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Classification of deadlift biomechanics with wearable inertial measurement units

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ABSTRACT

The deadlift is a compound full-body exercise that is fundamental in resistance training, rehabilitation programs and powerlifting competitions. Accurate quantification of deadlift biomechanics is important to reduce the risk of injury and ensure training and rehabilitation goals are achieved. This study sought to develop and evaluate deadlift exercise technique classification systems utilising Inertial Measurement Units (IMUs), recording at 51.2 Hz, worn on the lumbar spine, both thighs and both shanks. It also sought to compare classification quality when these IMUs are worn in combination and in isolation. Two datasets of IMU deadlift data were collected. Eighty participants first completed deadlifts with acceptable technique and 5 distinct, deliberately induced deviations from acceptable form. Fifty-five members of this group also completed a fatiguing protocol (3-Repition Maximum test) to enable the collection of natural deadlift deviations. For both datasets, universal and personalised random-forests classifiers were developed and evaluated. Personalised classifiers outperformed universal classifiers in accuracy, sensitivity and specificity in the binary classification of acceptable or aberrant technique and in the multi-label classification of specific deadlift deviations. Whilst recent research has favoured universal classifiers due to the reduced overhead in setting them up for new system users, this work demonstrates that such techniques may not be appropriate for classifying deadlift technique due to the poor accuracy achieved. However, personalised classifiers perform very well in assessing deadlift technique, even when using data derived from a single lumbar-worn IMU to detect specific naturally occurring technique mistakes.

1. Introduction

The deadlift is a compound full-body exercise that is fundamental in resistance training, rehabilitation and powerlifting (Escamilla et al., 2000; Hales, 2010). It is a complex movement that requires training to ensure correct form (Hales, 2010). Aberrant deadlift biomechanics have been shown to increase load shear forces in the lower back (Cholewicki et al., 1991), potentiating the risk of injury. Thus, reliable assessment of deadlift biomechanics is necessary to mitigate injury risk.

The assessment of deadlift biomechanics is typically undertaken using 3-D motion capture or subjective visual analysis, both of which have limitations. Using 3-D motion capture systems is expensive and data processing can be time intensive (Bonnet et al., 2013). Subjective visual assessment can prove unreliable as visually assessing numerous constituent components simultaneously is challenging (Whiteside et al., 2016). Wearable inertial measurement units (IMUs) could bridge the gap between laboratory and clinical acquisition and assessment of human biomechanics as they allow for an inexpensive method of acquiring objective human movement data in unconstrained environments (McGrath et al., 2012). In this paper the term IMU system will describe IMU sensors, sensor signals, associated signal processing and exercise classification algorithm output.

A growing body of literature has investigated how these systems can be used for exercise biomechanics evaluation and feedback (Giggins et al., 2014; Gleadhill et al., 2016; Melzi et al., 2009; O'Reilly et al., 2015; Pernek et al., 2015; Taylor et al., 2012; Velloso et al., 2013; Whelan et al., 2015, 2016a, 2016b). These studies have demonstrated that IMU systems can monitor exercise biomechanics with moderate to excellent accuracy. Of these, only Gleadhill et al. (2016) analysed the deadlift using an IMU system. The authors compared an IMU system to a traditional

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3D motion capture system in identifying temporal features in deadlift technique variations. They found high agreement between the two systems and stated that the work provided the foundations to use IMU systems for activity recognition and technique analysis. While a promising first step, they only analysed correlations between the two systems and did not attempt to classify technique deviations, meaning application in a real world environment may be limited. Furthermore, no information is provided regarding the deadlift technique variations investigated or if these variations were induced or natural.

The majority of the above research classified exercise technique as acceptable or aberrant using universal classifiers. A universal classifier is built using a large data set collected from multiple participants. This type of classifier will function when presented with new data from individuals not included in the training data. These classifiers are often developed using induced deviations (i.e. deviations intentionally performed by participants). However, natural deviations may be nuanced and subsequently more difficult to classify. Therefore, universal classifiers may not always be suitable for exercise analysis. This may be particularly true in the deadlift, as the intricacies associated with an optimal biomechanics can vary greatly between individuals (Hales, 2010). Furthermore, in a natural environment a variety of deviations may present in different quantities, some occurring less frequently than others. This makes collecting a large and balanced data set of natural deviations challenging, which is necessary for the development of a robust universal classification system (Chawla, 2005; He and Garcia, 2009; Kotsiantis et al., 2007). For these reasons a personalised classifier may be more appropriate for deadlift analysis.

