Evaluating Performance of the Lunge Exercise with Multiple and Individual Inertial Measurement Units

Darragh Whelan*
Insight Centre for Data Analytics
University College Dublin
Dublin, Ireland
darragh.whelan@insight-centre.org

Martin O'Reilly*
Insight Centre for Data Analytics
University College Dublin
Dublin, Ireland
martin.oreilly@insight-centre.org

Tomás Ward
Insight Centre for Data Analytics
National University Of Ireland, Maynooth
Maynooth, Ireland
tomas.ward@nuim.ie

Eamonn Delahunt
School of Public Health, Physiotherapy and Sports Science
University College Dublin
Dublin, Ireland
eamonn.delahunt@ucd.ie

Brian Caulfield
Insight Centre for Data Analytics
University College Dublin
Dublin, Ireland
brian.caulfield@insight-centre.org

ABSTRACT

The lunge is an important component of lower limb rehabilitation, strengthening and injury risk screening. Completing the movement incorrectly alters muscle activation and increases stress on knee, hip and ankle joints. This study sought to investigate whether IMUs are capable of discriminating between correct and incorrect performance of the lunge. Eighty volunteers (57 males, 23 females, age: 24.68± 4.91 years, height: 1.75± 0.094m, body mass: 76.01±13.29kg) were fitted with five IMUs positioned on the lumbar spine, thighs and shanks. They then performed the lunge exercise with correct form and 11 specific deviations from acceptable form. Features were extracted from the labelled sensor data and used to train and evaluate random-forests classifiers. The system achieved 83% accuracy, 62% sensitivity and 90% specificity in binary classification with a single sensor placed on the right thigh and 90% accuracy, 80% sensitivity and 92% specificity using five IMUs. This multi-sensor set up can detect specific deviations with 70% accuracy. These results indicate that a single IMU has the potential to differentiate between correct and incorrect lunge form and using multiple IMUs adds the possibility of identifying specific deviations a user is making when completing the lunge.

Categories and Subject Descriptors

J.3 [**Computer Applications**]: Life and Medical Sciences - Medical information systems, Health informatics

Pervasive Health '16, May 17-19, 2016, Cancun, Mexico

General Terms

Exercise, Classification, Inertial Measurement Units, Lunge, Functional Screening Tools, Biofeedback, Rehabilitation

*Joint lead authors

1. INTRODUCTION

The lunge is a challenging, functional exercise that is used for strengthening, screening and rehabilitation. It is favoured as a strengthening exercise as it is weight bearing and promotes muscle activation patterns similar to those of gait [26]. The lunge is used in sports conditioning programmes, as the ability to complete the movement is critical in activities such as squash and badminton [9]. The movement forms part of the 'Functional Movement Screen' [8] and is used to assess range of motion in the ankle [6]. It is an ideal screening tool as it is representative of lower extremity function during activity [25]. The exercise is also used for rehabilitating conditions such as patellofemoral pain [10] and following surgery [2] as it can be completed at home and needs no equipment.

The challenging nature of the lunge means it is difficult to maintain good form throughout the movement. Incorrect lunge performance has been shown to alter muscle activation and increase stress on knee, hip and ankle joints [11]. Therefore feedback regarding technique is important to ensure good form is maintained throughout the movement. Rehabilitation staff, sports scientists and strength and conditioning (S&C) coaches often provide this feedback. This is not always possible due to cost and availability issues, meaning patients and clients are left to complete the exercise alone. This may result in ineffective training and rehabilitation in addition to increasing the risk of injury [23].

Clinicians who use the lunge as a screening tool have assessed the movement pattern using two distinct methods; high tech biomechanical assessment or subjective examination. Both of these have inherent disadvantages. The use of biomechanical marker based systems such as Vicon are time intensive, expensive and the application of markers may hinder normal movement [1, 4]. Therefore these systems have not tended to be accepted into routine clinical practice. In a clinical setting, subjective evaluation has the potential for bias and poor inter/intra rater reliability as can be seen when analysing the single leg squat [31]. As the lunge has a large number of potential deviations (Table 1), subjective analysis is difficult and often flawed.

Inertial measurement units (IMUs) offer the potential for low cost, objective biomechanical analysis. These sensors are small, easy to set up and allow for the collection of data from subjects in an unconstrained environment [20]. Utilising IMUs for exercise monitoring is becoming increasingly popular, with commercially available products such as Jawbones™ and Fitbits™ using the sensors for activity tracking. Gym based exercises trackers that use IMUs are becoming increasing popular. The sensors are perfectly positioned to quantify performance of these movements in a clinical setting, as they are not hampered by location, occlusion and lighting issues unlike other biomechanical analysis tools [22]. Furthermore, these IMU based systems have been shown to be as effective as marker-based systems in measuring joint angles [17, 27].

