers, participants were asked to run for approximately 30 s with a good running technique (i.e. upright posture and high knee lift), and then shift to running for a further 30 s with poor posture (i.e. leaning forward with a low knee lift). The accelerometers were strapped to the side of the chest, orientated vertically (parallel to the longitudinal axis of the body) and to the side of the right thigh, just above the knee, orientated horizontally (parallel to the sagittal axis of the leg).

In this application data were sampled at 10 Hz, because this was shown to be sufficient to determine the very coarse postural changes we were considering. To gain an indication of changes in average body angle and knee angle we used the DC component of the accelerometer trace, which was calculated as the mean of a sliding window of 100 samples (i.e. 10 s).

Figure 8 shows the DC component of body and leg mounted accelerometer data as a runner shifted from a good running technique to a poor one. Using a good technique, the mean value of body accelerometer data is below 0 and around the $-1.4$ to $-1.6$ g levels for the leg. In poor technique the mean body accelerometer value rises to above 0 and the leg rises to above $-1.4$ g. In this situation, the data clearly shows the transition from good to poor technique, suggesting that accelerometer data could be used to analyse technique, at least at a qualitative level.

Such transitions could be used to provide feedback to the runner, or wirelessly to the coach.

### 5.3.1 Ratios of heart-rate and accelerometer data

Individually, heart-rate and movement data are of great value to an athlete, his coach and sports scientists. Combining them though can provide a much richer, more detailed, picture of the athlete's condition. Accelerometers can be used to quantify movement; heart-rate data can be used to quantify the physiological responses of the body; ratios of the two could help determine responses to physical stress, psychological stress, environmental stress and temporal effects.

Changes in heart-rate that follow changes in accelerometer data show a physiological response to changes in physical stress. If the intensity of body movement increases (as indicated by an increase in accelerometer values) so the heart-rate will increase to meet the demands of the metabolising muscles and visa versa. Changes in heart-rate that do not follow changes in accelerometer values indicate that other factors are affecting the athlete. Over time a gradual increase in heart-rate with no increase in accelerometer value could indicate fatigue. This could be verified by monitoring the accelerometer data to see if it shows signs of the athlete slowing down or of the athlete's technique changing. A sudden rapid increase in heart-rate with no increase in accelerometer value could be a sign of the fight or flight response indicating that the athlete is under some psychological stress, feeling anxious or fearful. Alternatively, the heart-rate could drop without the accelerometer value dropping, which could indicate that the athlete is feeling more relaxed. Perhaps more seriously, a rapid increase in heart-rate with no apparent psychological stress or increased exercise intensity could be an indication of a physiological response to a medical condition or an environmental stress, such as heat. In hot conditions, the heart-rate will increase rapidly, due to cardiac drift, as the body attempts to meet the demands of the muscles and the need to increase blood supply to the extremities to cool the core body temperature, as such, these wearable systems could also be used for health monitoring or as warning systems.

**Fig. 8** Qualitative changes in running technique determined from mean accelerometer data

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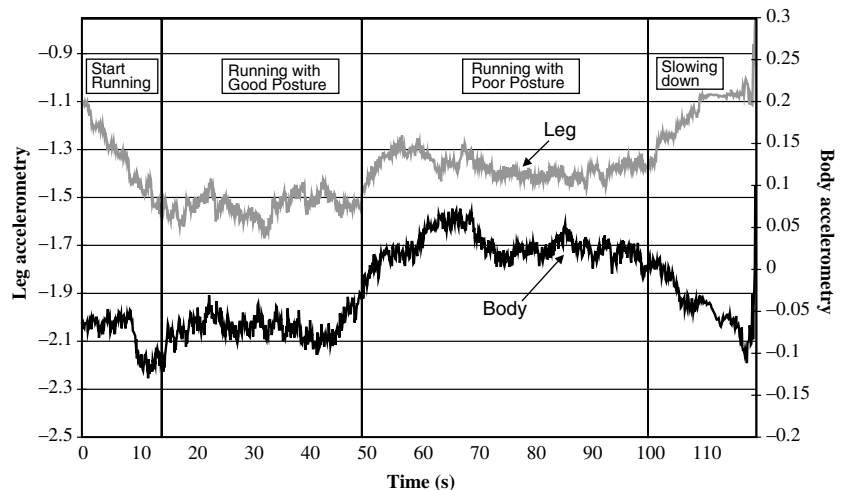
## 5.4 Technique analysis

