Evaluating Performance of the Single Leg Squat Exercise with a Single Inertial Measurement Unit

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ABSTRACT

The single leg squat (SLS) is an important component of lower limb rehabilitation and injury risk screening tools. This study sought to investigate whether a single lumbar-worn IMU is capable of discriminating between correct and incorrect performance of the SLS. Nineteen healthy volunteers (15 males, 4 females, age: 26.09 ± 3.98 years, height: 1.75 ± 0.14m, body mass: 75.2 ± 14.2kg) were fitted with a single IMU on the lumbar spine and asked to perform 10 left leg SLS. These repetitions were recorded and labelled by a chartered physiotherapist. Features were extracted from the labelled sensor data. These features were used to train and evaluate a random-forests classifier. The system achieved an average of 92% accuracy, 78% sensitivity and 97% specificity. These results indicate that a single IMU has the potential to differentiate between a correctly and incorrectly completed SLS. This may allow such devices to be used by clinicians to help track rehabilitation of patients and screen for potential injury risks. Furthermore, the classifier described may be a useful input to an exercise biofeedback application.

Categories and Subject Descriptors

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

General Terms

Exercise, Classification
  *Joint lead authors

1. INTRODUCTION

The single leg squat (SLS) is an important exercise for rehabilitation and injury risk screening. It is often used to identify risk factors for and rehabilitate lower limb injuries such as patellar tendonopathy and anterior cruciate ligament injury [10, 11]. This is because the SLS provides a simple test of knee alignment during weight bearing activities as well as identifying deficiencies in core strength, landing, running and cutting tasks [8]. Furthermore, it requires no equipment to complete meaning it can be used in a clinical setting easily [10].

However, it is often difficult to quantify and standardise the movement. To date objective data has been ascertained using marker based motion analysis systems [11]. However using this approach is time intensive, expensive and the application of markers may hinder normal athletic movement [1]. Therefore these marker-based systems have tended not to be accepted into routine practice. Clinical assessment of the SLS is usually completed with a single visual rating of the movement and is usually rated as acceptable or minor, moderate or marked movement dysfunction. Unfortunately visual analysis of the SLS has only moderate inter and intra rater reliability [5]. As a result poor clinical decisions may be made and patients may complete their rehabilitation exercise incorrectly.

Recent technological advances have allowed for the possibility of inertial measurement units (IMUs) to be used as a method of quantifying, assessing and tracking movements such as the SLS. These sensors are small, inexpensive, easy to set up and allow for the objective assessment of human movement in an unconstrained environment [3]. Therefore they offer the potential to bridge the gap between clinic and laboratory based assessment by allowing for the collection of objective data in a quick and easy manner. Furthermore, they may allow therapists to track their patients rehabilitation compliance and form remotely.

For increased end user cost effectiveness and practicality a single sensor set-up is most desirable. Authors have

found encouraging results when investigating the potential of single sensor set-ups to identify deviations in early stage rehabilitation exercises such as heel slide and straight leg raise [3, 4]. However patients are likely to move beyond these simple exercises relatively early in their rehabilitation programmes. With the added complexity of exercises such as the SLS more deviations can occur making it difficult for a single IMU to detect such movement breakdown.

This study aims to evaluate if a single worn IMU located on the lumbar spine is capable of distinguishing between different levels of performance in the SLS. This may have the potential for applications in rehabilitation by allowing a greater standardisation of exercise performance and tracking a patients' rehabilitation remotely.

2. METHODS

Data were acquired from participants as they completed 10 SLS with as good form as possible. These repetitions were recorded using a HD video and subsequently rated by a chartered physiotherapist by adapting a previously developed scale [9]. The signals obtained from 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.

2.1 Participants

Nineteen healthy volunteers (15 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 his or her SLS 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 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, the IMU was secured on the participant at the level of the 5th lumbar vertebra using an elasticated strap (Figure 1). The orientation and location of the IMU was 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 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.

Following the warm-up, participants were then encouraged to complete 10 reps of a left SLS with as good form as possible. 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 range as smooth as possible. Their right leg should be kept as extended as possible in front of them and they were to flex their left knee between 60 and 90 degrees. A video was shown to participants to outline exactly what was expected from participants and all participants were allowed trial repetitions to ensure they were comfortable with the exercise before commencing their set of 10 repetitions.
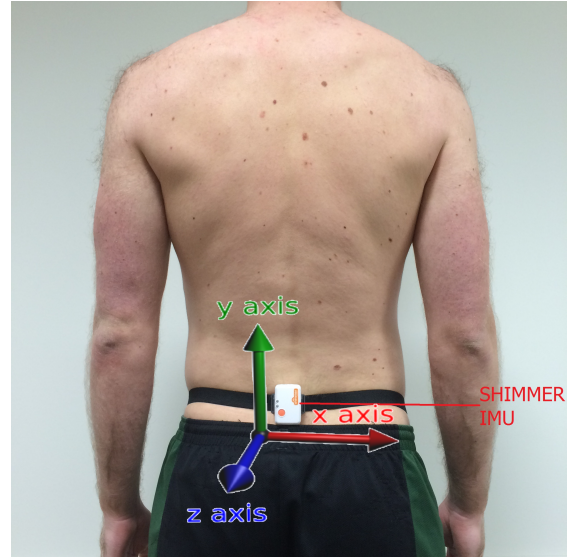

Figure 1: Shimmer IMU placement and orientation. Sensor axes shown. A clockwise rotation about an axis is a positive angular velocity for the corresponding gyroscopic signal.