A number of studies have evaluated the viability of multiple IMUs to quantify exercise performance [14, 18, 24, 28, 29, 30]. However there is minimal evidence evaluating the ability of IMUs to accurately quantify lunge performance. Fitgerald *et al* [12] used a system that involved ten inertial sensors incorporated within a body suit to automatically monitor an individual's exercise programme and tested the system using a case study. Qualitative data analysis indicated the system could identify kinematic differences between a non-injured and injured athlete completing a lunge, possibly signifying deficits in neuromuscular control in the injured athlete. Leardini *et al* [17] and Tang *et al* [27] examined IMUs and their potential to track body segments while completing the lunge. Both concluded that they had good accuracy compared to a laboratory based optical measurement system such as Vicon. Chen *et al* [7] and Gowing *et al* [15] evaluated the ability of IMUs to identify lunges among a group of other movements. Chen *et al* found that combining IMUs with the Microsoft Kinect™, lunges could be identified with 100% accuracy. Gowing *et al* demonstrated IMUs could identify a range of movements with greater accuracy than the Microsoft Kinect (91% overall accuracy), however no specific results were given for the lunge. To our knowledge no study has analysed the ability of an IMU based system to objectively analyse form during the lunge exercise.

The lunge is an important movement in S&C, screening and rehabilitation. To date biomechanical analysis of the movement has come in the form of expensive lab based evaluation or subjective visualisation by clinicians. Both of these are not ideal and there is a need for biomechanical analysis of the lunge that is quick, low-cost, easy to use and provides objective data. To this end, IMUs may provide the perfect platform to analyse the lunge and provide feedback to patients, athletes and clinicians. This paper evaluates the ability of IMUs to analyse performance of the lunge. We hypothesise that such a system has the potential to distinguish between good and bad performance of the lunge. Furthermore we aim to identify eleven common deviations during the lunge using IMUs. We propose to do this leveraging cheap and ubiquitous sensor technology in order to ensure that the system is practical and affordable for the end user.

2. METHODS

This study was undertaken to determine the minimal IMU sensor set that can discriminate between different levels of lunge performance and identify poor exercise technique. Data were acquired from participants as they completed the lunge with normal technique for 10 repetitions. IMU data were then acquired while three repetitions of the same exercise was completed with eleven commonly observed deviations from correct technique.

Figure 1: Image showing the lunge exercise and the five sensor positions: (1) The spinous process of the 5th lumbar vertebra, (2&3) the mid-point of both femurs on the lateral surface (determined as half way between the greater trochanter and lateral femoral condyle), (4&5) and on both shanks 2cm above the lateral malleolus

2.1 Participants

Eighty healthy volunteers (57 males, 23 females, age: 24.68± 4.91 years, height: 1.75± 0.094m, body mass: 76.01±13.29kg) were recruited for the study. No participant had a current or recent musculoskeletal injury that would impair his or her lunge performance. All participants had prior experience with the exercise and completed it regularly as part of their own training regime for at least one year. Each participant signed a consent form prior to completing the study. The University Human Research Ethics Committee approved the study protocol.

2.2 Exercise Technique and Deviations

Participants completed the initial lunge with good form as described by the National Strength and Conditioning Association (NSCA) guidelines [p.324-325] [3]. This involved participants placing their left foot in front of the torso and right foot behind the torso with toes pointing forward and the torso kept upright. This torso position was maintained throughout the movement. The downward phase then started from this position. The leading left knee was flexed in order to lower the trailing right knee toward the floor. The lead knee was kept directly over the lead foot which remained on the floor. The leading knee continued to flex until it was roughly 90 degrees perpendicular with the lower leg in the sagittal plane and the trailing knee was 3-6 cm above the floor. The upward phase immediately followed, whereby the lead knee extended back to starting position whilst an upright torso posture was maintained.

The deviations from the aforementioned correct technique that were completed were front knee valgus (KVL), front knee varus (KVR), front knee to far forward (KTF), hip shift right (HSR), hip shift left (HSL), bent over (BO), back foot turned out (BFO), stutter step (SS), pushing backwards (PB), step too short (STS) and step too long (STL). These are outlined in Table 1.

Table 1: List and description of Lunge exercise performance.

