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Authors(s)	O'Reilly, Martin, Whelan, Darragh, Chanialidis, Charalampos, Friel, Nial, Delahunt, Eamonn, Ward, Tomás, Caulfield, Brian
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Evaluating Squat Performance with a Single Inertial Measurement Unit

Martin O'Reilly*[†‡], Darragh Whelan*[†‡], Charalampos Chanialidis[†], Nial Friel[†], Eamonn Delahunt [‡], Tomás Ward[†] and Brian Caulfield[†‡]
[†]Insight Centre for Data Analytics
[‡]School of Public Health, Physiotherapy and Population Science
University College Dublin
Email: martin.oreilly@insight-centre.org, darragh.whelan@insight-centre.org
**Joint lead authors*

***Abstract*—Inertial measurement units (IMUs) may be used during exercise performance to assess form and technique. To maximise practicality and minimise cost a single-sensor system is most desirable. This study sought to investigate whether a single lumbar-worn IMU is capable of identifying seven commonly observed squatting deviations. Twenty-two volunteers (18 males, 4 females, age: 26.09±3.98 years, height: 1.75±0.14m, body mass: 75.2±14.2 kg) performed the squat exercise correctly and with 7 induced deviations. IMU signal features were extracted for each condition. Statistical analysis and leave one subject out classifier evaluation were used to assess the ability of a single sensor to evaluate performance. Binary level classification was able to distinguish between correct and incorrect squatting performance with a sensitivity of 64.41%, specificity of 88.01% and accuracy of 80.45%. Multi-label classification was able to distinguish between specific squat deviations with a sensitivity of 59.65%, specificity of 94.84% and accuracy of 56.55%. These results indicate that a single IMU can successfully discriminate between squatting deviations. A larger data set must be collected and more complex classification techniques developed in order to create a more robust exercise analysis IMU-based system.**

I. INTRODUCTION

Incorrect exercise performance (i.e. faulty exercise form and technique) may result in ineffective training, inadequate rehabilitation, as well as increasing the likelihood of training induced injuries. This is especially pertinent for athletes who train with free-weights [1]. Training induced injuries are frequently caused by excessive tissue loading as a result of aberrant exercise form and technique [2]. Therefore, feedback on exercise performance is an important consideration to ensure that athletes perform prescribed exercises correctly. Traditionally this feedback has been provided on-site by professional strength and conditioning (S&C) coaches or rehabilitation staff. However, such direct supervision and individualized feedback on exercise performance is not always a possibility, as is the situation when a large number of athletes are training simultaneously [3]. Furthermore, it has also been challenging to provide objective exercise performance data to athletes in this environment with most assessments being subjective in nature.

To date marker-based motion analysis systems have been used to provide objective data relative to exercise performance [4]. However, there are a number of limitations with such an approach; set-up is time intensive, the equipment is expensive and the application of markers may hinder normal athletic movement [2], [5]. Furthermore, this type of analysis is typically performed in specialised research or commercial motion analysis laboratories. These environments may artificially constrict, simplify or influence the movement patterns of those being tested [6]. Therefore, these marker-based systems have not tended to be accepted into routine practice.

Recent technological advances support the use of inertial measurement units (IMUs) as a viable option for the assessment and quantification of exercise performance beyond the motion analysis laboratory [2]. These IMUs offer a number of potential advantages over traditional marker-based systems; they are small, inexpensive, easy to set-up and enable the assessment of human movement in an unconstrained environment [7]. Accelerometers and gyroscopes are becoming an increasingly popular method of assessing and quantifying human movement as they are present in many smartphones. This means that these ubiquitous technologies may have the potential to measure human movement and provide feedback relative to the quality of the movement performed [8].

IMUs have been used in a number of different ways from measuring energy expenditure [9] to gait analysis [10] to medical monitoring [11]. These sensors have also been used in the athletic arena in sports such as skiing [12] and golf [13]. Recently the utilization of IMUs as a method of tracking gym and rehabilitation exercises has been investigated. Lin and colleagues [14] evaluated data obtained from IMUs at the hip, knee and ankle during a number of lower limb exercises. Data from the IMUs were used to estimate joint angles; with the authors comparing the IMU derived joint angles to those quantified via a marker-based motion analysis capture system. The authors concluded that these joint angles were accurate when compared to those obtained via the more traditional methodology. However, the quality of the exercise performance was not classified. Pernek and colleagues [8] used accelerometers to assess exercise performance during gym-based resistance type exercises. They assessed movement quality based on the speed of exercise performance. However, different exercise goals may require varying movement speeds and as such, the assessment of movement quality based on speed alone does not offer a holistic way of evaluating exercise technique.

