TECHNICAL REPORT

# Technology in Strength and Conditioning Tracking Lower-Limb Exercises With Wearable Sensors

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[1]*Insight Center for Data Analytics, University College Dublin, Dublin, Ireland;* [2]*School of Public Health, Physiotherapy and Sports Science, University College Dublin, Dublin, Ireland; and* [3]*Insight Center for Data Analytics, Maynooth University, Kildare, Ireland*

## Abstract

O'Reilly, MA, Whelan, DF, Ward, TE, Delahunt, E, and Caulfield, B. Technology in strength and conditioning tracking lower-limb exercises with wearable sensors. *J Strength Cond Res* 31(6): 1726–1736, 2017—Strength and conditioning (S&C) coaches offer expert guidance to help those they work with achieve their personal fitness goals. However, because of cost and availability issues, individuals are often left training without expert supervision. Recent developments in inertial measurement units (IMUs) and mobile computing platforms have allowed for the possibility of unobtrusive motion tracking systems and the provision of real-time individualized feedback regarding exercise performance. These systems could enable S&C coaches to remotely monitor sessions and help gym users record workouts. One component of these IMU systems is the ability to identify the exercises completed. In this study, IMUs were positioned on the lumbar spine, thighs, and shanks on 82 healthy participants. Participants completed 10 repetitions of the squat, lunge, single-leg squat, deadlift, and tuck jump with acceptable form. Descriptive features were extracted from the IMU signals for each repetition of each exercise, and these were used to train an exercise classifier. The exercises were detected with 99% accuracy when using signals from all 5 IMUs, 99% when using signals from the thigh and lumbar IMUs and 98% with just a single IMU on the shank. These results indicate that a single IMU can accurately distinguish between 5 common multijoint exercises.

**Key Words** inertial measurement units, compound exercise, exercise biofeedback, exercise classification

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## Introduction

Resistance exercise is an important component of any balanced exercise program (25). It can lower blood pressure, improve glucose metabolism, and reduce cardiovascular disease risk (28). Athletes also partake in resistance exercise to improve sporting performance (2) and reduce the risk of musculoskeletal injuries (12). Strength and conditioning (S&C) coaches offer expert guidance, monitoring, and motivation during resistance training. However, many people train without this support because of financial and availability issues (39). Furthermore, monitoring multiple athletes within a team setting is difficult and time consuming for S&C coaches. It has been shown that exercising without this guidance has a significant impact on exercise adherence and technique (19), which indicates that tracking exercise routines is beneficial for both coaches and gym users.

Recent technological advances have supported the use of inertial measurement units (IMUs) to record exercise sessions. Inertial measurement units are small, inexpensive sensors that consist of accelerometers, gyroscopes, and magnetometers. They are able to acquire data pertaining to the linear and angular motion of individual limb segments and the centre of mass of the body (8). With appropriate signal processing, this allows for the quantification of human performance in a wide variety of fields such as measuring energy expenditure and analyzing gait (18,35). In this article, the term IMU system is used to describe the IMU device and its signals, the associated signal processing applied to them and the output of the exercise classification algorithms. These IMU systems can robustly handle the variety of postures and environmental complexity associated with weight training unlike camera-based motion analysis systems, which are hampered by location, occlusion, and lighting issues in such settings (25). Therefore, systems developed using IMU data may offer the potential for gym users and coaches to track training progress.

Using IMUs for exercise monitoring is becoming increasingly popular, particularly in cardiovascular training and physical activity monitoring (25). Commercially available products that use IMUs for activity tracking include Fitbits and Jawbones. These devices have the potential to improve cardiovascular exercise adherence and are used in public health interventions (21). To date, the use of IMUs in the S&C arena is less common. Exercise progress is often tracked through the use of paper-based or computerized logbooks such as JeFit. This manual input of data can prove cumbersome, lead to a risk of recall bias, and can decrease training motivation (31,34). IMU systems may aid in real-time exercise session recording, allowing coaches and gym users to adjust training programs during workout routines. Data can also be pushed to a network storage location, e.g., through cloud-based services, meaning immediate access to workout logs on a range of mobile devices. Storing data on a cloud service could also allow coaches to provide feedback from a separate location asynchronously. This is especially pertinent for S&C coaches who are not able to access clients for extended periods. Furthermore, an IMU system could allow for the collection of exercise data over an extended period. The analysis of such data can facilitate coaches in optimizing training intensity by monitoring training frequency, exercise adherence and sets completed. This is vital for ensuring that goals are obtained and motivation is maintained (32).

These advantages have led to a number of researchers investigating the ability of IMUs to identify exercises and track repetitions automatically. Chang et al. (10) used a smartphone and 2 IMUs, located in a weightlifting glove and on the hip, to differentiate between 9 upper- and lower-limb exercises. The authors were able to identify exercises with 90% overall recognition accuracy. Seeger et al. (37) used 2 IMUs placed in a weightlifting glove and on the torso to differentiate between 16 gym exercises consisting of 5 cardiovascular exercises (e.g., running, rowing) and 11 upper- and lower-limb weightlifting exercises using machines (e.g., lat pull-down, cable triceps extensions) and free weights (e.g., dumbbell lateral raise, barbell curl). Classification accuracy ranged from 71 to 100% for the 16 activities (37). However, the cross-validation method used by these authors is not stated making it difficult to ascertain the quality of their system in a real-world environment. This is because results may have been affected by biasing classifiers with training and test data from the same participants (38).

Pernek et al. (31) used a single IMU to assess exercise performance. The IMU was placed on different body positions or an exercise machine depending on the activity completed. This system was able to count repetitions with an overall accuracy of 99%. The users chose which exercise they would be completing, so no activity recognition accuracy was required. Further work by Pernek et al. (32) showed the ability of their system to differentiate between 6 upper-limb exercises with 86% accuracy using 5 IMUs and 84% accuracy with a single IMU. Muehlbauer et al. (26) used an IMU built into a smartphone to differentiate between 10 upper-limb exercises with an overall accuracy of 94%. Giggins et al. (14) also used a single IMU at different locations on the lower limb to differentiate between 7 early stage rehabilitation exercises with accuracies ranging between 93 and 95%.