Deviation	Explanation
N	Normal lunge
KVL	Left knee coming towards mid-line during downwards phase
KVR	Left knee moving away from mid-line during downward phase
KTF	Left knee ahead of toes during downward phase
HSR	Excessive lean to left hand side during entire lunge exercise
HSL	Excessive lean to right hand side during entire lunge exercise
BO	Excessive flexion of hip and torso during entire lunge exercise
BFO	Right foot externally rotated
SS	Loss of balance during upward phase resulting stuttered steps
PB	Pushing backwards during upwards phase
STS	Starting stance too short
STL	Starting stance too long

2.3 Experimental Protocol

When participants arrived to the laboratory the testing protocol was explained to them. Following this they completed a ten minute warm-up on an exercise bike maintaining a power output of 100W at 75-85 revolutions per minute. Next, IMUs were secured on the participant at the following five locations; the spinous process of the 5th lumbar vertebra, the mid-point of both femurs (determined as half way between the greater trochanter and lateral femoral condyle), and on both shanks 2cms above the lateral malleolus (Figure 1). The orientation and location of the IMUs were consistent for all study participants.

A pilot study was used to determine an appropriate sampling rate and the ranges for the accelerometer and gyroscope on board the IMUs (SHIMMER, Shimmer research, Dublin, Ireland). In the pilot study squat data was collected at 512Hz. A Fourier transform was then used to detect the characteristic frequencies of the signal which were all found to be less than 20Hz. Therefore, a sampling rate of 51.2Hz was deemed appropriate for this study based upon the Nyquist criterion. The Shimmer IMU was configured to stream tri-axial accelerometer (±16g), gyroscope ($\pm 500^o$/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.

Participants were then instructed on how to complete the lunge with good form and biomechanical alignment as outlined in the NSCA guidelines as explained in section 2.2. They completed ten repetitions with this good form. Once the lunge had been completed with normal technique the participant was instructed to complete the exercise with the deviations specified in Table 1. They completed three repetitions of each deviation as required. Verbal instructions and a demonstration were provided to all participants and they completed trial repetitions to ensure they were comfortable completing the deviations. All lunges were completed using body weight only. A Chartered Physiotherapist and an S&C trained individual were present throughout all data collection to ensure the lunge had been completed as instructed. If the movement completed was not in accordance with the description in Table 1, the participants were asked to repeat the repetitions.

2.4 Data Analysis

Nine signals were obtained from each inertial measurement unit; accelerometer x, y, z gyroscope x, y, z and magnetometer x ,y , z. These signals were low-pass filtered at f_c=20 Hz using a Butterworth filter of order n=8 to remove high frequency noise and ensure all data analysed related to each participant's movement. Six additional signals were then computed. The 3-D orientation of the inertial measurement unit was computed from the accelerometer, gyroscope and magnetometer signals using the gradient descent algorithm as developed by Madgwick et. al [19] which resulted in the quaternion W, X, Y and Z signals. The acceleration magnitude was also computed from the accelerometer x, y and z signals. Finally the gyroscope magnitude was computed from the gyroscope x, y and z signals.

Each repetition from each exercise was extracted from the IMU data and resampled to a length of 250 samples in order to normalise the data where participants had completed lunges at different tempos. Descriptive features were than extracted from the aforementioned 15 signals. Time-domain and frequency-domain descriptive features were computed in order to describe the pattern of each of the 15 signals when the five different exercises were completed. These features were namely signal peak, valley, range, mean, standard deviation, skewness, kurtosis, signal energy, level crossing rate, variance, 25th percentile, 75th percentile, median and the variance of both the approximate and detailed wavelet coefficients using the Daubechies 5 mother wavelet to level 6. This resulted in 16 features for each of the 16 available signals producing a total of 240 features per sensor unit.

The random-forests method was employed to perform classification [5]. This technique was chosen as it has been shown recently to be particularly effective in analysing exercise technique with IMUs when compared to the Naive-Bayes and Radial-basis function network techniques [21]. 400 trees were used in the random-forest classifier.

Classifiers were developed and evaluated for the following ten combinations of variables; the 1200 (5x240) variables computed from every IMU, the 720 (3x240) variables from both shanks and the Lumbar IMU, the 720 variables from both thighs and the Lumbar IMU, the 480 (2x240) variables from both shanks, the 480 variables from both thighs and the 240 variables from each of the five individual IMUs. This was to compare classification scores using five sensors, three sensors, two sensors and one sensor at different anatomical locations.