Taylor and colleagues [15] attempted to more accurately evaluate exercise performance using IMUs. Five body worn accelerometers were used to evaluate three lower limb single joint exercises (standing hamstring curl, straight leg raise and reverse hip abduction) in healthy college students. The authors were able to discriminate correct from incorrect exercise performance, with their subsequently developed exercise classifier exhibiting an overall average accuracy of 80% for standing hamstring curl, 65% for reverse hip abduction and 62% for straight leg raise. These results were based on leave-one-subject-out cross-validation (LOSOCV) testing. However, they only recorded data from nine participants and the use of a non-expert in labelling correct or incorrect exercise performance was a methodological limitation.

The same authors built on this work in 2012 [16] and evaluated the use of multi-label classifiers to assess exercise performance in patients with knee osteoarthritis using five IMUs. On this occasion each IMU contained a tri-axial gyroscope as well as an accelerometer. Again their classifiers displayed high accuracy (86%), sensitivity (84%) and specificity (99%) in detecting errors that can occur during the performance of the exercises investigated. However, the overall results and their wider extrapolation are limited by the small participant sample size (n = 8). Furthermore, the exercises utilized were all single joint exercises (standing hamstring curl and straight leg raise) and the number of sensors used may not always be practical. While these exercises may be used in a clinical population during the early stage of rehabilitation they are likely to be inadequate as the rehabilitation progresses or for higher-level conditioning.

Velloso and colleagues [3] have also attempted to evaluate the quality of exercises using IMUs. They defined exercise quality as "the adherence to the execution of an activity to its specification". They evaluated two upper limb single joint exercises (biceps curl and lateral raise). Using a leave-one-subject-out testing protocol they obtained an overall recognition performance of 78.2%. The authors also reported that participants responded favourably to feedback that aided with the correct completion of the exercises. A recent study by Giggins et al [7] suggested that a single IMU may be used to identify poor technique in five of seven single joint exercises investigated (heel slide, straight leg raise, knee extension, hip abduction and hip extension). However, these results were based solely on statistical analysis with the absence of classifier evaluation. A follow up study by the same authors [17] showed that a single IMU worn on the thigh could achieve on average 82% sensitivity, 72% specificity and 83% accuracy in binary classification across the seven exercises and 49% sensitivity, 77% specificity and 61% accuracy in multi-class classification across a subset of four of the exercises. These results were based on LOSOCV testing.

A number of studies have demonstrated the viability of multiple IMUs to assess and quantify exercise performance [8], [14]. More recent research has also shown that it may be possible to evaluate these exercises more comprehensively [3], [15], [16], and possibly with a single IMU [7], [17]. This study differs from previous work in the field as it aims to evaluate if a single body-worn IMU is capable of distinguishing between seven levels of performance in a compound exercise (i.e. body weight squat). This may have the potential for applications in the areas of injury screening, S&C and rehabilitation.

II. Methods

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

A. Participants

Twenty two healthy volunteers (18 males, 4 females, age: 26.09±3.98 years, height: 1.75±0.14m, body mass: 75.2±14.2kg) were recruited for the study. No participant had a current or recent musculoskeletal injury that would impair their squat performance. All participants had prior experience with the squat exercise and regularly used it 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.

B. Exercise Technique and Deviations

Participants completed the initial squat with good form as described by the National Strength and Conditioning Association (NSCA) guidelines [p.320-322] [18]. This involved participants holding their chest up and out with the head tilted slightly up. As participants moved down into the squat position they were instructed to allow their hips and knees to flex while keeping their torso to floor angle relatively constant. Furthermore, they were required to keep their heels on the floor and knees aligned over their feet. Participants were required to continue flexing at the hips and knees until their thighs were parallel to the floor. As they moved upward a flat back was to be maintained and they were instructed to keep their chest up and out. Hips and knees were to be extended at the same rate with heels on floor and knees aligned over feet. Participants then extended their hips and knees to reach starting position.