In summary, IMU-based systems are becoming increasingly prevalent in exercise tracking and S&C. An IMU system that can automatically recognize exercises could allow coaches and gym users to log and review their workout sessions in a more automated fashion than current practice allows. In this article, we investigate whether a system developed from IMU-derived data can distinguish between 5 commonly completed lower-limb exercises. This would prove a foundation for more comprehensive exercise classification systems. Furthermore, we aim to achieve this using an unobtrusive IMU setup and by leveraging cheap and ubiquitous sensor technology to ensure that the system is affordable for coaches and gym users.

## Methods

### Experimental Approach to the Problem

This study used an opportunistic approach to the development of a wearable IMU system for automatically detecting complex lower-limb exercises. Participants were equipped with wearable IMUs (SHIMMER, Shimmer Research, Dublin, Ireland) on the lumbar spine, both thighs, and both shanks and completed one set of 10 repetitions of the following exercises: (a) bodyweight squats; (b) barbell deadlifts; (c) single-leg squats; (d) and

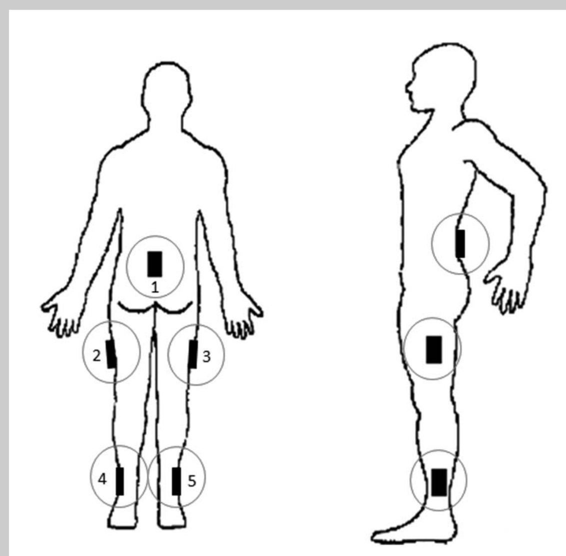


**Figure 1.** The 5 IMU positions: (1) spinous process of the fifth lumbar vertebra, (2 and 3) mid-point of both femurs on the lateral surface (determined as halfway between the greater trochanter and lateral femoral condyle), (4 and 5) and on both shanks 2 cm above the lateral malleolus.

**Figure 2.** Image showing the five exercises completed for this study: Bodyweight squat (upper left), bodyweight lunge (upper right), barbell deadlift (middle left), single leg squat (middle right) and tuck jump (bottom).

bodyweight lunges. They also completed 10 seconds of the tuck jump exercise (27). The same researcher completed IMU placement for all participants using a standardized and repeatable protocol. After data collection, a total of 342 variables were extracted from the IMU signals for every exercise repetition from each IMU. These variables were used to develop and evaluate the quality of an automated exercise detection system for lower-limb exercises. This was done for each individual IMU and combinations of multiple IMUs.

**Subjects**

Eighty-two healthy volunteers aged 16–38 (59 males and 23 females, age: 24.68 ± 4.91 years, height: 1.75 ± 0.09 m, body mass: 76.01 ± 13.29 kg) were recruited for the study. Participants did not have a current or recent musculoskeletal injury that would impair performance of multijoint lower-limb exercises. All participants had been completing each of the 5 exercises as part of their training regime for at least 1 year. The Human Research Ethics Committee at University College Dublin approved the study protocol and written informed consent was obtained from all participants before testing. In cases in which participants were under the age of 18, written informed consent was also obtained from a parent or guardian.

**Procedures**

The testing protocol was explained to participants upon their arrival at the laboratory. After this, they completed a 10-minute warm-up on an exercise bike (Lode B. V., Groningen, the Netherlands) maintaining a power output of 100 W at 75–85 revolutions per minute. Next, IMUs were secured on a participant by a chartered physiotherapist at the following 5 locations: spinous process of the fifth lumbar vertebra, mid-point of both femurs (determined as halfway between the greater trochanter and lateral femoral condyle), and on both shanks 2 cm above the lateral malleolus (Figure 1). The orientation and location of all the IMUs were consistent for all the study participants across all exercises.

A pilot study was used to determine an appropriate sampling rate and the ranges for the accelerometer and gyroscope on board the IMUs. In the pilot study, squat, lunge, deadlift, single-leg squat, and tuck jump data were collected at 512 samples/s. A Fourier transform was then used to determine signal and noise characteristics of the signal that were all found to be less than 20 Hz. Therefore, a sampling rate of 51.2 samples/s was deemed appropriate for this study based on the Shannon sampling theorem and the Nyquist criterion (16). The Shimmer IMU was configured to stream triaxial accelerometer (±16 g), gyroscope (±500 °/s), and magnetometer (±1 Ga) data with the sensor ranges chosen based on data from the pilot study. Each IMU