Initially binary classification was evaluated to establish how effectively each individual IMU and each combination of IMUs can distinguish between correct and incorrect performance of the lunge exercise. All repetitions of normal performance of the lunge were labelled '0' and all repetitions of the lunge performed with one of the deviations as outlined in Table 1 were labelled '1'. Finally multi-label classification was evaluated on the IMU data set to investigate how effectively each individual IMU and each combination of IMUs could be used to discriminate between correct performance of the squat exercise and each of the eleven deviations from correct technique as described in Table 1. All repetitions of normal performance of the squat remained labelled as '0' and each of the different deviations were labelled '1-11'.

The quality of exercise classification was established using leave-one-subject-out-cross-validation (LOSOCV) and the random-forests classifier with 400 trees. Each participant's data corresponds to one fold of the cross validation. At each fold, one participant's data is held out while the random forests classifier is trained and then this held out data is used to assess the classifier's ability to correctly categorise new data it is presented with. The use of LOSOCV ensures that there is no biasing of the classifiers, whereby the test subjects data is completely unseen by the classifier prior to testing. Previous research by Taylor *et al* showed that not employing this method of testing can greatly skew results [29]. In our system each individual repetition was classified.

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):

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

In binary classification the '0' label was considered positive and '1' label as negative. Therefore a single sensitivity and specificity score is suitable to describe the quality of the various sensor combinations. In multi-class classification, for every sensor combination evaluated the sensitivity and specificity were calculated for each of the twelve deviations and then the mean and standard deviation across the twelve values was taken, using the formulas below:

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

$$Specificity = \frac{TN}{TN + FP} \quad (3)$$

Sensitivity measures the effectiveness of a classifier at identifying a desired label, while specificity measures the classifiers ability to detect negative labels. A 'positive' label is the desired label. For example in binary classification a lunge completed with correct form is considered the positive class.

Table 2: Total accuracy scores from LOSOCV for binary and multi-Label classification

	Binary (%) (Correct or Incorrect)	**Multi-Label (%) (Specific Deviation)**
Left Shank	71.69	34.64
Left Thigh	77.02	36.90
Lumbar	77.12	40.18
Right Thigh	82.90	38.56
Right Shank	81.07	33.10
All IMUs	89.59	69.85
Lumbar + Shanks	87.30	59.52
Lumbar + Thighs	87.24	60.80
Shanks	84.47	49.87
Thighs	85.31	47.56

3. RESULTS

Total accuracy scores for each sensor position are shown in Table 2. A single sensor set up is able to detect whether a lunge is completed correctly with 72-83% accuracy but can only detect the exact mistake a user is making with 35-41% accuracy. A multi-sensor set-up using 5 IMUs worn on the lumbar, both thighs and both shanks is capable of distinguishing between good and bad performance of the lunge with 90% accuracy. Furthermore, this sensor set up can detect the exact mistake a user is making from the list shown in Table 1 with 70% accuracy.

Sensitivity and specificity scores are shown for all sensor combinations in Table 3. Moderate sensitivity and specificity scores are achieved for a single sensor system in Binary classification. The sensor on the thigh of the trailing leg in the lunge movement is capable of 62% sensitivity and 90% specificity. The left shank was the poorest position for binary classification using a single sensor with a sensitivity of 40% and specificity of 82%. The five sensor set up is most effective for both binary and multi-class classification. A reduced sensor set using three sensors positioned on the lumbar and both shanks also produces good classification scores.

Figure 2 and 3 are confusion matrices showing the exact percentage of reps correctly and incorrectly classified. The rows demonstrate the class the rep actually belongs to and the columns show which class the classifier outputted. In both figures the top left shows the percentage of TPs, top right: FNs, bottom right: TNs and bottom left: FNs. The true positive rate for the single sensor on the right thigh is 66% and for the five sensor set is 71%. The true negative rate for the single sensor on the right thigh is 88% and for the five sensor set is 95%.