Like activity analysis, accelerometer data can be used to record specific aspects of technique when performing an action. We have investigated this for analysing sporting techniques. An example of this is shown in Figs. 9, 10 and 11. These figures show resultant data from biaxial accelerometers, mounted on the chest and wrist, while a participant performed three athletic throwing actions: shot put, javelin and discus. In the first instance, the figures can be used to demonstrate differences between the throwing techniques. Within each throwing technique, the figures could be used by a coach. With reference to a trace from an ideal throw, a coach may be able to spot flaws so as to be able to suggest improvements in an individuals technique. A coach may be able to use the data to discover and point out key points in an activity, such as timings and sequencing of peaks in acceleration from the body to the arm as there is proximal to distal transfer of momentum to maximise release velocity. Although there might be some concern as to the absolute accuracy of the accelerometer value, relative changes in peaks can be used to highlight improvements, i.e. a coach demonstrating that a certain change in technique can result in a greater acceleration of the body or the arm.

## 5.5 Skilled performance

A skill is learned movement, which enables a person to bring about predetermined results with maximum certainty, often with minimum expenditure of energy or time [36]. This definition highlights key elements of skilled performance that could be demonstrated with the use of accelerometers.

The first element is that a skill is learnt. Practice is needed to progress from novice to expert. Using accelerometers, patterns of performance can be recorded. Through time and practice, these patterns should show changes towards that of skilled performance. An example of novice and expert performance is shown in Figs. 12 and 13. These graphs are recorded from accelerometers mounted on the wrists of jugglers. The novice



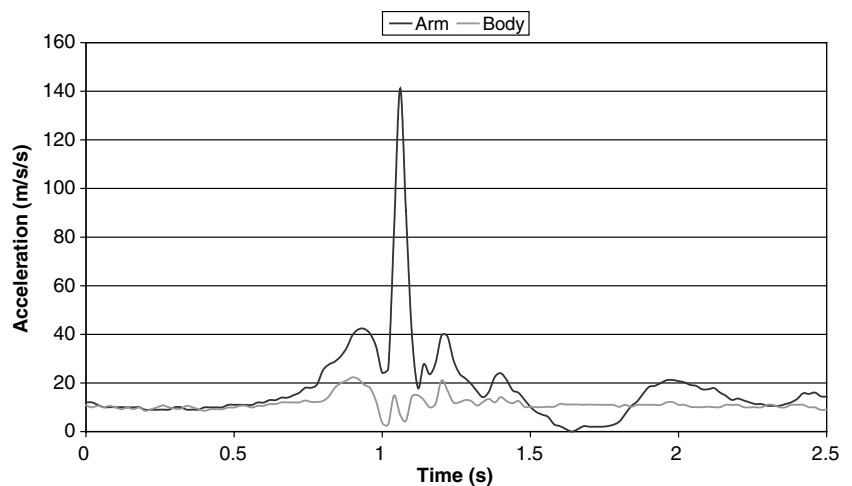**Fig. 9** Arm and body accelerometer data during the shot put throwing technique



