Technology in Rehabilitation: Evaluating the Single Leg Squat Exercise with Wearable Inertial Measurement Units

Article *in* Methods of Information in Medicine · October 2016

DOI: 10.3414/ME16-02-0002

Technology in Rehabilitation: Evaluating the Single Leg Squat Exercise with Wearable Inertial Measurement Units

D.F. Whelan*[┼╫], M.A. O'Reilly*[┼╫], T.E. Ward[╪], E. Delahunt[╫], B. Caulfield[┼╫]
[┼] Insight Centre for Data Analytics, University College Dublin
[╫] School of Public Health, Physiotherapy and Sports Science, University College Dublin
[╪] Insight Centre for Data Analytics, Maynooth University

Joint lead authors

1 Summary

Background: The single leg squat (SLS) is a common lower limb rehabilitation exercise. It is also frequently used as an evaluative exercise to screen for an increased risk of lower limb injury. To date athlete/patient SLS technique has been assessed using expensive laboratory equipment or subjective clinical judgement; both of which are not without shortcomings. Inertial measurement units (IMUs) may offer a low cost solution for the objective evaluation of athlete/patient SLS technique.

Objectives: The aims of this study were to determine if in combination or in isolation IMUs positioned on the lumbar spine, thigh and shank are capable of: (A) distinguishing between acceptable and aberrant SLS technique; (B) identifying specific deviations from acceptable SLS technique.

Methods: Eighty-three healthy volunteers participated (60 males, 23 females, age: 24.68 +/- 4.91 years, height: 1.75 +/- 0.09 m, body mass: 76.01 +/- 13.29 kg). All participants performed 10 SLSs on their left leg. IMUs were positioned on participants' lumbar spine, left shank and left thigh. These were utilized to record tri-axial accelerometer, gyroscope and magnetometer data during all repetitions of the SLS. SLS technique was labelled by a Chartered Physiotherapist using an evaluation framework. Features were extracted from the labelled sensor data. These features were used to train and evaluate a variety of random-forests classifiers that assessed SLS technique.

Results: A three IMU system was moderately successful in detecting the overall quality of SLS performance (77% accuracy, 77% sensitivity and 78% specificity). A single IMU worn on the shank can complete the same analysis with 76% accuracy, 75% sensitivity and 76% specificity. Single sensors also produce competitive classification scores relative to multi-sensor systems in identifying specific deviations from acceptable SLS technique.

Conclusions: A single IMU positioned on the shank can differentiate between acceptable and aberrant SLS technique with moderate levels of accuracy. It can also capably identify specific deviations from optimal SLS performance. IMUs may offer a low cost solution for the objective evaluation of SLS performance.

Additionally, the classifiers described may provide useful input to an exercise biofeedback application.
Keywords: Exercise Therapy; Biomedical Technology; Lower Extremity; Physical Therapy Speciality; Inertial Measurement Units

2 Introduction

The single leg squat (SLS) is a commonly used rehabilitative exercise following lower limb musculoskeletal injury (1). Additionally, it is frequently utilized as an evaluative exercise to assess athletes' risk of incurring lower limb musculoskeletal injury (2). The SLS is a popular evaluative exercise as it allows clinicians/practitioners to simultaneously assess trunk, pelvis, hip, and knee kinematics during a weight-bearing activity (3). Therefore, it is necessary that patient/athlete performance of the SLS can be evaluated effectively and reliably.

To date, objective quantification of patient/athlete performance of the SLS has been determined using marker-based motion analysis systems (1). This approach is time intensive, expensive (over €100,000 for a complete system) and the application of skin-mounted markers may hinder normal movement (4). As such, beyond the research laboratory, these systems are not frequently used for the objective quantification of patient/athlete SLS technique. As an alternative, real-time visual evaluation of patient/athlete performance of the SLS is more commonly used. In this instance, kinematics of the trunk, pelvis, hip and knee are simultaneously evaluated to provide an overall assessment of the patient's/athlete's performance of the exercise (3). It is difficult to standardise SLS performance evaluation due to the experience of the rater (3), the method used to rate performance of the exercise (ordinal vs. dichotomous scales) or the instructions given to the raters (5). Inaccurate evaluation of patient/athlete performance of the SLS could have implications for clinical and exercise progression decisions.