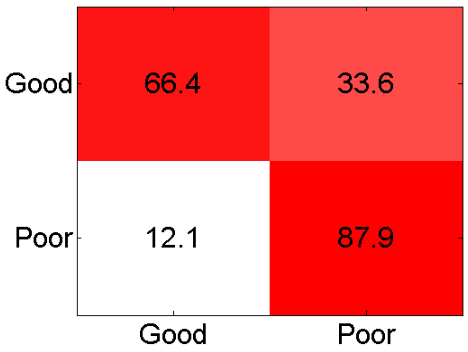

Figure 2: Heatmap confusion matrix showing binary classification results with right thigh sensor. Rows show the actual class of a repetition and columns show the classifier's prediction

Figure 3: Heatmap confusion matrix showing binary classification results with all five sensors. Rows show the actual class of a repetition and columns show the classifier's prediction

Figure 4 shows a confusion matrix for muti-class classification when using the 5 sensor set up. 'Normal' (N) performance of the squat is detected with a 68% TP rate. 6% of normal lunges were confused by the classifier to be 'step too short' (STS) and 7% of normal lunges were mistaken to be 'step too long' (STS). The 'push back' (PB) deviation is the worst detected deviation with a TP rate of just 46%, almost 10% of PB reps were mistaken to be 'normal' (N) by the system. The best detected deviation was 'stutter step' (SS) with a TP rate of 81%.

4. CONCLUSIONS AND FUTURE WORK

The results presented in this paper indicate that five sensors are capable of distinguishing between good and bad lunges with almost 90% accuracy. The best three sensor set up (lumbar spine and shanks) can distinguish between good and bad performance with an accuracy of 87% while the best single sensor set up (right thigh) can identify good lunge technique with 83% accuracy. Overall accuracy is reduced when attempting to identify the specific error that has occurred with accuracy scores ranging from 70% with all five sensors to 33% using the right shank sensor only. Table 3 shows high specificity scores for binary and multi label classification. This indicates the sensors are capable of identifying if a deviation has not occurred. Lower sensitivity scores are reported meaning it is more difficult for the sensors to identify if a specific deviation is present during lunges.

Table 3: Sensitivity and specificity scores with standard deviation from LOSOCV for binary and multi-label classification

	Binary (%) (Correct or Incorrect)		**Multi-Label (%$\pm\sigma$) (Specific Deviation)**	
	Sens	**Spec**	**Sens**	**Spec**
Left Shank	40	82	38±25	94±3
Left Thigh	51	83	39±3	94±3
Lumbar	50	87	43±24	95±3
Right Thigh	62	90	33±25	94±3
Right Shank	58	88	29±24	94±3
All IMUs	80	92	70±10	97±1
Lumbar + Shanks	73	91	62±13	96±2
Lumbar + Thighs	73	91	61±13	96±2
Both Shanks	67	89	49±23	95±2
Both Thighs	69	90	44±2	95±3

The ability of a sensor set up to monitor lunge technique has benefits in an S&C, screening and rehabilitation setting. There is a need for supervision of athletes to ensure that exercise programmes are completed correctly. The five-sensor set up presented here is able to identify if the athlete is completing the lunge correctly 90% of the time and provide this feedback to the user. This can reduce the risk of injury and ensure strength goals are achieved. The sensors can also automatically track the exercise and provide an automated gym logbook for athletes to track their training progress.

The system presented in this paper can also act as an automated musculoskeletal injury risk screening tool. The lunge is a common screening test [8, 25] as it is weight bearing and functional. Screening athletes, in a clinical setting, is time consuming and is predominantly completed using subjective examination. This potentially causes bias and reliability issues. An IMU based system of biomechanical analysis would mean greater objectively and improved time management for clinicians.

Furthermore, this system would allow for home-based rehab, as the lunge is a commonly used exercise following injury and surgery [16]. Physiotherapy provided in rehabilitation centres is often quite expensive so offering the possibility of self administered training systems which the patient could complete at home would be very beneficial [17]. Furthermore, the sensors would allow the transfer of exercise data to a cloud-based server. This means therapists can