The deviations from the aforementioned correct technique that were completed were knee valgus (KVL), knee varus (KVR), weight shift right (WSR), weight shift left (WSL), knees to far forward (KTF), heels elevated (HE) and bent over (BO). These are outlined in table 1.

TABLE I: List and description of squat exercise performance.

Deviation	Explanation
N	Normal squat
KVL	Knees coming together during downward phase
KVR	Knees coming apart during downward phase
WSR	Excessive lean to right hand side during entire squat exercise
WSL	Excessive lean to left hand side during entire squat exercise
KTF	Knees ahead of toes during downward phase
HE	Heels off ground during entire squat exercise
BO	Excessive flexion of hip and torso during entire squat exercise

C. Experimental Protocol

A pilot study was used to determine an appropriate sampling rate and the ranges for the accelerometer and gyroscope on board the IMU (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 ($\pm$16G), gyroscope ($\pm 500^o$/s) and magnetometer ($\pm$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.

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 the IMU was secured on the participant at the level of the 5^{th} lumbar vertebra using an elasticated strap. This sensor placement was selected based on clinical judgement as to the location that would most likely identify deviations and is shown below in Figure 1. The orientation and location of the IMU was consistent for all study participants.

Participants were then instructed on how to complete the squat with good form and biomechanical alignment as outlined in the NSCA guidelines as explained in section B. They completed ten repetitions with this good form. Once the squat 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. Verbal instructions and a demonstration were provided to all participants and they were allowed a trial to ensure they were comfortable completing the deviations. All squats were completed using body weight only. A Chartered Physiotherapist was present throughout all data collection to ensure the squat had been completed as instructed.

D. Data Analysis

Data were low-pass filtered at f_c=20 Hz using a Butterworth filter of order n=8 in order to remove high frequency noise and ensure all data analysed related to each participants movement as confirmed using the Fourier transform during the pilot study. For each repetition of the exercise a total of fifteen features were extracted from the IMU to allow for statistical analysis. These were maximum, minimum and range of the acceleration (accel) signals in X, Y and Z planes and maximum and minimum angular velocity (gyro) in X, Y and Z planes. Initially a repeated measures t test was considered as an appropriate comparison between the eight squat conditions. However, it was shown using a normal quantiles plot that the difference between the means of any two conditions did not follow the Gaussian distribution (Figure 2) and thus the data is not normally distributed. Therefore, the non-parametric pairwise Wilcoxon signed-rank test was used to analyse whether there was a difference in the IMU parameters between the various squat techniques. A P value $<$0.05 was considered statistically significant. Bonferroni adjustments were not used as in this case it would be unnecessary and could have increased the likelihood of Type II errors, hiding real changes in the signal features from being considered significant [19].

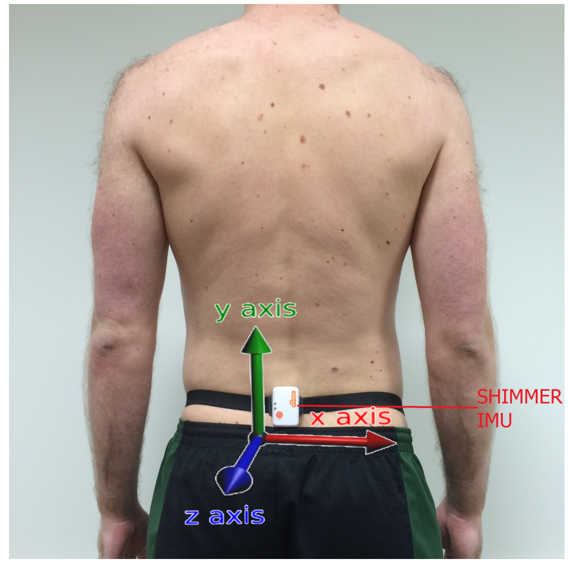

Fig. 1: Shimmer IMU placement and orientation. Sensor axes shown. A clockwise rotation about an axis is a positive angular velocity for the corresponding gyroscopic signal.