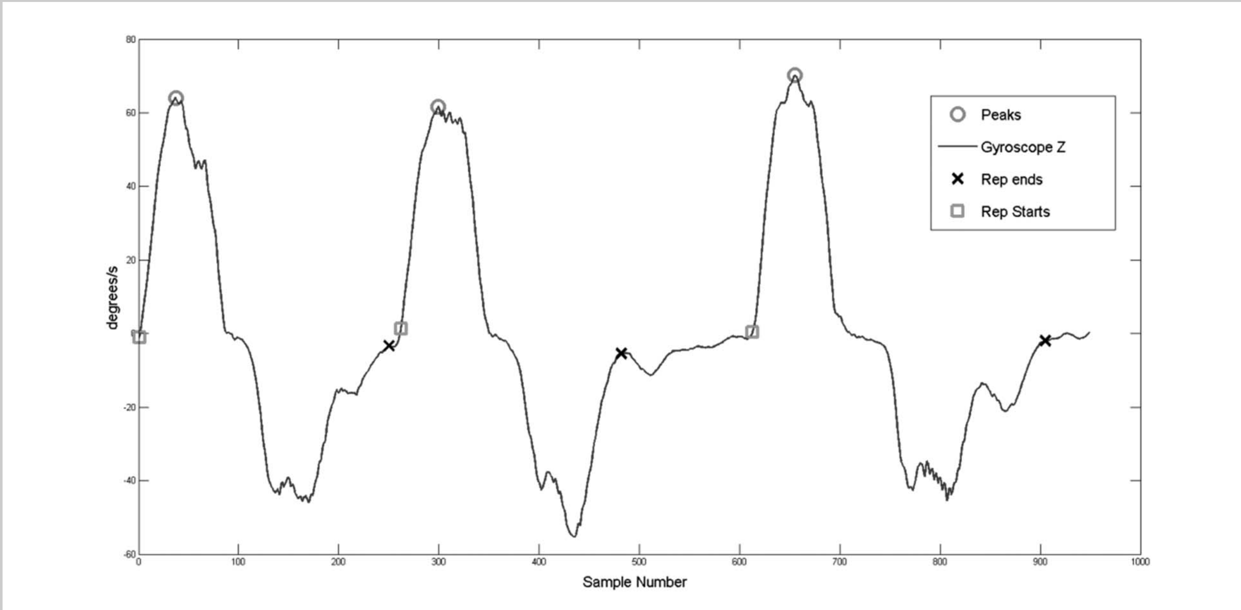


**Figure 3.** Plot showing detection of peak, start, and end points of exercise repetitions through identifying neighboring zero-crossing values to the peak locations. The signal shown is the gyroscope Z signal from the left thigh, during 3 repetitions of a deadlift.

was calibrated for these specific sensor ranges using the Shimmer 9DoF Calibration application (8).

After the warm-up, participants completed one set of 10 repetitions of the following exercises: bodyweight squats, barbell deadlifts at a load of 25 kg, bodyweight lunges, and single-leg squats (Figure 2). The correct technique for each exercise was demonstrated and participants were allowed to familiarize themselves by completing practice repetitions of the upcoming movement. The bodyweight squats, barbell deadlifts, and bodyweight lunges were completed in accordance with the guidelines described by the National Strength and Conditioning Association (5). Single-leg squats were completed with participant's best possible form according to the scoring criteria outlined by Whatman et al. (40). This involved maintaining their trunk and pelvis in a neutral position, keeping their patella in line with the second toe, preventing their foot from moving into excessive pronation, and keeping the movement throughout the range as smooth as possible. Their right leg was extended in front of them, and they flexed their left knee to between 60° and 90°.

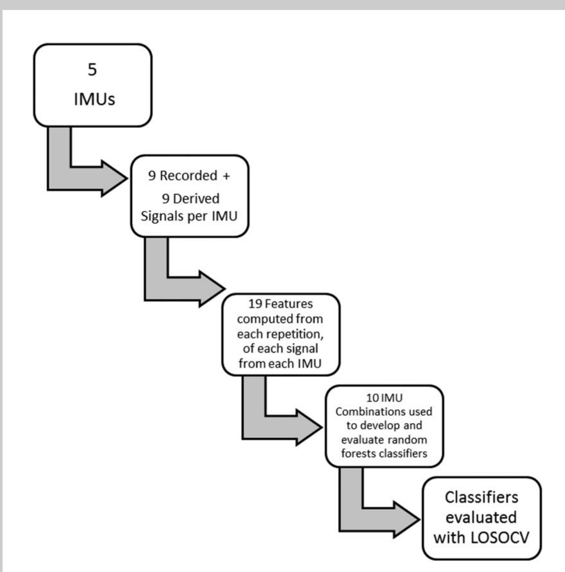


**Figure 4.** Diagram linking the number of IMUs, number of recorded and derived signals, number of features extracted, and the variety of feature combinations used to test classifiers.

The final exercise completed by all participants was the tuck jump exercise (27). Each participant completed as many tuck jumps as possible in 10 seconds while attempting to maintain good form throughout. Participants were allowed a familiarization set before recording data.

### Statistical Analyses

Nine signals were collected from each IMU; accelerometer $x$, $y$, $z$, gyroscope $x$, $y$, $z$, and magnetometer $x$, $y$, $z$. Data were analyzed using MATLAB (2012, MathWorks, Natwick, MA, USA). To ensure that the data analyzed applied to each participant's movement and to eliminate unwanted high-frequency noise, the 9 signals were low-pass filtered at $f_c = 20$ Hz using a Butterworth filter of order $n = 8$. Nine additional signals were then calculated. The 3-D

**Table 1.** IMU combinations compared and the number of features used for classification.

| Multiple IMUs | No. features | Individual IMUs | No. features |
|---|---|---|---|
| All 5 IMUs | 1,710 (5 × 342) | Left shank | 342 |
| Lumbar and shanks | 1,026 (3 × 342) | Left thigh | 342 |
| Lumbar and thighs | 1,026 (3 × 342) | Lumbar | 342 |
| Both shanks | 684 (2 × 342) | Right thigh | 342 |
| Both thighs | 684 (2 × 342) | Right shank | 342 |

orientation of the IMU was computed using the gradient descent algorithm developed by Madgwick et al. (22). The resulting W, X, Y, and Z quaternion values were also converted to pitch, roll, and yaw signals. The pitch, roll, and yaw signals describe the inclination, measured in radians, of each IMU in the sagittal, frontal, and transverse planes, respectively. The magnitude of acceleration was also computed using the vector magnitude of accelerometer *x*, *y*, *z*. The magnitude of acceleration describes the total acceleration of the IMU in any direction. This is the sum of the magnitude of inertial acceleration of the lumbar spine and acceleration due to gravity. Additionally, the magnitude of rotational velocity was computed using the vector magnitude of gyroscope *x*, *y*, *z*.

The IMU signals were then programmatically segmented in to epochs that relate to single, full repetitions of the completed exercises. Many algorithms are available to segment human motion during exercise. These include the sliding window algorithm, top-down, bottom-up algorithms, zero-velocity crossing algorithms, template-base matching methods, and combination algorithms of the above (41). These algorithms all have advantages and disadvantages. For the purpose of the creation of a functioning exercise detection classifier, a simple peak-detection algorithm was used on the gyroscope signal with the largest amplitude for any particular exercise. The start and end points of each repetition were found by looking for the corresponding zero-crossing points of the gyroscope signal leading up to and following the location of a peak in the signal. Figure 3 demonstrates example results of the segmentation algorithm used on the gyroscope Z signal, from an IMU positioned on the left thigh during 3 repetitions of the deadlift exercise.