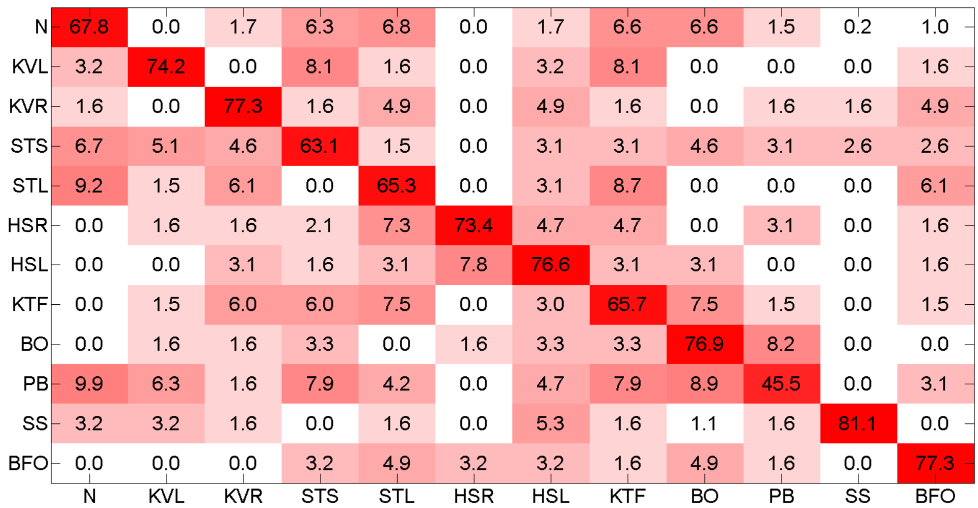

Figure 4: Heatmap confusion matrix showing multi-class classification results with all five sensors. Rows show the actual class of a repetition and columns show the classifier's prediction

monitor patient compliance and form during the prescribed exercise.

These benefits have led to a number of researchers evaluating the ability of sensor set-ups to monitor form during strengthening exercises. IMU based systems are able to detect tempo of movement and deviations from correct form in single joint exercises such as the standing hamstring curl [29], heel slide [13], SLR [14] and bicep curl [30]. This work builds on the previous research by analysing lunge form. The lunge is a compound, non-symmetrical exercise making it more difficult to track than single joint exercises. While some authors have analysed the lunge using IMUs [12, 17, 27] , none have quantitatively assessed form using the sensors. The complex nature of the lunge means a number of mistakes can occur at a variety of joint positions [3], making it more difficult to ascertain exact deviations using an IMU sensor set. This explains the relatively low sensitivity scores seen in Table 3.

The lower sensitivity and accuracy scores in tables 2 and 3 for multi label classification are especially prevalent in reduced sensor set-ups (less than three sensors). A minimal sensor set up is advantageous as it is less cumbersome, easier to operate and reduces the risk of sensor placement error. Furthermore, it would reduce cost for end users. A number of authors have investigated a single sensor set-up at evaluating exercise performance displaying relatively high overall accuracy scores [14, 23, 24, 32]. The scores presented here for a single sensor performing multi-class recognition are lower than those reported in these studies for a number of possible reasons. The lunge exercise is a multi-joint lower limb exercise unlike those presented in Giggins *et al* [14] and Pernek *et al* [24]. The use of multiple joints make it more difficult to detect deviations in form with a minimal sensor set up due to the increased number of possible deviations and additional complexity of the exercise biomechanics. Our previous work [23, 32] evaluated multi-joint exercises (squat and single leg squat) using a single sensor set up and found relatively good overall accuracy scores. However, the number of potential deviations that we attempted to classify with the sensors was reduced compared to the eleven deviations shown in this paper (Table 1). This makes it more difficult for the sensors to classify each deviation, explaining some of the lower scores shown in Table 2 and 3. A larger data set may allow for greater analysis that could improve overall accuracy and sensitivity scores.

There are a number of contextual factors in this investigation that must be considered. No gold-standard 3-dimensional motion capture system was used to confirm that each deviation occurred. However, a Chartered Physiotherapist and individual trained in S&C were present for all data collection and confirmed the deviations in exercise form through visual observation. A gold-standard 3-dimensional motion capture system was not used as it may influence the participants' movement patterns due to its bulky set up. Furthermore, researchers have already shown the reliability of IMU sensor set ups compared to these systems [17, 27]. Another issue is that all deviations were deliberately induced and completed by healthy individuals. When deviations occur naturally, the exact way in which they occur may differ from that seen here. In the future it may be possible to induce more natural deviations through the use of additional weight, fatiguing participants or collecting data from an injured cohort. Additionally, the eleven deviations studied may be a non-exhaustive list of all those which can occur during the lunge exercise. A possible solution to this is the creation of an "other" class, for cases when exercise deviations fall outside of the pre-defined deviations listed in Table 1.

Future work will evaluate the classification system presented as part of an automated musculoskeletal injury screening tool, exercise monitoring and rehabilitation tracking system. For the rehabilitation application it is expected that the classification system will be evaluated on individuals partaking in a rehabilitation programme. Improving the system for these individuals may involve collecting additional training data from this cohort as only healthy participants were used in the present study. It is hoped that more exercise data and streamlined feature selection techniques will improve the overall accuracy and sensitivity of the system. The aim is to produce a system that contains the minimal amount of IMUs required to ensure tolerable accuracy. This accuracy may change depending on the need of end users. For example, gym users may require less accuracy than clinicians screening for musculoskeletal injury risk. Size and weight of the sensing device and feedback methods will also be considered. The system should be easy set-up, not hinder the users' movements and have an intuitive user interface. Exercises such as deadlift and squat will also be analysed to increase the range of exercises the system can evaluate.