A personalised classifier is developed using data provided by a single person. IMU signals are collected from participants and each individual repetition is assessed and labelled by a movement expert through live or post hoc video analysis. IMU signals for each repetition can then be associated with this repetition's movement pattern. When the data set used for training the IMU system is collected this way, the system can be individualised. While this may prove more labour intensive than using an IMU system based on a universal classifier, it may be appropriate when analysing complex exercises like the deadlift.

The objective of this study was to determine whether an IMU system could identify deviations from acceptable deadlift biomechanics. The aims of this study were: (a) determine if in combination or in isolation, IMUs positioned on the lumbar spine, thigh and shank are capable of distinguishing between acceptable and aberrant deadlift biomechanics; (b) determine the capabilities of an IMU system at identifying specific deviations from acceptable deadlift biomechanics; (c) compare a personalised to a universal classifier in identifying the above; (d) compare the above on a large data set of deliberately induced technique deviations and a smaller data set of naturally occurring technique deviations.

2. Methods

2.1. Experimental approach to problem

Two experiments were employed to enable the development of a wearable IMU system for assessing deadlift technique. In the first experiment 80 participants completed deadlifts with acceptable form and deliberately induced technique deviations (Table 1). In the second experiment 55 participants performed a 3-repetition maximum strength (3 RM) deadlift protocol to elicit natural deadlift biomechanics breakdown. A Chartered Physiotherapist labelled video data of each deadlift repetition as acceptable or containing one of the technique deviations (Table 1). The physiotherapist has extensive training in strength and conditioning and has previous experience evaluating deadlift biomechanics. In both experiments data were acquired from 5 IMUs (SHIMMER, Shimmer Research, Dublin, Ireland) (Fig. 1). A total of 306 variables were extracted from the sensor signals from each IMU for every deadlift repetition. These variables were used to develop and evaluate an automated classification system. This was undertaken using data derived from each individual IMU and combinations of multiple IMUs. A universal and a personalised classification system were evaluated for every participant.

Table 1
List and description of deadlift exercise deviations used in this study and the number of repetitions (n) extracted for each class when using induced deviations ad naturally occurring technique deviations.

Deviation	Description	Induced reps (n)	Natural reps (n)
ACC	Acceptable deadlift technique	796	854
SBB	Shoulders behind bar at start position	212	0
RB	Rounded back at any point during movement	211	40
HEX	Hyperextended spine at any point during movement	191	85
BT	Bar tilting	393	12
OTH	Other	0	17

2.2. Participants

Eighty healthy volunteers (57 males, 23 females, age: 24.68 ± 4.91 years, height: 1.75 ± 0.094 m, body mass: 76.01 ± 13.29 kg) were recruited for the first experiment in this study. Fifty-five members of this cohort also participated in the second experiment (37 males, 18 females, age = 24.21 ± 5.25 years, height = 1.75 ± 0.1 m, body mass = 75.09 ± 13.56 kg). All participants had prior experience with the exercise and no musculoskeletal injury that would impair deadlift performance. Each participant signed a consent form prior to study commencement. The University Human Research Ethics Committee approved the study protocol.

2.3. Procedures

The testing protocol was explained to participants upon their arrival at the laboratory. Prior to testing a ten-minute warm-up on an exercise bike (Lode B.V., Groningen, The Netherlands) was completed. Next, a Chartered Physiotherapist secured the IMUs to the following pre-determined specific anatomic locations on the participant using neoprene straps; over clothing at the spinous process of the 5th lumbar vertebra, the mid-point of both the right and left thighs (determined as half way between the greater trochanter and lateral femoral condyle), and on both shanks 2 cms above the lateral malleolus (Fig. 1). The orientation and location of the IMUs were consistent across participants and local frame x, y and z axes were used for each IMU (Fig. 1). The straps used were specifically designed for exercise environments and minimised unwanted IMU position deviation due to clothing and movement artefact.

The IMU settings chosen (sampling frequency: 51.2 Hz, tri-axial accelerometer (±2 g), gyroscope (±500 °/s) and magnetometer (±1.9 Ga)) replicate those used in previous research and were based on pilot data analysis as described in Whelan et al. (2016b). Each IMU was calibrated for these specific sensor ranges and the Shimmer 3 default local coordinate system using the Shimmer 9DoF Calibration application (http://www.shimmersensing.com/shop/shimmer-9dof-calibration).