Recent technological advances have allowed for the possibility of using inertial measurement units (IMUs) as part of a method for capturing human movement during the performance of exercises such as the SLS. IMUs are able to acquire data pertaining to the linear and angular motion of individual limb segments and the centre of mass of the body. They are small, inexpensive, easy to set-up and facilitate the acquisition of human movement data in unconstrained environments (6). Thus, they offer the potential to bridge the gap between laboratory-based and day-to-day "real-world" acquisition of human movement.

Body worn systems incorporating multiple IMUs have been shown to be effective at differentiating exercises and evaluating exercise performance. Chang et al. (7) incorporated accelerometers into a workout glove and belt clip with the aim of differentiating between, and counting the number of repetitions of, nine different upper and lower limb exercises. Their system achieved 95% exercise classification and repetition counting accuracy. A case study completed by Fitzgerald et al. (8) used 10 IMUs to provide feedback to a healthy non-injured athlete and an athlete five weeks post-knee injury during the performance of a lunge exercise. Analysis of the gyroscope signals from the IMUs identified lower limb movement deviations in the injured athlete when compared to the non-injured athlete. Seeger et al. (9) used three IMUs to differentiate between a total of 16 cardiovascular and weight-lifting exercises. Classification accuracy ranged from 71-100% for the different exercises. However, multiple sensor systems are expensive for end-users. They may also prove impractical due to the increased risk of placement error and comfort issues. Furthermore a multiple sensor set-up would put a bigger strain on power usage and Bluetooth™ capabilities of the sensors and hosting smartphone. Consequently, the transferability of a multiple sensor set-up to day-to-day "real-world" situations is not practical (10).

For increased end user cost effectiveness and practicality a single sensor set-up is far more desirable. Giggins et al. (11) demonstrated the ability of a single IMU to successfully differentiate seven commonly prescribed orthopaedic rehabilitation exercises (heel slide, hip abduction, hip extension, hip flexion, inner range quads, knee extension, straight leg raise). Accuracies of 93-95%

were observed. Muehlbauer et al. (12) reported that a single sensor placed on the upper arm could distinguish between 10 different upper body exercises with an overall recognition rate of 94%. Pernek et al. (13) used a single sensor in a smartphone to count repetitions of resistance exercises; observing an overall repetition count accuracy of 99%.

Evaluation of exercise performance is also vital to ensure that not only is the exercise completed but that it is completed with acceptable technique. Taylor et al. (14) used five IMUs to identify five technique deviations in the standing hamstring curl and four deviations in the straight-leg raise. They were able to classify the different deviations with 80% accuracy, 75% sensitivity and 90% specificity. Velloso et al. (15) used four IMUs to classify deviations from normal form during a unilateral dumbbell bicep curl. They achieved an overall accuracy of 74-86% in identifying specific deviations. Giggins et al. (16) demonstrated an overall accuracy of 79-81% using different combinations of one, two or three sensors placed on the lower limb to analyse exercise technique in seven exercises (heel slide, hip abduction, hip flexion, hip extension, knee extension, inner range quads and straight-leg raise). These studies demonstrate that it is possible to evaluate exercise performance of simple exercises using multiple IMUs. However, the ability of an IMU based system to evaluate more complex exercises such as the SLS is less understood.

3 Objectives

The research question this study seeks to address is: "How well can an IMU-based system quantify performance of the SLS?" The aims of this study were to determine if in combination or in isolation, IMUs positioned on the lumbar spine, thigh and shank are capable of: (A) distinguishing between acceptable and aberrant SLS technique; (B) identifying specific deviations from acceptable SLS performance.

4 Methods

Data were acquired from participants as they completed 10 SLS repetitions on their left leg with their best possible form. All repetitions were recorded using a high-definition video camera. Each participant's performance of each SLS repetition was rated by a Chartered Physiotherapist using a scale developed by Whatman et al. (Table 1) (3). Data derived from the IMUs during each repetition were compared to this rating to determine if a single IMU on the lumbar spine could discriminate between different levels of SLS performance and identify the specific deviations from acceptable SLS form.