Each extracted repetition of exercise data was resampled to a length of 250 samples; this was undertaken to minimize the influence of the speed of repetition performance on signal feature calculations. It also ensured the computed features related to differences in movement patterns and not the participant's exercise tempo. Time-domain and frequency-domain descriptive features were computed to describe the pattern of each of the 18 signals when the 5 different exercises were completed. These features were namely "Mean", "RMS", "Standard Deviation", "Kurtosis", "Median", "Skewness", "Range", "Variance", "Max", "Index of Max", "Min", "Index of Min", "Energy", "25th Percentile",

**Table 2.** Overall accuracy for each combination of IMUs.

| IMU(s) | Total accuracy (%) |
|---|---|
| All 5 IMUs | 98.68 |
| Lumbar and shanks | 98.70 |
| Lumbar and thighs | 98.24 |
| Both shanks | 98.45 |
| Both thighs | 98.28 |
| Left shank | 97.70 |
| Left thigh | 96.41 |
| Lumbar | 94.64 |
| Right thigh | 97.37 |
| Right shank | 98.18 |

**Table 3.** Overall sensitivity and specificity for each combination of IMUs.

| IMU(s) | Sensitivity (%) ± *SD* | Specificity (%) ± *SD* |
|---|---|---|
| All 5 IMUs | 98.66 ± 1.37 | 99.67 ± 0.35 |
| Lumbar and shanks | 98.66 ± 1.09 | 99.67 ± 0.38 |
| Lumbar and thighs | 98.26 ± 2.56 | 99.56 ± 0.30 |
| Both shanks | 98.42 ± 1.32 | 99.61 ± 0.41 |
| Both thighs | 98.31 ± 2.48 | 99.57 ± 0.29 |
| Left shank | 97.74 ± 2.24 | 99.42 ± 0.41 |
| Left thigh | 96.47 ± 3.90 | 99.09 ± 0.57 |
| Lumbar | 94.58 ± 5.71 | 98.67 ± 1.30 |
| Right thigh | 97.41 ± 2.98 | 99.34 ± 0.51 |
| Right shank | 98.18 ± 1.02 | 99.54 ± 0.35 |


**Figure 5.** Heat map confusion matrix for actual exercise versus predicted exercise for all 5 IMUs.

"75th Percentile", "Level Crossing Rate", "Fractal Dimension" (17) and the "variance of both the approximate and detailed wavelet coefficients using the Daubechies 4 mother wavelet to level 7" (1). This resulted in 19 features for each of the 18 available signals producing a total of 342 features per IMU.

Figure 4 summarizes the aforementioned, whereby 5 IMUs recorded 9 signals each, 9 more signals were derived from these resulting in a total of 18 signals per IMU. Nineteen features were computed per exercise repetition for each signal from each IMU. This resulted in a total of 1710 features (342 per IMU, 19 per signal). These features were then used to develop and evaluate a variety of classifiers as described in Figure 4.

The random forests method was used to perform classification (7). This technique was chosen as it has been shown to be produce superior accuracy, sensitivity, and specificity scores in analyzing exercise technique with IMUs in comparison with the Naïve-Bayes and Radial-basis function network techniques (23). Four hundred decision trees were used in each random forest classifier. Classifiers were developed and evaluated for the 10 combinations of IMUs as shown in Table 1.


**Figure 6.** Heat map confusion matrix for actual exercise versus predicted exercise for right shank IMU.

The quality of the exercise classification system was established using leave-one-subject-out cross-validation (LOSOCV) and the random forest classifier with 400 trees (13). Each participant's data correspond to one fold of the cross-validation. At each fold, one participant's data are held out as test data while the random forest classifier is trained with all other participants' data. The held out data are used to assess the classifier's ability to correctly categorize unseen data. The use of LOSOCV ensures that there is no biasing of the classifiers, meaning that the test subject data are completely unseen by the classifier before testing. Previous research by Taylor et al. (38) has shown that not using this method of testing can skew results significantly. In our system, each individual repetition was classified. For each set of repetitions, the mode-predicted value was then given to each individual repetition. Therefore, in a situation in which a set of 10 repetitions of a squat were classified as 8 squats, 1 lunge, and 1 single-leg squat, all 10 repetitions were labeled as squat.

The scores used to measure the quality of classification were total accuracy, average sensitivity, and average specificity. Accuracy is the number of correctly classified repetitions of all the exercises divided by the total number of repetitions completed; this is calculated as the sum of the true positives (TP) and true negatives (TN) divided by the sum of the true positives, false positives (FP), true negatives, and false negatives (FN):

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}}$$

For every IMU combination evaluated, the sensitivity and specificity were calculated for each of the 5 exercises, sequentially treating each label as the "positive" class, and then the mean and SD across the 5 values was taken. Sensitivity and specificity were computed using the formulas below:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

Sensitivity measures the effectiveness of a classifier at identifying a desired label, whereas specificity measures the classifier's ability to detect negative labels.

Upon establishing the most effective IMU for exercise classification, feature importance was calculated to reduce model complexity and develop an understanding of which of the aforementioned features are most