**Fig. 10** Arm and body accelerometer data during the javelin throwing technique
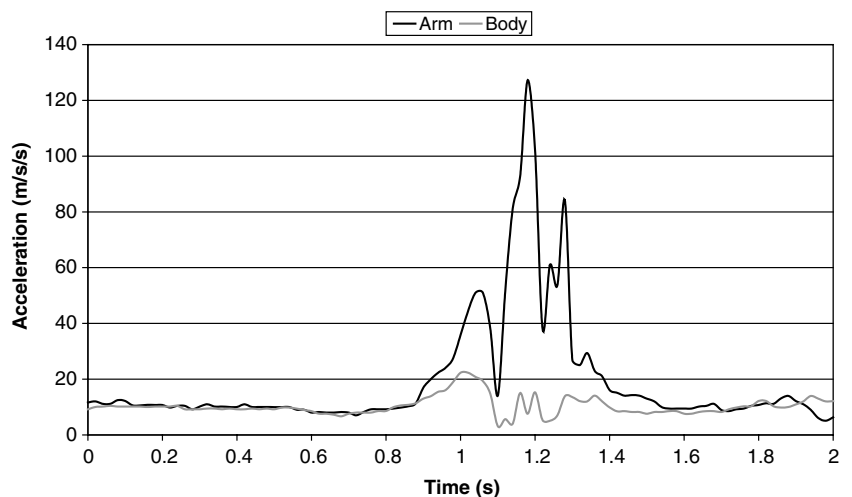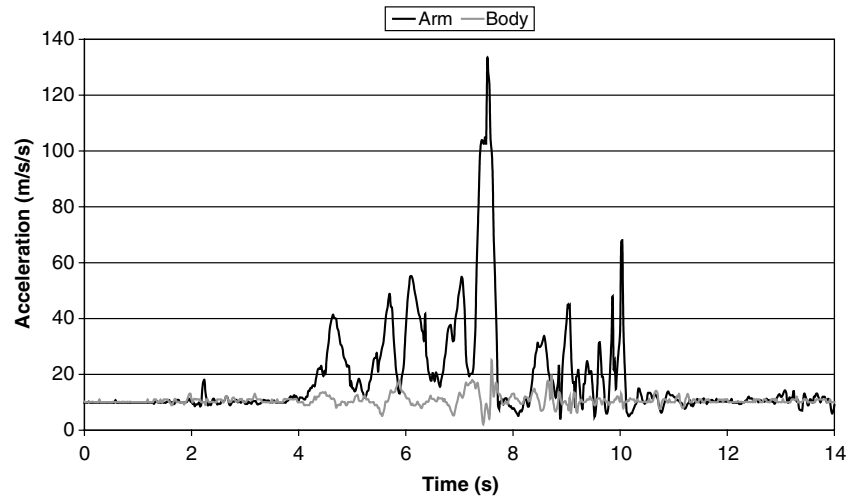
**Fig. 11** Arm and body accelerometer data during the discus throwing technique



juggler's graph shows a quasi-erratic pattern, being less consistent and regular than the expert juggler. Through practice a novice can mark his improvement by comparing his graph with that of the expert.

In juggling, specifically cascade juggling where the balls cross between the hands such that one hand catches at the same rate as the other hand throws; the key phenomenon is synchronisation of coupled oscillation [37]. This is demonstrated in the juggling graphs of both the novice and expert, where a peak in the right hand acceleration matches a trough in the left hand. For the novice, though, synchronicity breaks down after 7 s, such that control is quickly lost and the juggling pattern is terminated by 9 s.

Skilled performance is efficient and economic. This may be demonstrated in the juggling traces as a greater amplitude in acceleration in the novice as well as the greater erraticism. Beek and Lewbel [37] have noted that juggling patterns are intrinsically variable, where, however solid a run, no two throws and no two catches are exactly the same. They also assert, that "analysing this changeability provides useful clues about the general strategy of jugglers to produce a solid pattern that minimises breakdown". The variability in the juggling technique is demonstrated in the expert trace with slight differences between subsequent peaks. The expert trace also highlights an individual aspect of general technique. This trace was recorded from a juggler who is predominantly left-handed. The accelerometer data shows that there is greater acceleration in the left hand than the right, suggesting an element of asynchronicity. It may be that the dominant left hand is used to control the run and recover from small errors. This may explain the greater range and variability in amplitude for the left hand.

### 5.6 Conclusion of assessment of performance

By primarily using accelerometer data in a pictorial form, we have investigated its use for analysing specific actions or activities. In this way we acknowledge its limitations as a tool for giving accurate absolute values of acceleration for human movement. To get these accurate values requires using expensive motion tracking systems, which often have to be set up in calibrated