Following promising results from the statistical analysis, classification work was completed. In order to improve the set of features for classification four additional signals were calculated from the filtered accelerometer, gyroscope and magnetometer signals. These were; pitch, roll, yaw computed using the gradient descent algorithm described by Madgwick et. al [20] and the overall acceleration magnitude. The maximum, minimum and range of acceleration X, Y, and Z, gyroscope X, Y and Z and the four additional signals were extracted for each repetition of each exercise condition. This resulted in a total of 30 features describing each repetition of each squat condition.

Initially binary classification was evaluated to establish if a single IMU worn on the lumbar region of the spine can distinguish between correct and incorrect performance of the squat exercise. All repetitions of normal performance of the squat were labelled '0' and all repetitions of the squat performed with one of the deviations as outlined in table 1 were labelled '1'. As supervised learning methods are suitable for labelled data, a back-propagation neural network (BP N-N) classifier was used was used to perform classification. Each classifier was trained and tested using leave-one-subject-out cross-validation (LOSOCV) and results were presented using the accuracy, sensitivity and specificity metrics. 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 classifiers ability to detect negative label [15]. Binary classification efficacy was established based on computing these measures for each number of hidden neurons in the range (1-30). Following this the optimal number of hidden neurons for The BP N-N classifier was established.

Finally multi-label classification was evaluated on the IMU data set to investigate if the single IMU could be used to discriminate between correct performance of the squat exercise and each of the seven 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 '1-7'. A BP N-N classifier was also used for the multi-label classification. The optimal number of hidden neurons was found and the classifier was evaluated following the same procedure as that used for the binary classifier.

III. Results

Figure 2 plots the quantiles of the difference of the means between two conditions (normal vs knees coming together) with the quantiles of the Gaussian distribution. If the data are normally distributed they will lie close to a sloped straight line. The plot shows that the data are not normally distributed. A similar result can be seen comparing any two other conditions. Therefore a non-parametric test was required to assess the signal differences between all of the squat conditions.

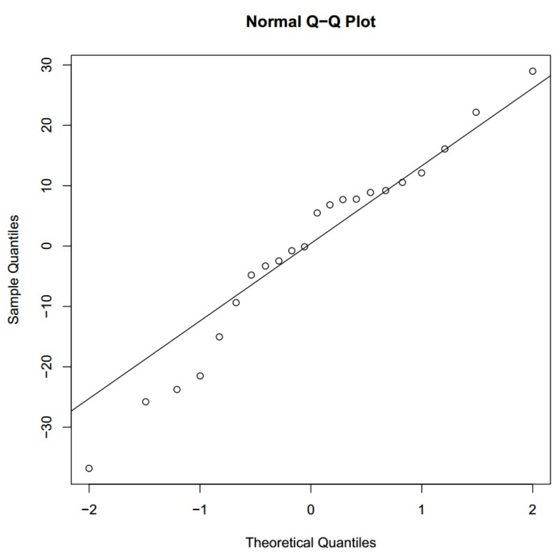

Fig. 2: Q-Q plot comparing mean difference between N (normal) & KVL (knee valgus) and the normal quantiles plot

Table 2 summarises the pairwise Wilcoxon signed-rank tests between each exercise condition. The column and row titles refer to the exercise technique being completed as described in the methodology in table 1. Each cell shows the number of features that were found to be significantly different between the two conditions being compared. A total of 15 features were compared (maximum, minimum and range of the accel signals in X, Y and Z planes and maximum and minimum of gyro signals in X, Y and Z planes). A P value <0.05 was considered statistically significant. For example there was one significantly different feature between WSL and WSR (valley gyro Y). 250 of the 420 pairwise Wilcoxon signed-rank tests returned statistically significant results.

Figure 3 shows an example boxplot for the mean valley of gyroscope X. BO shows a large significant difference from all other squat conditions with a P value of 3.82×10^{-6} when compared with WSR and a P value of 1.91×10^{-6} when compared with all six other squat conditions. HE is significantly different from all conditions except KTF for this feature. KVR is significantly different from BO, HE, KVL and KTF but not N, WSL or WSR. Overall 23 of the 28 comparisons were significantly different. As can be seen in figure 3, there is overlap between the mean valleys for all the squat conditions. Similar boxplots can be seen for all of the analysed features.