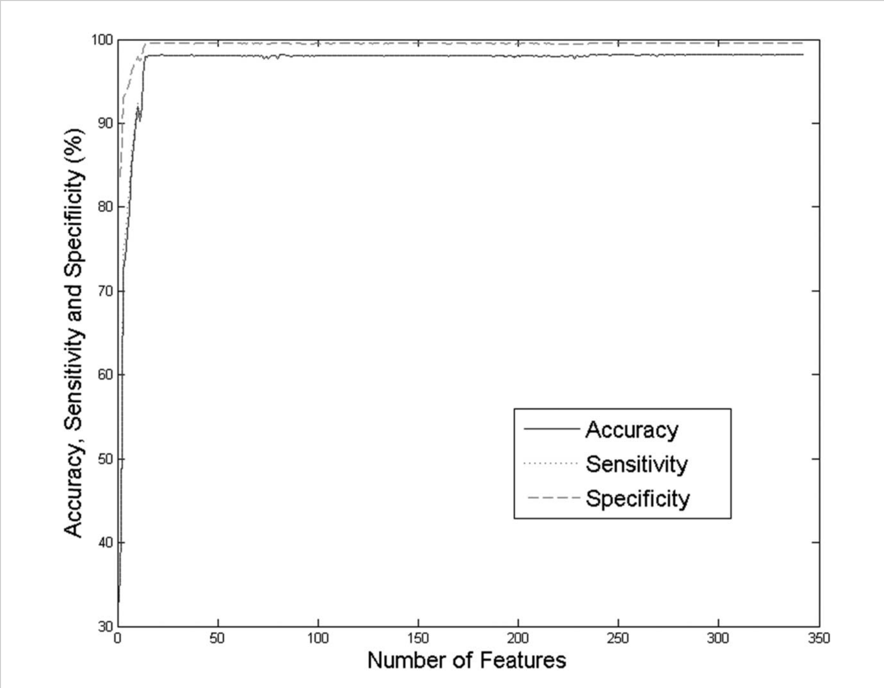


**Figure 7.** Graph showing accuracy, sensitivity, and specificity of exercise classification with the right shank IMU using 1–324 of the available features, ranked in the order of importance.

valuable for correct classification outcomes. This in turn could lead to a more efficient end-user application, increasing the rate of feedback to users and improving the computational efficiency of the system. We used the method described by Liaw and Wiener (20) to establish variable importance. Benchmark accuracy was established through using all of the computed features to train and test a random forest classifier as previously described. The process was to then permute the values of each feature and measure how much the permutation decreases the accuracy of the model. For unimportant features, the permutation should have little to no effect on model accuracy, whereas permuting important features should significantly decrease it. After permutation of each feature, features were ranked based on their importance. Random forest classifiers were then trained and evaluated using just the top-ranked feature, then the top 2 ranked features, and so on until all 342 features were used. Accuracy, sensitivity, and specificity were plotted against the number of features used for classification. This plot allowed the identification of the number of top-ranked features, which achieved classification quality comparable to that of using all features.

In reviewing the accuracy, sensitivity, and specificity scores produced by each classifier, 90% or over was considered an excellent result, 80–89% was considered a "good" quality result, 60–79% was considered a "moderate" result, and anything less than 59% was deemed a poor result. The authors chose these values after reviewing existing literature on identifying exercises with IMUs. In reviewing such literature, an existing accepted standard for a good, moderate, or poor classifier could not be found (10,14,26,31,32,37). Therefore, the above system was agreed on by the authors to facilitate interpretation of our range of results.

## Results

Table 2 demonstrates the total accuracy for each individual IMU and the various combinations of multiple IMUs in identifying the exercise completed. Five IMUs are able to classify the exercise completed with 98.7% accuracy. The best 3-IMU combination is the lumbar and both shanks. This IMU set classifies the exercises with 98.7% accuracy. An IMU placed on each shank (i.e., a 2-IMU setup) classifies each exercise with 98.5% accuracy. The best single IMU position for classification is the right shank with 98.2% accuracy.

Table 3 shows the average sensitivity and specificity for the individual and multiple IMU combinations in correctly identifying the 5 exercises being completed. The 5-IMU combination had an average sensitivity and specificity of 98.7 and 99.7%, respectively. The best single IMU position was the right shank with an average sensitivity of 98.2% and average specificity of 99.5%.

Figures 5 and 6 are classification confusion matrices for differing combinations of IMUs. The horizontal rows represent the actual exercise from which a repetition being tested comes, and the vertical columns demonstrate the classifier's predicted label. For instance, the fourth row in Figure 5 highlights that for all the single-leg squat repetitions classified, 96.8% were correctly identified as single-leg squat repetitions, 1.6% were misclassified as bodyweight squats, and 1.6% were misclassified as deadlifts. In Figure 6, it can be seen that there is slightly more misclassification when the system uses features derived from just the right shank IMU.

Figure 7 shows the classification accuracy, sensitivity, and specificity using incrementing numbers of top-ranked features from the right shank IMU. It is evident that using

**TABLE 4.** The 22 most important features for exercise detection with the right shank IMU.

| Rank | Feature |
|---|---|
| 1 | Gyroscope X–Variance |
| 2 | Gyroscope Z–75th Percentile |
| 3 | Accelerometer X–Max |
| 4 | Accelerometer Z–RMS |
| 5 | Accelerometer Z–Range |
| 6 | Magnetometer X–Kurtosis |
| 7 | Magnetometer Y–Min |
| 8 | Magnetometer Y–75th Percentile |
| 9 | Magnetometer Y–Index of Maximum |
| 10 | Magnetometer Z–Kurtosis |
| 11 | Magnetometer Z–25th Percentile |
| 12 | Pitch–Range |
| 13 | Pitch–Detailed Wavelet Coefficients |
| 14 | Acceleration magnitude–75th Percentile |
| 15 | Gyroscope Magnitude–Index of Maximum |
| 16 | Quaternion W–Variance |
| 17 | Quaternion W–Level Crossing Rate |
| 18 | Quaternion X–Level Crossing Rate |
| 19 | Quaternion Y–Kurtosis |
| 20 | Quaternion Y–Min |
| 21 | Gyroscope X–Mean |
| 22 | Gyroscope X–RMS |

the 22 top features produces comparable results to using the 342 available features. The random forest trained and evaluated with these 22 features produced an overall accuracy of 98.2%, sensitivity of 98.2%, and specificity of 99.5% when assessed with LOSOCV. The 22 features used are listed in the order of importance in Table 4.

## DISCUSSION

The main objective of this study was to investigate whether a system based on data derived from IMUs can distinguish between 5 commonly completed compound and plyometric exercises. Furthermore, it aims to identify the minimal amount of IMUs that could be used to achieve acceptable performance. Overall, the results presented indicate that excellent lower-limb exercise activity recognition can be achieved with data from multiple and single IMUs. A system consisting of 5 or 3 IMUs can detect the exercise type with an overall accuracy of 99%. Inertial measurement units placed on both shanks or on the right shank alone are able to identify exercises with greater than 98% accuracy. These results form the foundation for an IMU system that could identify 5 lower-limb exercises and act as an adjunct to current training practices.