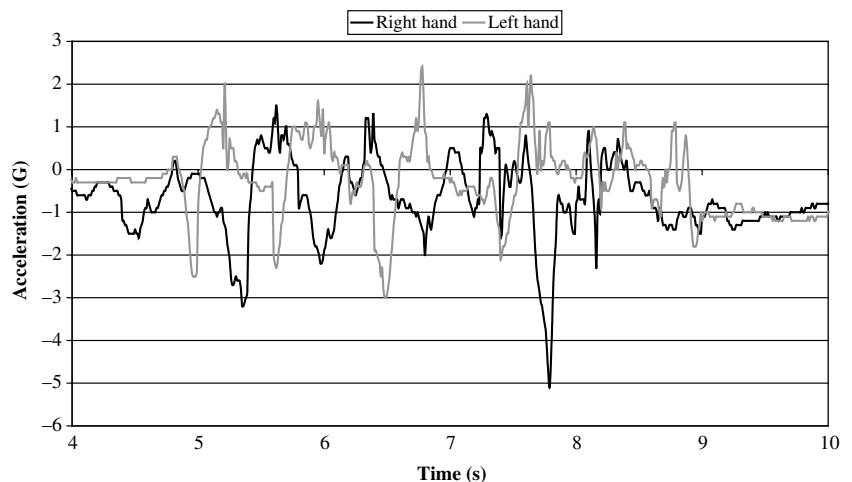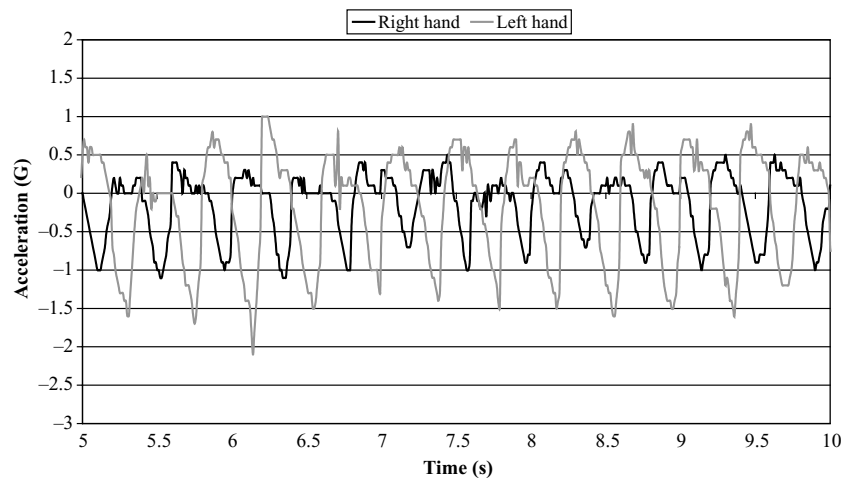**Fig. 12** Right and left hand accelerometer data from a novice juggler

**Fig. 13** Right and left hand accelerometer data from an expert juggler



environments. Accelerometers can easily be worn and, in conjunction with wearable recording systems, they can be used anywhere. By using accelerometers, patterns of movement can be determined and relative values can be compared. These in themselves can provide useful insights into aspects of human movement, which may be of use to coaches of sporting or athletic activities, human movement scientists, teachers, physical educators or sports scientists.

## 6 Overall findings and recommendations

This paper describes the use of accelerometers in wearable systems for a number of applications. In particular, systems for the detection of activity status (including ambulatory mode), assessment of performance (such as match or technique analysis and studying skilled performance) and for teaching were explored. In carrying out these studies a number of general observations were made.

To obtain accurate, usable data, the method adopted for fixing the accelerometer to the body is important. Loose attachment to clothing may give a noisy signal that is difficult to interpret. Ultimately, it must be remembered that the accelerometer measures the acceleration of the accelerometer. This can be used to estimate the acceleration of the thing it is attached to, and if the attachment is firm, the estimation can be assumed to be highly accurate. However, if the attachment is loose, such that the accelerometer moves with respect to the object it is fixed to, the estimation will be poor. Initially, to measure aspects of human movement, we intended to have accelerometers sewn into clothing. But, as clothing moves considerably with respect to the body, to get usable data, we had to resort to fixing the accelerometers to adjustable straps that were then attached tightly to the body.