4.1 Participants

Eighty-three healthy volunteers participated. No participant had a current or recent musculoskeletal injury that would impair their SLS performance. All participants had prior experience with the exercise. Each participant signed a consent form prior to completing the study. The University Human Research Ethics Committee approved the study protocol.

4.2 Experimental Protocol

The testing protocol was explained to participants upon their arrival to the research laboratory. All participants completed a 10-minute warm-up on an exercise bike; during which they were required to maintain a power output of 100W and cadence of 75-85 revolutions per minute. Following the warm-up, an investigator (the same investigator for all participants) secured three IMUs (SHIMMER, Shimmer research, Dublin, Ireland) on the participant at the following anatomical locations: the level of the 5th lumbar vertebra, the mid-point of the left femur (determined as half way between the greater trochanter and lateral femoral condyle), and on the left shank 2 cm above the lateral malleolus (Figure 1). The orientation and location of the IMU was consistent across all study participants.

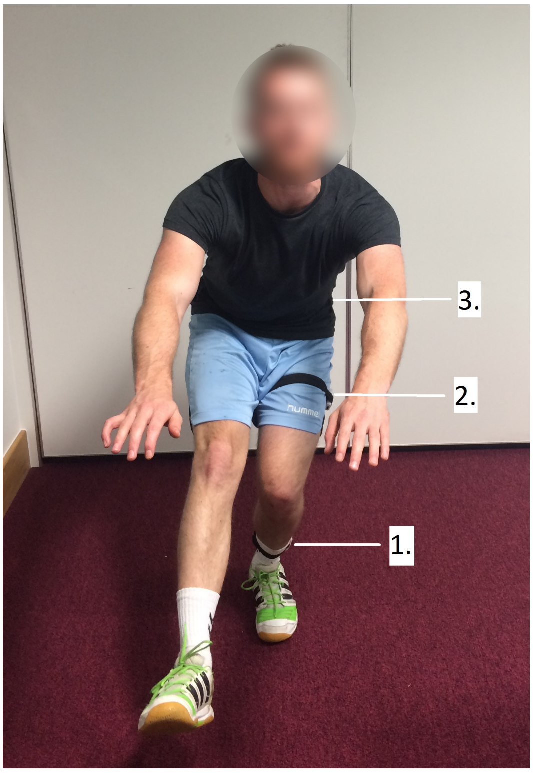

Figure 1: Image showing IMU positions and SLS exercise

(1 = left shank; 2 = left thigh; 3 = lumbar spine)

A pilot study was used to determine an appropriate sampling rate and the ranges for the accelerometer and gyroscope within the IMU. In the pilot study data during performance of the SLS data was collected at 512 samples/s. A Fourier transform was then used to detect the characteristic frequencies of the signal which were all found to be less than 20 Hz. Therefore, a sampling rate of 51.2 Hz was deemed appropriate for this study based upon the Shannon sampling theorem and the Nyquist criterion (17). The Shimmer IMU was configured to stream tri-axial accelerometer (+/- 2G), gyroscope (+/- 500°/s) and magnetometer (+/- 1Ga) data with the sensor ranges chosen also based upon data from the pilot study. The IMU was calibrated for these specific sensor ranges using the Shimmer 9DoF Calibration application (18).

Participants completed 10 repetitions of a left leg SLS with their best form. A Charted Physiotherapist demonstrated and instructed all participants on how to complete the SLS with acceptable technique. 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 available range of motion as smooth as possible. Their right leg was kept as extended as possible in front of them while the left knee was flexed between 60 and 90 degrees. All participants were allowed trial repetitions to ensure they were comfortable with the exercise before commencing their set of 10 repetitions.

4.3 Data Labelling

Participants' performance of the SLS was recorded using a high-definition video camera. A Chartered Physiotherapist with more than six years post-graduation experience and an MSc in Sports and Exercise Medicine reviewed all recorded SLS repetitions. Each repetition was separated and reviewed on multiple occasions in a systematic format. For every repetition a score of 0 or 1 was given to each section as outlined in the scoring system shown in Table 1. This was adapted from the scoring system described by Whatman et al. (3). In order to establish the overall score of each repetition a '1' (movement dysfunction) was given to repetitions that scored a '1' in two or more of the six categories. All other repetitions were rated as '0' (acceptable movement pattern). The Chartered Physiotherapist involved in the study developed the method of assigning an overall score following consultation with colleagues who work in musculoskeletal physiotherapy and sports medicine.