In experiment 1 the participants completed 10 deadlift repetitions with acceptable form and 3 repetitions of each deviation (Table 1). In order to ensure standardisation, form was considered acceptable if it was completed as defined by the National Strength and Conditioning Association (NSCA) (Baechle and Earle, 2004). In experiment 2, participants completed a 3 RM test. This involves increasing load incrementally until an individual cannot maintain acceptable form and is described in detail by Horvat et al. (2007).

2.4. Data labelling

Each deadlift repetition was separated and viewed on multiple occasions in a systematic format by the Chartered Physiotherapist. Repetitions were labelled as acceptable or the most dominant deviation from acceptable form was chosen.

2.5. Signal processing

Signal processing and classification analyses were completed using MATLAB (2012, The MathWorks, Natwick, USA). Spectral analysis was completed on the IMU data. It was found that all data pertaining to movement was in the 0–20 Hz frequency band. Therefore the accelerometer x, y, z, gyroscope x, y, z and magnetometer x, y, z signals were first low pass filtered at $fc = 20$ Hz using a Butterworth filter of order $n = 8$. Nine additional signals were then calculated as follows: IMU 3-D orientation was computed using the gradient descent algorithm developed by Madgwick et al. (2011). The resulting W, X, Y and Z quaternion values are a mathematical representation of an object's 3D orientation in space and are not subject to

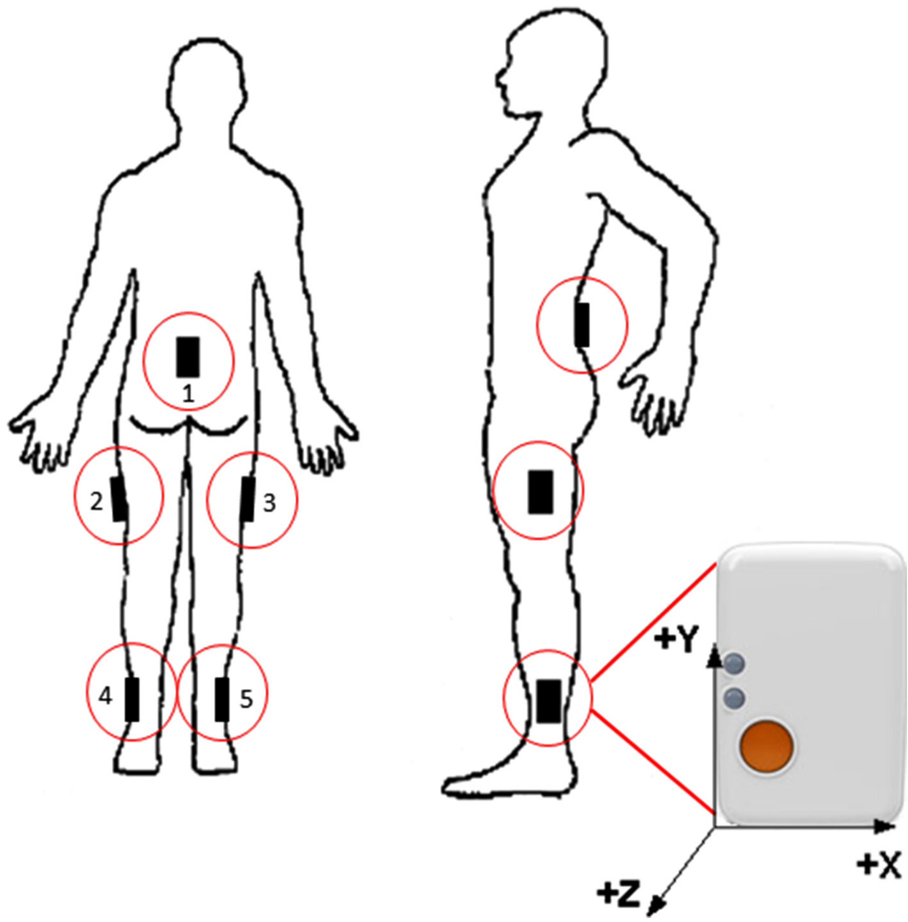

Fig. 1. Image showing the five IMU positions: (1) the spinous process of the 5th lumbar vertebra, (2&3) the mid-point of both femurs on the lateral surface (determined as half way between the greater trochanter and lateral femoral condyle), (4&5) and on both shanks 2 cms above the lateral malleolus. Local shimmer axes *x*, *y* and *z* are also shown.