The classification results are shown in table 3. These results are based on a total of 30 features describing each repetition (maximum, minimum and range of accel X, Y, and Z, maximum, minimum and range of gyro X, Y and Z, pitch, roll, yaw and the overall accel magnitude). The first column presents the efficacy scores obtained using binary classification with 6 hidden neurons used for the BP N-N classifier. Considering the small size of the data set used, relatively high average efficacy scores were achieved. Observations in test set of data were classified accurately on average of 80.45% of the time, with 64.41% mean sensitivity, 88.01% mean specificity and a mean positive likelihood ratio of 5.37. The efficacy scores of the multi-label classification scores for the BP N-N classifier with 15 hidden neurons are shown in the second column of table 3. Moderate average efficacy scores were achieved with an average of 56.55% of observations in test set being classified with the correct label (0-7). The other efficacy scores were 59.65% mean sensitivity, 94.84% mean specificity and an average positive likelihood ratio of 11.6. Some deviations were detected with reasonably high sensitivity, for instance KVL achieved a score of 79.1% and BO a score of 88.67%. However, sensitivity scores were poor for WSL, WSR and KVR with results ranging from 15-45%. Moderate scores were achieved for KTF and HE 66.5% and 72.1% respectively.

TABLE II: Results of pairwise Wilcoxon signed-rank tests. Each cell shows the number of features that were found to be significantly different ($P<0.05$) between the two conditions being compared. Fifteen features were analysed between each exercise condition.

	BO	**HE**	**KVR**	**KVL**	**KTF**	**N**	**WSL**
HE	10						
KVR	9	7					
KVL	7	8	6				
KTF	8	9	6	5			
N	7	9	5	8	7		
WSL	14	12	7	13	11	13	
WSR	13	12	7	13	11	12	1

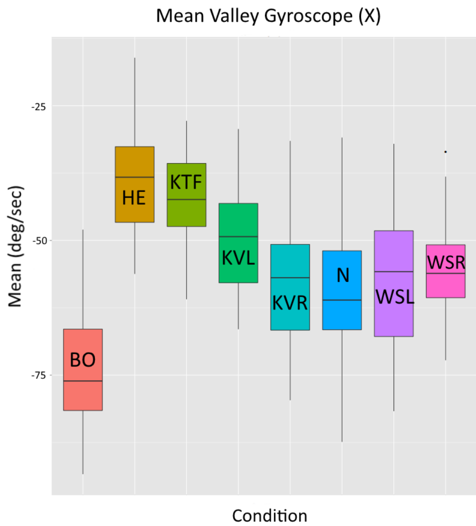

Fig. 3: Boxplot for valley, gyroscope (X) across all squat conditions studied. Correct performance and 7 deviations were compared.

TABLE III: Mean LOSOCV results of binary and multi-label classifier

	Binary Classification (Correct or Incorrect)	**Multi-Label Classification (Correct or Specific Deviation)**
Sensitivity (%)	64.41	59.65
Specificity (%)	88.01	94.84
Accuracy (%)	80.45	56.55
+ Likelihood Ratio	5.4	11.56

IV. Discussion

The aim of this study was to investigate if a single IMU placed on the lumbar spine can distinguish between varying levels of squat performance. Statistical analysis showed at least one sensor signal feature could identify differences between all eight of the squat exercise conditions examined, as described in table II. Binary classification indicated correct and incorrect squat performance could be identified with 80% accuracy, 64% sensitivity and 88% specificity. A multi-label classifier was able to distinguish between the eight different squat conditions (correct squat technique and the seven deviations as outlined in table 1) with 57% accuracy, 60% sensitivity 95% specificity. This serves as preliminary evidence that a single IMU may be an effective method of monitoring multi-joint exercise performance in both rehabilitation and S&C contexts.