Table 1: SLS data labelling system used adapted from Whatman et. al.

Visual rating sheet		
Trunk	Moves out of neutral in frontal or transverse plane	N:0 Y:1
Pelvis 1:	Moves out of neutral in frontal or transverse plane or moves away from midline	N:0 Y:1
Knee	Patella moves out of line with 2nd toe	N:0 Y:1
Foot	Moves in to excessive pronation	N:0 Y:1
Oscillation	Observable oscillation	N:0 Y:1
Loss of Balance	Visible loss of balance	N:0 Y:1
Overall Score	Movement dysfunction	N:0 Y:1

4.4 Data Analysis

Nine signals were collected from each IMU: accelerometer *x, y, z;* gyroscope *x, y, z;* and magnetometer *x, y, z*. To ensure the data analysed applied to each participant's movement and in order to eliminate unwanted high-frequency noise, the nine 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 orientation of the IMU was computed using the gradient descent algorithm developed by Madgwick et al*.* (19). The resulting quaternion values (W, X, Y and Z) were then converted to pitch, roll and yaw signals. The pitch, roll and yaw signals describe the inclination, measured in radians, of the lumbar spine, left thigh and left shank in the sagittal, frontal plane and transverse planes respectively. The magnitude of acceleration was also computed using the vector magnitude of accelerometer *x, y* and *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* and *z*.

All ten repetitions from each participant's SLS dataset were programmatically extracted using the IMU data and resampled to a length of 250 samples; this was undertaken to minimise 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 in order to describe the pattern of each of the eighteen signals when the five different exercises were completed. These features were namely signal mean, RMS, standard deviation, kurtosis, median, skewness, range, maximum, minimum, variance, energy, 25th percentile, 75th percentile, level crossing rate, fractal dimension and the variance of both the approximate and detailed wavelet coefficients using the Daubechies 5 mother wavelet to level 6. This resulted in seventeen features for each of the eighteen available signals producing a total of 306 features per sensor unit.

The random-forests method was employed to perform classification (20). A random forest is an ensemble of decision trees that will output a prediction value, in this case SLS quality. Each decision tree is constructed by using a random subset of the training data. After you have trained your forest, you can then pass each test row through it, in order to output a predicted class. This technique was chosen as it has been shown to be effective in analysing exercise technique with IMUs when compared to the Naïve-Bayes and Radial-basis function network techniques (21). Four hundred decision trees were used in each random-forest classifier. Classification quality was compared with and without performing principal component analysis (PCA) on the training data. Using PCA produced lower accuracy, sensitivity and specificity scores and therefore, PCA was not included in the final exercise classification system.

Six separate random forests were used to analyse if a specific deviation had occurred as described in Table 1. A seventh random forest predicted the overall score of each SLS repetition. For each of the above classifiers a variety of training features were used in order to establish classification quality when using three, two and individual IMUs. Classifiers were developed and evaluated using the following seven combinations of variables; the 918 (3 x 306) variables computed from every IMU, the 612 (2 x 306) variables from the left shank and lumbar IMUs, the 612 (2 x 306) variables from the left thigh and lumbar IMUs, the 612 (2 x 306) variables from the left shank and left thigh IMUs, and the 306 variables from each of the three individual IMUs.

To establish the quality of each classifier in discriminating between acceptable and aberrant SLS technique or identifying a specific deviation from acceptable SLS performance, repeated random sub-sample validation (RRSSV) was used. This method of classifier evaluation was chosen as the data set used to train the classifier was relatively small. Leave-one-subject out cross-validation (LOSOCV) was not deemed necessary for this study due to the high inter-repetition variability of SLS performance in each participant's set of the exercise.