gimbal lock (Kuipers, 1999). The rotation quaternions were also converted to pitch, roll and yaw signals. The pitch, roll and yaw signals describe the inclination, measured in radians, of each IMU in the sagittal, frontal and transverse plane respectively. The magnitude of acceleration and rotational velocity were also computed using the vector magnitude of accelerometer *x*, *y*, *z* and gyroscope *x*, *y*, *z* respectively. Following this, each exercise repetition was programmatically extracted from the IMU data and resampled to a length of 250 samples. This was undertaken to time-normalise the data and minimise the influence of repetition tempo on signal feature calculations.

2.6. Classification

Time-domain and frequency-domain descriptive features were computed in order to characterise each exercise repetition. The 17 features computed for each signal were 'mean', 'RMS', 'standard deviation', 'kurtosis', 'median', 'skewness', 'range', 'variance', 'maximum', 'minimum', 'energy', '25th percentile', '75th percentile', 'fractal dimension', 'level crossing-rate' and the variance of both the approximate and detailed wavelet coefficients using the Daubechies 5 mother wavelet to level 6 (Fig. 2). These replicate those used in recent similar work (Whelan et al., 2016a, 2016b). These features, when used in combination, describe the shape of the various signals from each IMU. When a person's motion is altered due to aberrant deadlift technique, the IMU signals will also change. The features used capture the diverse range of signal changes that can occur due to aberrant deadlift biomechanics. All computed features form a feature-vector for each repetition that is used along with the repetition's label to train classification algorithms.

The random-forests method was employed to perform classification (Breiman, 2001). During analysis several types of classifiers were tested including K-Nearest Neighbours, Support Vector Machines and Naïve Bayes classifiers, however none were shown to provide improved results on the datasets and some increased computational time. A total of 128 trees were used for each random forest. This number was chosen after observing the accuracy rate for incrementing number of trees from 1 to 500. While an increased number of trees will always improve classification accuracy, this increase was considered negligible when using more than 128 trees. Additional trees also reduce end user application efficiency. Initially, binary classification was evaluated using data from experiment 1 to establish how effectively each individual IMU and combination of IMUs could distinguish between acceptable and aberrant deadlift technique in a large, balanced data set of deliberately induced technique deviations. Multi-label classification was then evaluated on this data set to investigate how effectively each individual IMU and each IMU combination could be used to discriminate between acceptable deadlift technique and each of the deliberate deviations from acceptable technique (Table 1). Equivalent binary and multi-label classifiers were then applied to the data set from experiment 2.

For each classification task, universal classifiers were evaluated using leave-one-subject-out-cross-validation (LOSOCV) (Fushiki, 2011). Where each class in the training data did not have an equal number of instances (i.e. equal number of acceptable and aberrant repetitions in binary classification), random instances of the overrepresented class(es) were removed in order to balance the training data.

The quality of the personalised exercise classification systems was established using leave-one-out-cross-validation (LOOCV) (Fushiki, 2011). Each deadlift repetition corresponds to one fold of the cross validation. At each fold, one repetition is held out as test data while the random forests classifier is trained with the same participant's other completed repetitions. Where each class in the training data did not have an equal number of instances (i.e. equal number of acceptable and aberrant repetitions in binary classification), random instances of the overrepresented class(es) were removed in order to balance the training data. The held out data is used to assess the classifier's ability to correctly categorise new data it is presented with. Participants were not included for this analysis if they did not have at least 2 repetitions belonging to each class being classified, as this would not allow for training and test data for that class.

The scores used to measure classification quality were accuracy, sensitivity and specificity computed according to the below formulae (TP = True Positive; TN = True Negative; FP = False Positive; FN = False Negative).

1. $Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$
2. $Sensitivity = \frac{TP}{TP+FN}$
3. $Specificity = \frac{TN}{TN+FP}$