The lunge is an important exercise in musculoskeletal screening, strengthening or rehabilitating individuals. The sensor system presented in this work is able to classify lunge performance as correct or incorrect with a relatively high accuracy using a five, three, two or single sensor set up. While a five-sensor set up can detect specific deviations in a person's lunge biomechanics with good accuracy, its ability to do so is diminished with a reduced sensor set. It is hoped that an increased data set and more sophisticated data analysis technique will help with this. A sensor based system that is able to offer low cost biomechanical analysis to end-users would be extremely beneficial to ensure strength and rehabilitation goals are achieved while also identifying those at risk of injury.

5. 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. The authors would also like to thank 'UCD Sport' for providing equipment which was used in this study.

6. REFERENCES

[1] A. Ahmadi, E. Mitchell, F. Destelle, M. Gowing, N. E. O'Connor, C. Richter, and K. Moran. Automatic activity classification and movement assessment during a sports training session using wearable inertial sensors. In *Proceedings of the 11th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, pages 98–103. IEEE, 2014.

[2] T. Alkjaer, E. B. Simonsen, S. P. Magnusson, H. Aagaard, and P. Dyhre-Poulsen. Differences in the movement pattern of a forward lunge in two types of anterior cruciate ligament deficient patients: copers and non-copers. *Clinical Biomechanics*, 17(8):586–593, 2002.

[3] T. R. Baechle and R. W. Earle. *NSCA's essentials of personal training*. Champaign, IL, 2004.

[4] B. Bonnechere, B. Jansen, P. Salvia, H. Bouzahouene, L. Omelina, F. Moiseev, V. Sholukha, J. Cornelis, M. Rooze, and S. Van Sint Jan. Validity and reliability of the kinect within functional assessment activities: Comparison with standard stereophotogrammetry. *Gait & posture*, 39(1):593–598, 2014.

[5] L. Breiman. Random forests. *Machine learning*, 45(1):5–32, 2001.

[6] A. Cejudo, P. S. de Baranda, F. Ayala, and F. Santonja. A simplified version of the weight-bearing ankle lunge test: Description and test-retest reliability. *Manual therapy*, 19(4):355–359, 2014.

[7] C. Chen, R. Jafari, and N. Kehtarnavaz. A real-time human action recognition system using depth and inertial sensor fusion. 2015.

[8] G. Cook, L. Burton, and B. Hoogenboom. Pre-participation screening: the use of fundamental movements as an assessment of function - part 1. *North American journal of sports physical therapy*, 1(2):62–72, 2006.

[9] J. Cronin, P. Mcnair, and R. Marshall. Lunge performance and its determinants. *Journal of Sports Sciences*, 21(1):49–57, 2003.

[10] R. F. Escamilla, N. Zheng, T. D. MacLeod, W. B. Edwards, A. Hreljac, G. S. Fleisig, K. E. Wilk, C. T. Moorman III, R. Imamura, and J. R. Andrews. Patellofemoral joint force and stress between a short-and long-step forward lunge. *Journal of orthopaedic & sports physical therapy*, 38(11):681–690, 2008.

[11] S. Farrokhi, C. D. Pollard, R. B. Souza, Y.-J. Chen, S. Reischl, and C. M. Powers. Trunk position influences the kinematics, kinetics, and muscle activity of the lead lower extremity during the forward lunge exercise. *Journal of orthopaedic & sports physical therapy*, 38(7):403–409, 2008.

[12] D. Fitzgerald, J. Foody, D. Kelly, T. Ward, C. Markham, J. McDonald, and B. Caulfield. Development of a wearable motion capture suit and virtual reality biofeedback system for the instruction and analysis of sports rehabilitation exercises. In *Proceedings of the Engineering in Medicine and Biology Society, 2007.*, pages 4870–4874. IEEE.

[13] O. Giggins, D. Kelly, and B. Caulfield. Evaluating rehabilitation exercise performance using a single inertial measurement unit. In *Proceedings of the 7th International Conference on Pervasive Computing Technologies for Healthcare*, pages 49–56. ICST.

[14] O. M. Giggins, K. T. Sweeney, and B. Caulfield. Rehabilitation exercise assessment using inertial sensors: a cross-sectional analytical study. *Journal of neuroengineering and rehabilitation*, 11(1):158–168, 2014.