Data was shuffled programmatically. The first 80% of data were used as the training set for the random forests classifier, initially resulting in 672 repetitions per training set. However, the training data was then balanced to avoid biasing the classifier. This was completed by counting the number of instances of each class (0 and 1) and removing a random selection of repetition from the class with more instances until there was an equal amount of training data to represent both classes. The remaining 20% of observations were used as the test set for the classifier resulting in 168 test repetitions per evaluation. Accuracy, sensitivity and specificity metrics were calculated. Accuracy measures the overall effectiveness of a classifier and is computed by taking the ratio of correctly classified examples and the total number of examples available. Sensitivity measures the effectiveness of a classifier at identifying a desired label, while specificity measures the classifier's ability to detect negative labels. This process was repeated ten times.

5 Results

The demographics of the participants were as follows: 60 males, 23 females, age: 24.68 +/- 4.91 years, height: 1.75 +/- 0.094m, body mass: 76.01 +/- 13.29kg.

Table 2 demonstrates the mean sensitivity, specificity and accuracy for the overall score following the ten cycles of RRSSV for systems using each individual IMU and each combination of IMUs. The best single sensor for classifying overall score was the left shank with an accuracy of 76%. The highest quality classification came from the two-sensor combination of the shank and thigh, which achieved 78% accuracy.

Table 2: Classification results for 'Overall SLS Score' for each IMU combination

	Accuracy	Sensitivity	Specificity
Left Shank	76%	75%	76%
Left Thigh	75%	71%	77%
Lumbar	73%	74%	72%
All 3 IMUs	77%	77%	78%
Lumbar + Shank	75%	78%	72%
Shank + Thigh	78%	78%	78%
Lumbar + Thigh	77%	75%	79%

Table 3 demonstrates the classification scores for the detection of each specific deviation as described in Table 1. Deviation of the pelvis from the neutral position was the most poorly detected deviation. The three-sensor combination detected this deviation with 70% accuracy and a single sensor located on the lumbar spine detected this deviation with 69% accuracy. In some cases (e.g. the foot moving into excessive pronation), the single sensor system outperformed the multi-sensor set-ups. The IMU positioned on the left shank produced an accuracy of 75% for this deviation, superior to the accuracy of 73% achieved when using all three IMUs. Single sensor set-ups appear comparable to multi-sensor set-ups for the detection of all six deviations.

Table 3: Classification results for specific deviations for each IMU combination

	Trunk: Moves out of neutral in frontal or transverse plane			Pelvis: Moves out of neutral in frontal or transverse plane or moves away from midline		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
Left Shank	70%	73%	69%	66%	67%	66%
Left Thigh	69%	62%	70%	65%	64%	65%
Lumbar	73%	72%	73%	69%	77%	68%
All 3 IMUs	74%	61%	76%	70%	80%	69%
Lumbar + Shank	76%	75%	76%	70%	73%	69%
Shank + Thigh	69%	67%	69%	66%	63%	67%
Lumbar + Thigh	75%	73%	75%	69%	70%	69%

	Foot: Moves in to excessive pronation			Oscillation: Observable Oscillation		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
Left Shank	75%	63%	77%	75%	63%	77%
Left Thigh	72%	67%	73%	72%	68%	74%
Lumbar	69%	60%	71%	70%	69%	71%
All 3 IMUs	73%	64%	75%	74%	76%	71%
Lumbar + Shank	74%	71%	74%	76%	77%	65%
Shank + Thigh	72%	69%	73%	75%	75%	72%
Lumbar+ Thigh	72%	64%	73%	70%	71%	69%

	Knee: Patella moves out of line with 2nd toe			Loss of Balance: Visible loss of balance		
	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
Left Shank	71%	73%	71%	73%	74%	61%
Left Thigh	71%	68%	71%	68%	68%	72%
Lumbar	72%	78%	70%	67%	67%	63%
All 3 IMUs	75%	76%	75%	71%	71%	70%
Lumbar + Shank	71%	62%	73%	76%	77%	65%
Shank + Thigh	74%	74%	74%	75%	75%	72%
Lumbar+ Thigh	74%	69%	75%	72%	73%	62%

6 Discussion

Our results indicate that an IMU sensor-based system is capable of evaluating SLS performance with moderate accuracy, sensitivity and specificity. A three-sensor set-up can distinguish between acceptable and aberrant SLS technique with 77% accuracy, 77% sensitivity and 78% specificity. Two sensors (shank and thigh) discriminate between acceptable and aberrant performance with 78% accuracy, sensitivity and specificity. A single sensor (left shank) can identify acceptable SLS performance with 76% accuracy, 75% sensitivity and 76% specificity. Specific deviations can also be classified with a moderate level of accuracy, sensitivity and specificity as shown in Table 3. Overall accuracy for specific deviations ranged from 65%-76%, sensitivity ranged from 60%-80% and specificity from 61%-77%.