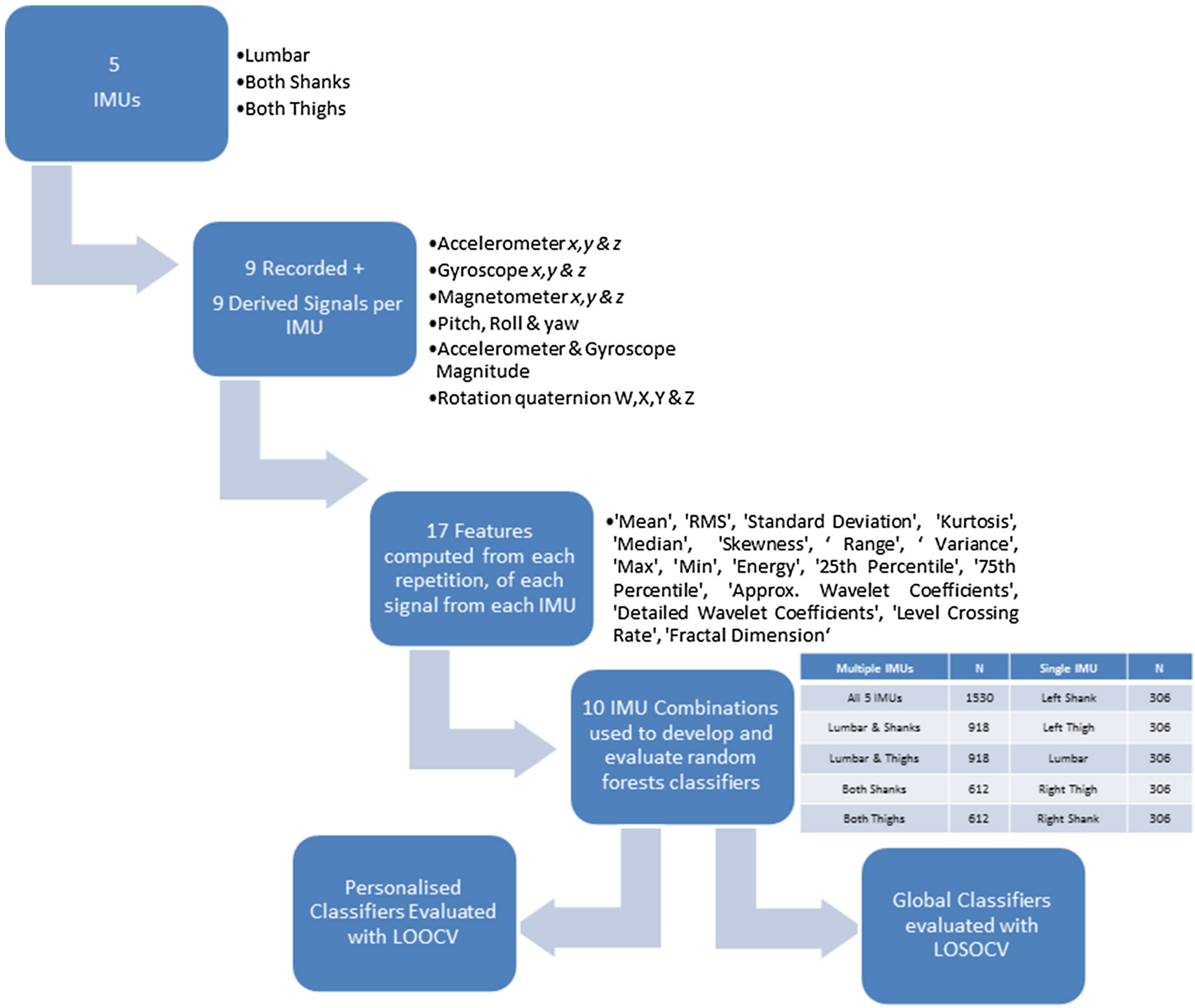

Fig. 2. Diagram linking number of IMUs, number of recorded and derived signals, number of features extracted and the variety of feature combinations used to test classifiers.

In reviewing the accuracy, sensitivity and specificity scores produced by each classifier, 90% or higher was considered an 'excellent' quality result, 80–89% was considered a 'good' quality result, 60–79% was considered a 'moderate' result and anything less than 59% was deemed a poor result. This classification accuracy rating system has been used in previously published work (Whelan et al., 2016a, 2016b). For personalised classifiers, each participant's scores were calculated then the mean and standard deviation across all participants were computed.

3. Results

3.1. Data set

Table 1 shows the total number of extracted deadlift repetitions for each class in experiment 1 (induced reps) and experiment 2 (natural reps). The data set from experiment 1 is larger and more balanced that that arising from experiment 2.

3.2. Experiment 1: Induced technique deviations

Binary classification results for the data set collected in experiment 1, where participants deliberately completed deadlifts with technique deviations, are demonstrated in Table 2. It shows the classification accuracy, sensitivity and specificity (Formulae 1–3) following cross-validation for both universal and personalised classifiers. Results are also compared for systems developed using data from each individual IMU and a variety of combinations of 5, 3 and 2 IMUs.