The confusion matrices in Figures 5 and 6 show a more detailed breakdown of classification results with all 5 IMUs and the right shank IMU. Excellent classification scores are achieved for all exercises with both IMU setups (>96%). The SL squat is the poorest classified exercise with a 5-IMU setup (97%). It is most often misclassified as a squat or deadlift, possibly because of the similar amount of knee flexion and ankle dorsiflexion present in these movements. Interestingly, the most commonly confused exercise combination is the lunge misclassified as an SL squat with the right shank IMU (Figure 6). A possible explanation for this might be that the dominant leg for each of these exercises was the left leg (left leg forward lunge, SL squat on the left leg). Therefore, the right shank would have been relatively stationary in either exercise. Despite this, the lunge was still classified correctly with almost 97% accuracy with this single IMU system. The tuck jump has the highest classification rates in both setups. This is most likely because IMU signals from this exercise differ drastically from the other 4 exercises because of the plyometric nature of the exercise.

These results are consistent with previous research in the area, which found that IMU systems could distinguish between exercises with good to excellent overall accuracy (10,14,26,32,37). Chang et al. (10) and Seeger et al. (37) were able to show that a 2-IMU system could differentiate between upper- and lower-limb exercises with 90% accuracy and 92% sensitivity, respectively. However, multiple IMU systems are more expensive and less practical for end users than single-IMU systems. This is due to the risk of placement error, power usage, and Bluetooth connectivity issues. Pernek et al. (32) demonstrated the ability of a single-IMU system to differentiate between 6 upper-limb exercises with 84% accuracy. Muehlbauer et al. (26) and Giggins et al. (14) were able to achieve an overall accuracy of 94% and 93–95% accuracy, respectively, when differentiating between upper- and lower-limb exercises using a single-IMU system.

It is difficult to compare our results directly with those of previous research because of differences in exercises investigated, number of exercises to be classified, number of IMUs, IMU position, and classification methods. However, the classification results presented in this article are higher than previous work. Furthermore, in contrast to some of the previous work, these excellent classification results can be maintained with a single IMU (98%). A single-IMU system would reduce overall cost and would not prove as cumbersome as multiple IMU systems. The excellent accuracy, sensitivity, and specificity scores using a single IMU presented in this study are very important for end users as incorrect exercise classification would have a significant impact on system use and reduce user satisfaction (25).

Similar to the setup used by Giggins et al. (14), our single-IMU system is able to differentiate between a range of exercises with a high level of accuracy. However, the system presented by Giggins et al. identified only simple exercises such as the heel slide and straight leg raise. This is similar to that of Seeger et al. (37) who classified exercises such as barbell curl and cable triceps extension. The system examined in this article is able to classify complex compound lower-limb exercises (squat, deadlift, SL squat, and lunge) and a plyometric activity (tuck jump). Compound and plyometric exercises are essential for improving power production (2) and are therefore included in many training programs. Furthermore, these types of movements form the basis for commonly used musculoskeletal injury risk screening tools such as the Tuck Jump Assessment (27) and the Functional Movement Screen (11). However, they are often more difficult to identify using IMU-based systems because of their complexity.

Figure 7 shows the classifier's ability to obtain similar accuracy, sensitivity, and specificity scores with around 6% of features compared with using all features with a right shank IMU. Table 4 highlights the 24 most important features for exercise detection with the right shank IMU. The main benefit of this reduced feature selection is the quicker processing time for exercise classification. This means that real-time feedback would be easier to implement. Furthermore, the reduced processing load would lead to increases in battery life, meaning an enhanced user experience. These are important elements within a commercial domain in which users would prefer a "set up and go" approach that involvesminimal interaction with the user interface (25).

Despite these encouraging results, there are a number of limitations with the IMU system presented in this article at present. First, it is not possible for IMUs to detect the load lifted during exercises. This means that end users would need to manually insert this before/after the movement. In addition to this, the system can only distinguish between 5 commonly completed lower-limb exercises. These were chosen because of their prevalence in S&C, musculoskeletal injury risk screening, and rehabilitation. It is hoped that future work will involve collection of a greater range of exercises. Finally, the system presented in this study does not monitor technique during movement. Technique is important to prevent stress on joints and reduce the risk of injury (15). Work is ongoing to achieve this, and results have already been published to this end (29,42,43,44). However, the results in this article provide an important first step in developing an IMU-based system to monitor lower-limb exercises, and future work aims to build on this foundation. Furthermore, they create an awareness of the capabilities of IMU systems among the S&C community.

## Practical Applications

The system presented in this article can automatically distinguish between 5 common lower-limb exercises. A system such as this has the potential to act as an important adjunct for gym users, coaches, and rehabilitation professionals.

Gym Users: Despite the documented benefits of strength training, participation among the general population is poor (9). Access to an S&C coach has a significant impact on both adherence and motivation (36); however, this is not always possible because of financial and availability issues. An IMU system based on the work presented in this article offers the potential to provide individual tracking of exercise and repetitions more cost effectively and ubiquitously than previously possible. This individual feedback can increase motivation (24). Automatic exercise tracking can increase activity and compliance as shown with pedometry (6). The consumer electronic market has recognized the potential in this but to date has mainly focused on tracking cardiovascular exercise. The results presented in this article offer the first step in the remote tracking of lower-limb strengthening exercises. Questionnaires and diaries regarding activity levels have been shown to be unreliable in certain disease populations (31). This recall error may have an adverse effect on subsequent exercise prescription as the exercise professional may overestimate or underestimate their client's current status. The ability of a system to automatically detect which exercise is being completed means that the risk of recall bias is removed. This could allow for greater transparency between the client and exercise professional, thus leading to more beneficial exercise prescription. Furthermore, an automated training diary is a very attractive concept for gym users (24). Automatic exercise classification is an integral feature of this setup as it could reduce unnecessary interaction with the system.

S&C Coaches: An IMU system like that presented in this article could act as a useful adjunct to current S&C practice. A system that identifies exercises could allow coaches to help monitor clients and athletes remotely. The ability to capture what exercise is completed and transferring these data to a cloud server would allow coaches to access it at any location with Internet access. By monitoring what exercises their client is completing, coaches could tailor plans to suit individual needs. This would be especially useful for coaches who train clients who travel extensively. In sports teams, S&C coaches often train large numbers of athletes simultaneously, making it difficult for them to monitor and provide feedback to individuals. The ability to track exercises could mean greater ability to provide individualized training plans as they can constantly monitor the exercises completed by their clients. This greater transparency would allow S&C coaches track their client's current status and adherence to the prescribed exercise program.