These results indicate that an IMU sensor set offers the possibility of monitoring SLS exercise form objectively outside of a laboratory setting. Importantly, a single sensor set-up has comparable accuracy, sensitivity and specificity to a multi sensor set-up if positioned appropriately. A single sensor set-up is a less cumbersome, more energy efficient and more cost effective solution for end users; which may increase the likelihood of adoption of this technology within a clinical setting.

Authors have previously utilized multiple (7-9) and single (11-13) IMU set-ups to differentiate exercise performance and count the number of exercise repetitions. However, patients are likely to move beyond the exercises evaluated in these aforementioned studies relatively early in their rehabilitation programmes. The increased complexity of the SLS means it is predominantly used in later stages of rehabilitation. Furthermore, these studies focused on the recognition of specific exercises and counting of exercise repetitions and not on the quality of movement during exercise performance.

A number of researchers have used multiple sensor systems to classify exercise performance with varying results. Taylor et al. (14) used five IMUs to identify five technique deviations in the standing hamstring curl and four deviations in the straight-leg raise. It is worth noting that only 7% of the exercise repetitions were classified by a biomechanics expert, which may have resulted in an increased possibility of incorrect data labelling. Velloso et al. (15) used a total of four sensors to classify four deviations from normal form during a unilateral dumb-bell bicep curl. They demonstrated an overall accuracy of 74-86% in identifying specific deviations. However, these deviations were induced and were possibly not representative of movement deviations that occur in a natural exercise environment. The scores presented in this paper are comparable with Taylor et al. (14) and Velloso et al. (15), while having the added benefit of being reproducible with a single sensor set-up. Furthermore the deviations observed in our dataset occurred without simulation (i.e. were not prescriptively induced), thus providing a more realistic representation of SLS exercise performance.

Giggins et al. (16) investigated the potential of a single sensor system to analyse natural deviations from acceptable form in a total of seven exercises (heel slide, hip abduction, hip flexion, hip extension, knee extension, inner range quads and straight-leg raise). They demonstrated an overall accuracy of 79-81% using different combinations of one, two or three sensors placed on specific lower limb body sites. While the accuracy results of our research are slightly lower (73-78%), it should be noted that the SLS is a more complex exercise than those evaluated by Giggins et al. (19). Furthermore, our classification system was able to detect deviations occurring at multiple body locations simultaneously unlike the majority of previous research in the area.

There are a number of contextual factors that are appropriate to consider for discussion purposes. A 3-dimensional motion capture system was not used to confirm that each deviation occurred. Instead, a Chartered Physiotherapist recorded the presence of any deviations noted during the performance of each SLS repetitions. The use of video analysis allowed for multiple viewings of each SLS repetition. The ability to view the movement on multiple occasions and slow down the playback speed allowed for a detailed analysis of each repetition. A single Chartered Physiotherapist performed this analysis. Future work should involve multiple biomechanical experts rating SLS performance to increase the reliability of the rating labels. However, this approach could prove challenging as it may not be possible to obtain an agreed consensus between different experts as to what constitutes acceptable movement biomechanics.

The overall accuracy, sensitivity and specificity scores presented in this work are slightly lower than that of other authors (14-16). This may be due to the small amount of acceptable SLS performances seen in the dataset (52 acceptable SLS vs 778 SLS with aberrant technique). It is hoped that future work will involve the collection of a greater number of acceptable SLSs. It is also envisaged that this future data collection will be combined with improved classification techniques to make it possible to not only identify where the deviation has occurred, but also to grade the severity of the deviation as described in the scale developed by Whatman et al. (3).