Multi-label classification results (i.e. detection of exact technique deviation) are demonstrated in Table 3. The results show classification efficacy when using data derived from each individual IMU and various combinations of multiple IMUs.

3.3. Experiment 2: Naturally occurring technique deviations

Table 4 compares the quality of universal classifiers and personalised classifiers in the binary classification of deadlift technique using the data set of naturally occurring technique deviations from experiment 2. Classification efficacy is shown for systems using multiple IMUs and systems developed using individual IMUs at various anatomical positions. The results shown in Table 5 show the capacity of IMU based systems to classify which natural deviation presents using universal and personalised classifiers.

4. Discussion

The objective of this study was to determine whether an IMU system could identify deviations from acceptable deadlift biome-

Table 2
Overall accuracy, sensitivity and specificity in binary classification (acceptable or aberrant technique) for each combination of IMUs following LOSOCV to evaluate global classifiers and LOOCV to evaluate personalised classifiers for induced technique deviations.

IMU placement(s)	Global classifiers			Personalised classifiers ($\bar{x}(SD)$)		
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
All 5 Sensors	75	57	89	93 (6)	90 (9)	96 (6)
Lumbar & Shanks	71	53	85	93 (6)	91 (7)	96 (7)
Lumbar & Thighs	74	56	87	91 (6)	89 (9)	93 (9)
Both Shanks	66	47	80	91 (6)	88 (9)	95 (7)
Both Thighs	73	58	84	90 (8)	86 (10)	93 (8)
Left Shank	64	48	76	88 (10)	86 (11)	89 (11)
Left Thigh	68	58	75	87 (8)	85 (9)	89 (10)
Lumbar	70	52	83	88 (8)	90 (9)	86 (11)
Right Thigh	72	59	82	89 (9)	86 (10)	91 (10)
Right Shank	63	42	79	90 (7)	87 (8)	92 (10)

Table 3
Overall accuracy, sensitivity and specificity in multi-class classification (exact deviation) for each combination of IMUs following LOSOCV to evaluate global classifiers and LOOCV to evaluate personalised classifiers for induced technique deviations.

IMU placement(s)	Global classifiers			Personalised classifiers ($\bar{x}(SD)$)		
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
All 5 Sensors	60	62	92	81 (11)	83 (13)	96 (2)
Lumbar & Shanks	56	59	91	81 (10)	83 (11)	96 (2)
Lumbar & Thighs	55	56	91	79 (12)	81 (13)	96 (3)
Both Shanks	38	43	88	75 (14)	77 (15)	95 (3)
Both Thighs	48	46	89	74 (13)	76 (14)	95 (3)
Left Shank	37	41	87	71 (15)	73 (17)	94 (3)
Left Thigh	37	38	87	67 (13)	69 (16)	93 (3)
Lumbar	49	52	90	72 (13)	75 (14)	94 (3)
Right Thigh	44	43	89	74 (14)	75 (14)	94 (3)
Right Shank	34	39	87	73 (13)	74 (15)	94 (3)

Table 4
Overall accuracy, sensitivity and specificity in binary classification (acceptable or aberrant technique) for each combination of IMUs following LOSOCV to evaluate universal classifiers and LOOCV to evaluate personalised classifiers for natural technique deviations.

IMU placement(s)	Global classifiers			Personalised classifiers ($\bar{x}(SD)$)		
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
All 5 Sensors	73	78	49	84 (13)	83 (17)	83 (17)
Lumbar & Shanks	70	76	34	83 (13)	81 (17)	82 (16)
Lumbar & Thighs	70	76	42	82 (12)	80 (16)	81 (20)
Both Shanks	65	72	27	82 (15)	79 (22)	78 (20)
Both Thighs	70	74	42	82 (14)	79 (16)	82 (23)
Left Shank	63	68	39	80 (15)	80 (17)	76 (24)
Left Thigh	67	70	48	80 (14)	79 (16)	77 (22)
Lumbar	70	76	34	80 (14)	80 (15)	78 (22)
Right Thigh	71	78	36	82 (13)	79 (16)	81 (21)
Right Shank	69	76	31	80 (15)	79 (21)	77 (23)

Table 5
Overall accuracy, sensitivity and specificity in multi-class classification (exact deviation) for each combination of IMUs following LOSOCV to evaluate global classifiers and LOOCV to evaluate personalised classifiers for natural technique deviations.