As IMUs are small, inexpensive, and easy to use they are ideally positioned to aid with the quantification of human movement. Furthermore, their portability facilitates the acquisition of human movement data beyond the laboratory setting, which may provide a more realistic assessment of an individual′s movement patterns [7]. The aforementioned advantages have resulted in a number of researchers investigating their utility in rehabilitation sessions and during the performance of gym-based exercises. However, to the authors′ knowledge this study is the first to determine if a single body-worn IMU can successful detect deviations from correct technique during performance of the squat exercise.

Using a LOSOCV method of testing Taylor et al [15] achieved overall accuracy of 80% for standing hamstring curl, 65% for reverse hip abduction and 62% for straight leg raise. However, the authors used a total of five IMUs to achieve this. The classification results presented in table III are comparable to this work while having the added benefit of using only one IMU. Taylor and colleagues [16] built on these results in 2012 using a number of different methods to classify human motion quality. Their highest accuracy for the standing hamstring curl was 86% and for the straight leg raise was 90%. However the authors used a 10 fold cross validation method which would be expected to give better results than the LOSOCV method used for classification in this paper.

A multiple IMU set-up was also used by Velloso and colleagues [3]. The authors achieved an overall recognition rate of 78.2% using LOSOCV in dumbbell biceps curl exercise. The exercise was performed with five variations using a total of four sensors. Unfortunately, multiple sensor systems are more expensive and less practical for users than single sensor systems. Therefore, the transferability of such a set-up to routine practice is questionable.

The results presented in this study are comparable to those achieved by Giggins et al [17]. Here the authors achieved 82% sensitivity, 72% specificity and 83% accuracy in binary classification in seven exercises and 49% sensitivity, 77% specificity and 61% accuracy in multi-class classification across a subset of four of the exercises. However, like in [3] the exercises completed were single joint exercises such as heel slides and knee extension. It is common for athletes and patients undergoing rehabilitation to move beyond these single joint exercises relatively early in their conditioning or rehabilitation programmes. Multi-joint movements also form an essential component of many screening tools such as the Functional Movement Screen. Therefore it is vital that the sensors are able to detect deviations from correct technique in commonly used multi-joint movements. Due to the added complexity of multi-joint compound exercises compared to single-joint exercises, more deviations from correct technique can occur making it harder for a single IMU to detect these deviations. This work has shown that it is possible to detect deviations in multi-joint exercises using a single IMU.

To the authors′ knowledge, this research is the first to detect a large number of deviations from correct technique in a multi-joint exercise using a single body-worn IMU. A single-sensor system that can monitor and evaluate performance of multi-joint exercises would be a cost-effective and practical way to provide relevant feedback to individuals whilst performing such exercises. Such information could aid clinicians and coaches′ assessment of exercise performance. This could prove particularly useful in providing movement analysis where the coach or clinician is not present for example in home-based rehabilitation, S&C programmes for teams or screening a large number of athletes simultaneously. This information could also be incorporated into stand-alone biofeedback systems that could be used directly by the people whilst exercising. Such feedback systems could potentially minimise the likelihood of poor form when people exercise alone and train them in correct exercise technique without a clinician or coach. Furthermore, such systems could also be used to provide automated objective data for screening tools such as the Functional Movement Screen [21].

There are number of contextual factors in this investigation which must be considered. There was no gold-standard 3-dimensional motion capture system used to confirm that each deviation did occur. However, deviations were confirmed through visual observation by a Chartered Physiotherapist. Furthermore, a gold-standard 3-dimensional motion capture system may also influence the participants′ movement patterns due to its bulky set up. When deviations occur naturally, the exact way in which they occur may differ compared to when a participant deliberately performs the deviation. Additionally, the seven deviations studied is not a non-exhaustive list of all those which can occur during the squat exercise.

The results presented in table II and III show great potential for a single-sensor system to analyse multi-joint exercise. To fulfil this potential, future work is required. More sophisticated classification techniques may be used to develop more accurate classification systems. Supervised machine learning algorithms using features such as those described in this study and additional features may be an effective method. These additional features may also be used to detect specific deviations such as WSL, WSR and KVR more effectively. The next step will be to train both supervised and unsupervised machine learning algorithms and compare their accuracy, efficiency and sensitivity in the classification of multi-joint exercise technique. In order to improve such measures it is appropriate to build a larger data set. The data set will also include other multi-joint exercises such as the lunge and deadlift as well as common deviations from correct form in these exercises. This will hopefully allow for the development of classification systems for these exercises.