Rehabilitation Professionals: The use of technology in medicine is growing and wearable technology is expected to assist with the detection and treatment of various diseases over the coming years (30). The 5 exercises investigated in this study are common rehabilitation exercises. An IMU system that can classify these rehabilitation exercises could allow them to be completed at home under remote supervision from rehabilitation professionals. This may allow patients to leave hospital earlier and/or attend fewer outpatient clinics, reducing health care costs (4). The movements classified in this work are also common in screening tools such as the Tuck Jump Assessment (27) and Functional Movement Screen (11). The ability to classify them is the first step in an automated musculoskeletal injury risk assessment system. These computer-assisted rehabilitation and screening systems may prove less labor intensive than current practice (3). This could improve therapist efficiency and increase the number of patients a therapist can screen for musculoskeletal injury risk.

In conclusion, the purpose of this study was to determine whether an IMU system could differentiate between 5 common lower-limb exercises. This is an important first step in the development of an IMU-based system for lower-limb exercise tracking. The findings of this research indicate that such a system can identify these exercises with an excellent degree of overall accuracy, even with a single IMU. This could be beneficial to gym users, coaches, and rehabilitation professionals. As the sensors contained within IMUs (accelerometers, gyroscopes, and magnetometers) are present within many smartphones, this offers the potential for exercises to be tracked and logged using only a smartphone. Our future work aims to monitor a user's technique while performing their exercise routine and provide feedback to maintain proper form throughout the exercises. We aim to develop a workout system that combines biomechanical analysis, workout planners, and an automated logbook. This would afford S&C coaches greater training insights for their clients and athletes.

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## References

1. Uk.mathworks.com. (2017). Single-level discrete 1-D wavelet transform - MATLAB dwt - MathWorks United Kingdom. [online] Available at: https://uk.mathworks.com/help/wavelet/ref/dwt.html. Accessed March 8, 2017.
2. Adams, K, O'Shea, JP, O'Shea, KL, and Climstein, M. The effect of six weeks of squat, plyometric and squat-plyometric training on power production. *J Strength Cond Res* 6: 36–41, 1992.
3. Ahamed, NU, Sundaraj, K, Ahmad, RB, Siva, N, Poo, T, and Rahman, S. Biosensors assisted automated rehabilitation systems: A systematic review. *Int J Phys Sci* 7: 5–17, 2012.
4. Avci, A, Bosch, S, Marin-Perianu, M, Marin-Perianu, R, and Havinga, P. Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey. In: Proceedings of the 23rd International Conference on Architecture of computing systems (ARCS). VDE, 2010, pp. 1–10; February 22–25, 2010; Hanover, Germany.
5. Baechle, TR and Earle, RW. *NSCA's Essentials of Personal Training.* Champaign, IL: Human Kinetics, 2004.
6. Bravata, DM, Smith-Spangler, C, Sundaram, V, Gienger, AL, Lin, N, Lewis, R, Stave, CD, Olkin, I, and Sirard, JR. Using pedometers to increase physical activity and improve health: A systematic review. *J Am Med Assoc* 298: 2296–2304, 2007.
7. Breiman, L. Random forests. *Machine Learning* 45: 5–32, 2001.
8. Burns, A, Greene, BR, McGrath, MJ, O'Shea, TJ, Kuris, B, Ayer, SM, Stroiescu, F, and Cionca, V. SHIMMER–a wireless sensor platform for noninvasive biomedical research. *IEEE Sensors J* 10: 1527–1534, 2010.
9. Centers for Disease Control and Prevention C. Adult participation in aerobic and muscle-strengthening physical activities United States 2011. *Morbidity Mortality Weekly Report* 62: 326–330, 2013.
10. Chang, KH, Chen, MY, and Canny, J. Tracking free-weight exercises. In: *UbiComp 2007: Ubiquitous Computing.* New York, NY: Springer, 2007. pp. 19–37; September 16–19, 2007; Innsbruck, Austria.
11. Cook, G, Burton, L, and Hoogenboom, B. Pre-participation screening: The use of fundamental movements as an assessment of function–part 1. *N Am J Sports Phys Ther* 1: 62–72, 2006.
12. Fitzgerald, D, Foody, J, Kelly, D, Ward, T, Markham, C, McDonald, J, and Caulfield, B. Development of a wearable motion capture suit and virtual reality biofeedback system for the instruction and analysis of sports rehabilitation exercises. Presented at Proceedings of the Engineering in Medicine and Biology Society, 2007; August 23–26, 207; Lyon, France.
13. Fushiki, T. Estimation of prediction error by using K-fold cross-validation. *Stat Comput* 21: 137–146, 2011.
14. Giggins, O, Sweeney, KT, and Caulfield, B. The use of inertial sensors for the classification of rehabilitation exercises. In: Proceedings of the Engineering in Medicine and Biology Society. IEEE, 2014, pp. 2965–2968; August 26–30, 2014; Chicago, IL.
15. Hall, M, Nielsen, JH, Holsgaard-Larsen, A, Nielsen, DB, Creaby, MW, and Thorlund, JB. Forward lunge knee biomechanics before and after partial meniscectomy. *Knee* 22: 506–509, 2015.
16. Jerri, AJ. The Shannon sampling theorem–its various extensions and applications: A tutorial review. In: Proceedings of the IEEE 65: 1565–1596, 1977.
17. Katz, MJ and George, EB. Fractals and the analysis of growth paths. *Bull Math Biol* 47: 273–286, 1985.
18. Kavanagh, JJ and Menz, HB. Accelerometry: A technique for quantifying movement patterns during walking. *Gait Posture* 28: 1–15, 2008.
19. Kranz, M, Möller, A, Hammerla, N, Diewald, S, Plötz, T, Olivier, P, and Roalter, L. The mobile fitness coach: Towards individualized skill assessment using personalized mobile devices. *Pervasive Mobile Comput* 9: 203–215, 2013.
20. Liaw, A and Wiener, M. Classification and regression by randomForest. *R News* 2: 18–22, 2002.
21. Lyons, EJ, Lewis, ZH, Mayrsohn, BG, and Rowland, JL. Behavior change techniques implemented in electronic lifestyle activity monitors: A systematic content analysis. *J Medical Internet Research* 16: e192, 2014.
22. Madgwick, SOH, Harrison, AJL, and Vaidyanathan, R. Estimation of IMU and MARG orientation using a gradient descent algorithm. Presented at Proceedings of the IEEE International Conference on Rehabilitation Robotics (ICORR); June 29-July 1, 2011; Zurich, Switzerland.
23. Mitchell, E, Ahmadi, A, O'Connor, NE, Richter, C, Farrell, E, Kavanagh, J, and Moran, K. Automatically detecting asymmetric running using time and frequency domain features. Presented at Proceedings of the 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN); June 9–12, 2015; Boston, MA.
24. Möller, A, Roalter, L, Diewald, S, Scherr, J, Kranz, M, Hammerla, N, Olivier, P, and Plötz, T. Gymskill: A personal trainer for physical exercises. Presented at Pervasive Computing and Communications; March 19–23, 2012; Lugano, Switzerland.
25. Morris, D, Saponas, TS, Guillory, A, and Kelner, I. RecoFit: Using a wearable sensor to find, recognize, and count repetitive exercises. Presented at Proceedings of the SIGCHI Conference on Human Factors in Computing Systems; April 26-May 1, 2014; Toronto, ON, Canada.
26. Muehlbauer, M, Bahle, G, and Lukowicz, P. What can an arm holster worn smart phone do for activity recognition?. In: Proceedings of the International Symposium on Wearable Computers (ISWC). IEEE, 2011, pp. 79–82; June 12–15, 2011; San Francisco, CA.