Along with the addition of a greater number of expert reviewers and acceptable SLS performances, future work will involve analysing a range of different movements, including squats, lunges, deadlifts and tuck jumps. It is hoped that a range of movements that are used commonly in rehabilitation and screening can be graded using data derived from an IMU based system. This could allow for the development of a system that can be used for musculoskeletal injury risk screening and exercise analysis.

6.1 Practical Implications

A single sensor system that is able to automatically evaluate SLS technique could be very beneficial to clinicians. The SLS is a commonly used exercise to assess lower limb function (22). The assessment of human movement proficiency is predominantly completed subjectively through the use of visual rating scales such as the Functional Movement Screen (23, 24), Tuck Jump Assessment (25) or lower extremity functional screening tests (3). The subjectivity inherent in rating these screening tools leads to the potential for bias and/or measurement error. Furthermore, the process of screening can prove time consuming for clinicians, particularly when there are a large amount of participants, e.g. in a sports team setting. An IMU based system can offer clinicians the potential to screen multiple athletes simultaneously in an objective manner. This could lead to a quicker and more reliable method of screening than currently available.

An IMU system also offers clinicians the potential to remotely monitor their patients' compliance and technique when completing rehabilitation exercises. This allows clinicians to evaluate their treatment more effectively. Furthermore, exercise technique feedback could be given to patients automatically. This means patients could correct their form during the exercise without the need for a clinician to be present (26). This would increase the potential of home centred care, which may be effective at reducing health care costs (27). The ability to remotely monitor the SLS and provide locally generated feedback would also prove very beneficial to strength and conditioning coaches as the SLS is often a component of their conditioning programmes.

7 Conclusions

An IMU based system is capable of differentiating between acceptable and aberrant SLS technique with moderate accuracy. The overall accuracy presented in this work is comparable to other research investigating early-stage rehabilitation exercises technique with IMUs. This study has shown that is possible to classify a more complex exercise with IMUs and maintain moderate levels of accuracy. Furthermore, it is shown that a single IMU can produce comparable results to a multi-sensor set-up. This suggests that the system can be cost-effective and practical to implement in a clinical setting. Future work should aim to develop a low cost biomechanical analysis system that is capable of measuring technique in a range of exercises. Such a system would offer clinicians the ability to screen for injury risks quickly and objectively while also allowing for the remote monitoring of their patients' rehabilitation.

8 Acknowledgments

This project is partly funded by the Irish Research Council as part of a Postgraduate Enterprise Partnership Scheme with Shimmer (EPSPG/2013/574) and partly funded by Science Foundation Ireland (SFI/12/RC/2289). The authors would also like to thank UCD Sport for providing equipment which was used in this study.