[15] M. Gowing, A. Ahmadi, F. Destelle, D. S. Monaghan, N. E. O'Connor, and K. Moran. Kinect vs. low-cost inertial sensing for gesture recognition. In *MultiMedia Modeling*, pages 484–495. Springer.

[16] M. Hall, J. H. Nielsen, A. Holsgaard-Larsen, D. B. Nielsen, M. W. Creaby, and J. B. Thorlund. Forward lunge knee biomechanics before and after partial meniscectomy. *The Knee*, pages 506–509, 2015.

[17] A. Leardini, G. Lullini, S. Giannini, L. Berti, M. Ortolani, and P. Caravaggi. Validation of the angular measurements of a new inertial-measurement-unit based rehabilitation system: comparison with state-of-the-art gait analysis. *Journal of neuroengineering and rehabilitation*, 11(1):1–7, 2014.

[18] J. F. Lin and D. Kulic. Human pose recovery using wireless inertial measurement units. *Physiological measurement*, 33(12):2099, 2012.

[19] S. O. H. Madgwick, A. J. L. Harrison, and R. Vaidyanathan. Estimation of imu and marg orientation using a gradient descent algorithm. In

Proceedings of the IEEE International Conference on Rehabilitation Robotics (ICORR), pages 1–7. IEEE.

[20] D. McGrath, B. R. Greene, K. J. O'Donovan, and B. Caulfield. Gyroscope-based assessment of temporal gait parameters during treadmill walking and running. *Sports Engineering*, 15(4):207–213, 2012.

[21] E. Mitchell, A. Ahmadi, N. E. O'Connor, C. Richter, E. Farrell, J. Kavanagh, and K. Moran. Automatically detecting asymmetric running using time and frequency domain features. In *Proceedings of the 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, pages 1–6. IEEE.

[22] D. Morris, T. S. Saponas, A. Guillory, and I. Kelner. Recofit: using a wearable sensor to find, recognize, and count repetitive exercises. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 3225–3234. ACM.

[23] M. O'Reilly, D. Whelan, C. Chanialidis, N. Friel, E. Delahunt, T. Ward, and B. Caulfield. Evaluating squat performance with a single inertial measurement unit. In *Wearable and Implantable Body Sensor Networks (BSN), 2015 IEEE 12th International Conference on*, pages 1–6. IEEE.

[24] I. Pernek, K. A. Hummel, and P. Kokol. Exercise repetition detection for resistance training based on smartphones. *Personal and ubiquitous computing*, 17(4):771–782, 2013.

[25] C. J. Powden, J. M. Hoch, and M. C. Hoch. Reliability and minimal detectable change of the weight-bearing lunge test: A systematic review. *Manual therapy*, pages 524–532, 2015.

[26] B. L. Riemann, S. Lapinski, L. Smith, and G. Davies. Biomechanical analysis of the anterior lunge during 4 external-load conditions. *Journal of athletic training*, 47(4):372, 2012.

[27] Z. Tang, M. Sekine, T. Tamura, N. Tanaka, M. Yoshida, and W. Chen. Measurement and estimation of 3d orientation using magnetic and inertial sensors. *Advanced Biomedical Engineering*, 4(0):135–143, 2015.

[28] P. E. Taylor, G. J. Almeida, J. K. Hodgins, and T. Kanade. Multi-label classification for the analysis of human motion quality. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 2214–2218. IEEE.

[29] P. E. Taylor, G. J. Almeida, T. Kanade, and J. K. Hodgins. Classifying human motion quality for knee osteoarthritis using accelerometers. In *Engineering in Medicine and Biology Society (EMBC)*, pages 339–343. IEEE.

[30] E. Velloso, A. Bulling, H. Gellersen, W. Ugulino, and H. Fuks. Qualitative activity recognition of weight lifting exercises. In *Proceedings of the 4th Augmented Human International Conference*, pages 116–123. ACM.

[31] C. Whatman, W. Hing, and P. Hume. Physiotherapist agreement when visually rating movement quality during lower extremity functional screening tests. *Physical Therapy in Sport*, 13(2):87–96, 2012.

[32] D. Whelan, M. O'Reilly, T. Ward, E. Delahunt, and B. Caulfield. Evaluating performance of the single leg squat exercise with a single inertial measurement unit. In *Proceedings of the 3rd 2015 Workshop on ICTs for improving Patients Rehabilitation Research Techniques*, pages 144–147. ACM.