Without processing the data, we found that generally, interpreting a trace of raw data was fairly straight forward; especially when the data was used pictorially for general overall activity (e.g. abseiling) or used to give representations of relative magnitudes and times of key events, as indicated by peaks and troughs. However, for specific actions, where detailed analysis of the trace was needed, the analysis sometimes proved difficult. For example, when considering the traces for technique analysis, we often had to think back to the activity being performed, and envision a displacement–time graph or a velocity–time graph, to help interpret the accelerometer data. This highlights a problem encountered during the teaching trials. Participants sometimes found the concept of a graphical representation of acceleration difficult to grasp. The students participating in the trials had not previously been exposed to this area of physics. When teaching this subject, students are usually taught firstly, about the relationship between displacement–time graphs and velocity, then velocity–time graphs and acceleration, rather than being shown acceleration data in the first instance. As such, when interpreting the data at this level, an understanding of the principles of Newtonian physics is beneficial.

When used for assessing technique and teaching, there is often a requirement that the data be captured and displayed in real time, with minimal delay. In initial trails with our wearable system, there was a 10 s delay between data capture and it being displayed graphically. In addition, the data was displayed in 10-s chunks rather than being streamed continuously. This sometimes made it difficult to map the steps in an activity to the trace. For example, in the technique analysis of the throwing activities, mapping the different stages of the throw (e.g. run up, body lean back, arm pull back, front foot planting, body thrust forward, arm projecting forward, follow through), had to be done when the activity was over, rather than seeing how each action affected the graph in real time. We have suggested that a trace of accelerometer data can be used as a referent model to improve technique for skilled performance. This may be best achieved if the trace can easily be dissected into the constituent actions of the whole activity. This could be achieved by inserting markers on the graph at specific moments in real time (e.g. when the front foot is planted, and again when the object being thrown is released).

For teaching, there was also the problem of the duration of the activity. For some students, the link between the activity and the graphical representation was weakened, because throwing a ball was a too rapid activity and did not give enough time for the student to realise how their movement affected the graph. We would suggest that for future teaching uses, movements for investigation should be less rapid, and less specific, to allow open-ended investigation by the student [2].

Sampling frequency is a common issue in biomechanical measurement, where consideration needs to be taken such that it is not too small, such that pertinent data are not missed, or too great such that extraneous data makes the sample noisy and difficult to interpret. Here there may be a trade-off between discerning the activity and considerations of data storage and processing. For activities involving determining movement state (e.g. walking, stair climbing, running) and slow changes in movement pattern (e.g. abseiling, body lean when running) we have found that a sampling rate of 10 Hz is adequate. Though it must be noted, that for determining ambulatory mode and body lean, average data was generated from 10-s samples, such that 100 data points were used. For more athletic and dynamic activities greater sampling rates have had to be used. Fifty Hertz was used to record whole body sporting activities, where the aim was solely to provide a pictorial representation of the movement (e.g. tennis, football). For activities where quantifications of dynamic activity were required to detect rapid state changes, a sampling frequency of 100 Hz was used. For the $\chi^3$ and match analysis applications, data sampled at 100 Hz were averaged over 1–2 s, such that 100–200 data points were used to generate the averages, which were applied to thresholds. This is the same amount of data as used for determining ambulatory mode and body lean when running. But as these changes in movement are more rapid, and happen in a shorter time span, a higher sampling frequency is required to collect the requisite amount of data. For throwing activities, sampling frequencies of 20 , 50 and 100 Hz have been used in these studies. For detailed analysis of such dynamic, rapid, actions the higher sampling frequency is most appropriate. However, we have used the lower sampling frequencies for applications where pictorial representations of the actions are required. By doing so, although values may be missed, the accelerometer traces are less noisy, and so easier to interpret, which we have found to be specifically appropriate for teaching applications.

## 7 Future work

The uses of body worn accelerometer data described in this paper have been limited to analysis of the raw data trace, or quantifications of magnitude in the time domain. This limitation has been deliberate to provide a starting point, for a full investigate of full range of potential uses of such data. In the future, we aim to extend the examples in different situations and to broaden the possible uses using analysis of the frequency component of the data. Currently, we are investigating the power spectrum of data collected from a wide range of daily activities, involving whole body movements and focussed manual interactions with everyday artefacts (such as work tools), to develop our context aware system.

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