2.3 Data Labelling

All repetitions were recorded using a high definition video placed in front of the participants. This video was then reviewed by a chartered physiotherapist with over six years experience in musculoskeletal and sports physiotherapy. Each repetition was separated and reviewed on multiple occasions in a systematic format. For each repetition a score of 0-1 was given to each section as outlined in the scoring system shown in Table 1, adapted from the 4 grade scoring system described by Whatman et al. (2012). An overall score of 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).

2.4 Data Analysis

Following the data collection and labelling, post analysis was performed on the data. Nine signals were obtained from the 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 participants movement. Four 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 described by Madgwick et. al

Table 1: **SLS data labelling system used, adapted from Whatman et. al [9]**

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	N:0 Y:1
Pelvis 2:	Moves away from the midline	N:0 Y:1
Knee	Patella moves out of line with second toe	N:0 Y:1
Foot	Moves into excessive pronation	N:0 Y:1
Oscillation	Observable oscillation	N:0 Y:1
Overall Score	Acceptable movement pattern	**0**
	Movement dysfunction	**1**

[6] and then converted from quaternion values to pitch, roll and yaw signals. The acceleration magnitude was also computed taking the root mean square of the accelerometer X,Y and Z signals.

Each SLS repetition was extracted from the data. Descriptive features were than extracted from the following ten signals; accelerometer X,Y,Z, gyroscope X,Y,Z, pitch, roll, yaw and acceleration magnitude. The magnetometer data was not used as it is location specific and values may vary significantly in environments outside of the laboratory used for this study. For each of the ten signals the following thirteen features were extracted; Arithmetic mean, median, mode, root mean square, standard deviation, variation, kurtosis, skewness, minimum, maximum, range, time of minimum and time of maximum. This resulted in 130 descriptive features for each of the 190 repetitions of the SLS analysed in this study.

The random-forests method was employed to perform classification [2]. 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 [7]. 130 trees were used in the random-forest classifier. Classification quality was compared with and without performing principal component analysis (PCA) on the training data. The results were not significantly effected and therefore, principal component analysis was not included in the final single IMU, SLS classification system.

2.5 Classifier Evaluation

To establish the quality of the classifier in discriminating between correct and incorrect performance of the SLS, repeated random-sample validation was used. This method of classifier evaluation was chosen as the data set used to train and the classifier was relatively small. Leave-one-subject cross-validation (LOSOCV) was not deemed necessary for this study due to the high repetition-repetition variability of SLS performance in each participant's set of the exercise.

Data was shuffled programmatically. The first eighty percent of data was used as the training set for the random-forests classifier resulting in 152 repetitions per training set. The remaining twenty percent of observations were used as the test set for the classifier resulting in 38 test repetitions per evaluation. Accuracy, sensitivity, specificity and +likelihood ratio 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 classifiers ability to detect negative labels, the likelihood ratio is a measure of the value of the classifier. This process was repeated ten times.

Table 2 demonstrates the mean sensitivity, specificity, accuracy and +likelihood ratio metrics for classification system following the ten cycles of random-sample validation. Strong mean accuracy and specificity results were achieved and a moderate sensitivity was achieved. The lower mean sensitivity score may be due to the lower number of examples of correct SLS technique in the data set, resulting in the random-forest classifier having less training data for this category.

Table 2: **Mean classification metrics from 10 cycles of repeated random-sample validation**

Binary Classification (Correct or Incorrect)	
Sensitivity (%)	77.6
Specificity (%)	96.7
Accuracy (%)	92.1
+ Likelihood Ratio	23.4

A total of 380 repetitions of the SLS were used to evaluate the performance of the classifier following 10 cycles of repeated random-sample validation with 38 repetitions in the test set per cycle. Table 3 demonstrates the actual label of the repetition provided by the chartered physiotherapist as described in Section 2.2. versus the predicted label of the repetition from the classifier's output. The system achieved 59 true-positives (TP) and 294 true-negatives (TN) with 10 false-positives (FP) and 17 false-negatives (FN).

3. CONCLUSIONS AND FUTURE WORK

The results of this study show promising potential for a single-sensor system to analyse the SLS exercise. An accuracy of 92%, sensitivity of 78% and specificity of 97% for binary classification exceeds existing research investigating the use of a single IMU to analyse rehabilitative exercise [4]. However, in order to develop a system which is more robust and valuable for clinicians and patients further in-depth

Table 3: **Confusion matrix demonstrating classification results**

Classifier's Predicted Output				
		Correct	*Incorrect*	Total
Actual	*Correct'*	TP: 59	FN: 17	76'
Label	*Incorrect'*	FP: 10	TN: 294	304'
	Total	69	311	

classification must be completed. Future work will involve establishing the capability of an IMU body sensor network in completing more in depth analysis of the SLS exercise. Initially a multi-label classifier should be developed to investigate if 4 grade evaluation of SLSs such as that used by [9] can be effectively computed. Following this it should be investigated exactly which deviation is occurring from correct performance of the SLS exercise and to what measure of severity the movement dysfunction is occurring. To enable this in-depth analysis a multi-sensor system may be most appropriate. Classification quality will be established for various multiple IMU and single IMU systems.

Sensor based classification systems such as that described in this paper are an important component for remote tracking of rehabilitative exercise. Such systems add value to the rehabilitation process for both patients and clinicians. A SLS classification system could also be used as an input to an automated injury screening tool and as part of an automated exercise biofeedback system. A single sensor system is most desirable to ensure practicality and cost-effectiveness for end users.

4. ACKNOWLEDGMENTS

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