9 References

1. Zwerver J, Bredeweg SW, Hof AL. Biomechanical analysis of the single-leg decline squat. Br J Sports Med. 2007;41(4):264-8.
2. Willson JD, Ireland ML, Davis I. Core strength and lower extremity alignment during single leg squats. Med Sci Sports Exerc. 2006;38(5):945-52.
3. Whatman C, Hing W, Hume P. Physiotherapist agreement when visually rating movement quality during lower extremity functional screening tests. Phys Ther Sport. 2012;13(2):87-96.
4. Ahmadi A, Mitchell E, Destelle F, Gowing M, OConnor NE, Richter C, et al., editors. Automatic Activity Classification and Movement Assessment During a Sports Training Session Using Wearable Inertial Sensors. Proceedings of the 11th International Conference on Wearable and Implantable Body Sensor Networks (BSN); 2014: IEEE.
5. Chmielewski TL, Hodges MJ, Horodyski M, Bishop MD, Conrad BP, Tillman SM. Investigation of clinician agreement in evaluating movement quality during unilateral lower extremity functional tasks: a comparison of 2 rating methods. J Orthop Sports Phys Ther. 2007;37(3):122-9.
6. McGrath D, Greene BR, O'Donovan KJ, Caulfield B. Gyroscope-based assessment of temporal gait parameters during treadmill walking and running. Sports Eng. 2012;15(4):207-13.
7. Chang K-H, Chen MY, Canny J. Tracking free-weight exercises. UbiComp 2007: Ubiquitous Computing. 4717: Springer; 2007. p. 19-37.
8. Fitzgerald D, Foody J, Kelly D, Ward T, Markham C, McDonald J, et al., editors. Development of a wearable motion capture suit and virtual reality biofeedback system for the instruction and analysis of sports rehabilitation exercises. Proceedings of the Engineering in Medicine and Biology Society, 2007; 2007; Lyon: IEEE.
9. Seeger C, Buchmann A, Van Laerhoven K. myHealthAssistant: a phone-based body sensor network that captures the wearer's exercises throughout the day. Proceedings of the 6th International Conference on Body Area Networks: ICST; 2011. p. 1-7.
10. Morris D, Saponas TS, Guillory A, Kelner I, editors. RecoFit: using a wearable sensor to find, recognize, and count repetitive exercises. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems; 2014: ACM.
11. Giggins O, Sweeney KT, Caulfield B. The use of inertial sensors for the classification of rehabilitation exercises. Proceedings of the Engineering in Medicine and Biology Society: IEEE; 2014. p. 2965-8.
12. Muehlbauer M, Bahle G, Lukowicz P. What can an arm holster worn smart phone do for activity recognition? Proceedings of the International Symposium on Wearable Computers (ISWC): IEEE; 2011. p. 79-82.
13. Pernek I, Hummel KA, Kokol P. Exercise repetition detection for resistance training based on smartphones. Pers Ubiquitous Comput. 2013;17(4):771-82.
14. Taylor PE, Almeida GJ, Hodgins JK, Kanade T, editors. Multi-label classification for the analysis of human motion quality. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2012: IEEE.

15. Velloso E, Bulling A, Gellersen H, Ugulino W, Fuks H, editors. Qualitative activity recognition of weight lifting exercises. Proceedings of the 4th Augmented Human International Conference; 2013: ACM.
16. Giggins OM, Sweeney KT, Caulfield B. Rehabilitation exercise assessment using inertial sensors: a cross-sectional analytical study. J Neuroeng Rehabil. 2014;11(1):158-68.
17. Jerri AJ. The Shannon sampling theorem—Its various extensions and applications: A tutorial review. Proc. IEEE. 1977;65(11):1565-96.
18. Shimmer 9DOF calibration [Available from: http://www.shimmersensing.com/shop/shimmer-9dof-calibration.
19. Madgwick SOH, Harrison AJL, Vaidyanathan R, editors. Estimation of IMU and MARG orientation using a gradient descent algorithm. Proceedings of the IEEE International Conference on Rehabilitation Robotics (ICORR); 2011: IEEE.
20. Breiman L. Random forests. Mach Learn. 2001;45(1):5-32.
21. Mitchell E, Ahmadi A, O'Connor NE, Richter C, Farrell E, Kavanagh J, et al., editors. Automatically detecting asymmetric running using time and frequency domain features. Proceedings of the 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN); 2015: IEEE.
22. Ugalde V, Brockman C, Bailowitz Z, Pollard CD. Single Leg Squat Test and Its Relationship to Dynamic Knee Valgus and Injury Risk Screening. PM&R. 2014;7(3):229-35.
23. Cook G, Burton L, Hoogenboom B. Pre-participation screening: the use of fundamental movements as an assessment of function - part 1. N Am J Sports Phys Ther. 2006;1(2):62-72.
24. Cook G, Burton L, Hoogenboom B. Pre-participation screening: the use of fundamental movements as an assessment of function - part 2. N Am J Sports Phys Ther. 2006;1(3):132-9.
25. Myer GD, Ford KR, Hewett TE. Tuck jump assessment for reducing anterior cruciate ligament injury risk. Athl Ther Today. 2008;13(5):39-44.
26. Giggins O, Kelly D, Caulfield B, editors. Evaluating rehabilitation exercise performance using a single inertial measurement unit. Proceedings of the 7th International Conference on Pervasive Computing Technologies for Healthcare; 2013: ICST.
27. Avci A, Bosch S, Marin-Perianu M, Marin-Perianu R, Havinga P. Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: a survey. Proceedings of the 23rd International Conference on Architecture of computing systems (ARCS): VDE; 2010. p. 1-10.