27. Myer, GD, Ford, KR, and Hewett, TE. Tuck jump assessment for reducing anterior cruciate ligament injury risk. *Athl Ther Today* 13: 39–44, 2008.

28. O'Donovan, G, Blazevich, AJ, Boreham, C, Cooper, AR, Crank, H, Ekelund, U, Fox, KR, Gately, P, Giles-Corti, B, and Gill, JM. The ABC of physical activity for health: A consensus statement from the British association of sport and exercise sciences. *J Sports Sciences* 28: 573–591, 2010.

29. O'Reilly, M, Whelan, D, Chanialidis, C, Friel, N, Delahunt, E, Ward, T, and Caulfield, B. Evaluating squat performance with a single inertial measurement unit. Presented at IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN); June 9–12, 2015; Boston, MA.

30. Pantelopoulos, A and Bourbakis, NG. A survey on wearable sensor-based systems for health monitoring and prognosis. *Appl Rev* 40: 1–12, 2010.

31. Pernek, I, Hummel, KA, and Kokol, P. Exercise repetition detection for resistance training based on smartphones. *Personal Ubiquitous Computing* 17: 771–782, 2013.

32. Pernek, I, Kurillo, G, Stiglic, G, and Bajcsy, R. Recognizing the intensity of strength training exercises with wearable sensors. *J Biomedical Informatics* 58: 145–155, 2015.

33. Pitta, F, Troosters, T, Probst, V, Spruit, M, Decramer, M, and Gosselink, R. Quantifying physical activity in daily life with questionnaires and motion sensors in COPD. *Eur Respiratory J* 27: 1040–1055, 2006.

34. Pozaic, T, Varga, M, Dzaja, D, and Zulj, S. Closed-loop system for assisted strength exercising. Presented at Information and Communication Technology Electronics and Microelectronics (MIPRO); May 20–24, 2013; Opatija, Croatia.

35. Rawson, ES and Walsh, TM. Estimation of resistance exercise energy expenditure using accelerometry. *Med Science Sports Exercise* 42: 622–628, 2010.

36. Ryan, RM, Frederick, CM, Lepes, D, Rubio, N, and Sheldon, KM. Intrinsic motivation and exercise adherence. *Int J Sport Psychol* 28: 335–354, 1997.

37. Seeger, C, Buchmann, A, and Van Laerhoven, K. myHealthAssistant: a phone-based body sensor network that captures the wearer's exercises throughout the day. In: Proceedings of the 6th International Conference on Body Area Networks. ICST, 2011, pp. 1–7; November 7–10, 2011; Beijing, China.

38. Taylor, PE, Almeida, GJ, Kanade, T, and Hodgins, JK. Classifying human motion quality for knee osteoarthritis using accelerometers. Presented at Engineering in Medicine and Biology Society (EMBC); August 31-September 4, 2010; Buenos Aires, Argentina.

39. Velloso, E, Bulling, A, Gellersen, H, Ugulino, W, and Fuks, H. Qualitative activity recognition of weight lifting exercises. Presented at Proceedings of the 4th Augmented Human International Conference; March 7–8, 2013; Stuttgart, Germany.

40. Whatman, C, Hing, W, and Hume, P. Physiotherapist agreement when visually rating movement quality during lower extremity functional screening tests. *Phys Ther Sport* 13: 87–96, 2012.

41. Whelan, D, O'Reilly, M, Huang, B, Giggins, O, Kechadi, T, and Caulfield, B. Leveraging IMU data for accurate exercise performance classification and musculoskeletal injury risk screening. Presented at IEEE 38th Annual International Conference of the Engineering in Medicine and Biology Society (EMBC); August 16–20, 2016; Orlando, FL.

42. Whelan, D, O'Reilly, M, Ward, T, Delahunt, E, and Caulfield, B. Evaluating performance of the single leg squat exercise with a single inertial measurement unit. Presented at Proceedings of the 3rd Workshop on ICTs for Improving Patients Rehabilitation Research Techniques; October 1–2, 2015; Lisbon, Portugal.

43. Whelan, D, O'Reilly, M, Ward, T, Delahunt, E, and Caulfield, B. Evaluating performance of the lunge exercise with multiple and individual inertial measurement units. Presented at Pervasive Health 10th EAI International Conference on Pervasive Computing Technologies for Healthcare; May 16–19, 2016; Cancun, Mexico.

44. Whelan, D, O'Reilly, M, Ward, T, Delahunt, E, and Caulfield, B. Technology in rehabilitation: evaluating the single leg squat exercise with wearable inertial measurement units. *Methods Inf Med* 56: 88–94, 2017.