The data analysis presented in this paper serves as a promising foundation to the continuing investigation as to whether a single IMU worn on the lumbar region of the spine can identify deviations from correct form in multi-joint exercises. If proven to be effective in doing so, a single sensor system may be used to provide more objective data on movement to clinicians and coaches. It may also form the basis to biofeedback systems that could be used in movement screening, rehabilitation and S&C contexts.

References

[1] Z. Y. Kerr, C. L. Collins, and R. D. Comstock, "Epidemiology of weight training-related injuries presenting to united states emergency departments, 1990 to 2007," *The American Journal of Sports Medicine*, vol. 38, no. 4, pp. 765–771, 2010.

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

[3] 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*. ACM, 2013, Conference Proceedings, pp. 116–123.

[4] A. Schmitz, M. Ye, R. Shapiro, R. Yang, and B. Noehren, "Accuracy and repeatability of joint angles measured using a single camera markerless motion capture system," *Journal of biomechanics*, vol. 47, no. 2, pp. 587–591, 2014.

[5] 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*, vol. 39, no. 1, pp. 593–598, 2014.

[6] L. Bao and S. S. Intille, *Activity recognition from user-annotated acceleration data*. Springer, 2004, pp. 1–17.

[7] 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*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2013, Conference Proceedings, pp. 49–56.

[8] I. Pernek, K. A. Hummel, and P. Kokol, "Exercise repetition detection for resistance training based on smartphones," *Personal and ubiquitous computing*, vol. 17, no. 4, pp. 771–782, 2013.

[9] E. S. Rawson and T. M. Walsh, "Estimation of resistance exercise energy expenditure using accelerometry," *Medicine and science in sports and exercise*, vol. 42, no. 3, pp. 622–628, 2010.

[10] J. J. Kavanagh and H. B. Menz, "Accelerometry: a technique for quantifying movement patterns during walking," *Gait & posture*, vol. 28, no. 1, pp. 1–15, 2008.

[11] M. Zhang and A. A. Sawchuk, "A customizable framework of body area sensor network for rehabilitation," in *Applied Sciences in Biomedical and Communication Technologies, 2009. ISABEL 2009. 2nd International Symposium on*. IEEE, 2009, Conference Proceedings, pp. 1–6.

[12] F. Michahelles and B. Schiele, "Sensing and monitoring professional skiers," *Pervasive Computing, IEEE*, vol. 4, no. 3, pp. 40–45, 2005.

[13] H. Ghasemzadeh, V. Loseu, and R. Jafari, "Wearable coach for sport training: A quantitative model to evaluate wrist-rotation in golf," *Journal of Ambient Intelligence and Smart Environments*, vol. 1, no. 2, pp. 173–184, 2009.

[14] J. F. Lin and D. Kuli, "Human pose recovery using wireless inertial measurement units," *Physiological measurement*, vol. 33, no. 12, p. 2099, 2012.

[15] 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), 2010 Annual International Conference of the IEEE*. IEEE, 2010, Conference Proceedings, pp. 339–343.

[16] P. E. Taylor, G. J. Almeida, J. K. Hodgins, and T. Kanade, "Multi-label classification for the analysis of human motion quality," in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*. IEEE, 2012, Conference Proceedings, pp. 2214–2218.

[17] 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*, vol. 11, no. 1, p. 158, 2014. [Online]. Available: http://www.jneuroengrehab.com/content/11/1/158

[18] T. R. . . Baechle, *NSCA's Essentials of Personal Training: National Strength and Conditioning Association; Roger W. Earle and Thomas R. Baechle (editors)*. Human Kinetics Publishers, 2004.

[19] T. V. Perneger, "What's wrong with bonferroni adjustments," *Bmj*, vol. 316, no. 7139, pp. 1236–1238

[20] S. O. H. Madgwick, A. J. L. Harrison, and R. Vaidyanathan, "Estimation of IMU and MARG orientation using a gradient descent algorithm," in *IEEE International Conference on Rehabilitation Robotics*, 2011.

[21] 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: NAJSPT*, vol. 1, no. 2, p. 62, 2006.