IMU placement(s)	Global classifiers			Personalised classifiers ($\bar{x}(SD)$)		
	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)
All 5 Sensors	54	18	87	78 (13)	74 (21)	90 (12)
Lumbar & Shanks	54	18	87	75 (13)	78 (13)	66 (34)
Lumbar & Thighs	32	18	82	77 (13)	75 (15)	81 (15)
Both Shanks	32	17	84	73 (18)	72 (22)	78 (21)
Both Thighs	48	13	83	74 (19)	72 (25)	77 (22)
Left Shank	47	11	82	71 (18)	74 (16)	70 (29)
Left Thigh	56	11	81	67 (20)	68 (21)	68 (23)
Lumbar	36	11	81	75 (14)	74 (15)	83 (12)
Right Thigh	38	13	77	71 (19)	71 (24)	71 (26)
Right Shank	53	15	84	69 (13)	65 (20)	78 (20)

chanics. The results in Section 3 indicate this is possible with good to excellent overall accuracy using a personalised classifier. Personalised classifiers outperform universal classifiers in attempting to identify both induced and natural deadlift deviations regardless of IMU set-up. IMU systems using a personalised classifier produce good to excellent accuracy when identifying induced deviations from acceptable deadlift biomechanics (Tables 2 and 3). Personalised classifiers can also identify natural deviations with moderate to good accuracy (Tables 4 and 5).

In reviewing the literature, no data was found on the ability of an IMU system to classify deadlift technique. Gleadhill et al. (2016) compared the ability of an IMU system in identifying temporal features in the deadlift to a motion capture system, finding high agreement. The results presented in this work build upon this research by using temporal and other time and frequency domain features to create a classification framework. Furthermore, the high agreement achieved by Gleadhill et al. (2016) are achieved with a 3 IMU system. The results presented in Section 3 indicate that a single IMU system is capable of classifying acceptable and aberrant deadlift technique with moderate to excellent accuracy. Single IMU systems are less expensive and more practical for end users due to reduced risk of placement error and power usage, making them more desirable for daily environment applications (Bonnet et al., 2012).

It is difficult to directly compare results with similar work due to differences in exercises investigated, dataset sizes, sensor positions and end user feedback. However, these results compare favourably to research in the area (Giggins et al., 2014; Melzi et al., 2009; O'Reilly et al., 2015; Taylor et al., 2012; Velloso et al., 2013; Whelan et al., 2015, 2016a). The majority of research to date has investigated the ability of IMU systems to monitor technique in simple exercises such as straight leg raises, dumbbell curls or heel slides (Giggins et al., 2014). This paper evaluates an IMU system's ability to assess deadlift biomechanics, a complex multi-joint exercise. The presented system can distinguish between six different deadlift classes (acceptable and five deviations) with moderate to good overall accuracy (Tables 3 and 5). The lower number of classes in some studies (Giggins et al., 2014; Taylor et al., 2012; Velloso et al., 2013) may make it easier for classifiers to identify specific deviations with higher efficacy. Furthermore, the system presented in this work is capable of identifying natural deviations from acceptable deadlift biomechanics. The majority of previous research identified induced deviations using a universal classifier (Giggins et al., 2014; O'Reilly et al., 2015; Taylor et al., 2012).

Universal classification techniques have been shown to classify naturally occurring deviations in the single leg squat with moderate accuracy (Whelan et al., 2015, 2016b). However, the ability of this classifier to identify specific deadlift deviations is poor (Table 5). This may be due to a number of factors. The number of acceptable deadlifts far outnumbers any other label (Table 1). This unbalanced data set makes it difficult to create universal classifiers that can be used for all individuals (Chawla, 2005; He and Garcia, 2009). As many deviations were sporadic, the use of a universal classifier to identify specific deadlift deviations may require a larger data set including more deviations. Additionally, the inter-subject variability in acceptable deadlift biomechanics, as described by the IMU sensor signal features, may exceed the intra-subject variability between acceptable technique and aberrant deadlift biomechanics. This would make universal classifier creation difficult.

In addition to producing higher overall classification accuracy, a personalised classifier may offer other benefits. Personalised classifiers are more computationally efficient than universal classifiers as they use less training data and therefore require less memory. Unlike universal classifier development, they negate the need for a large data set to classify exercise biomechanics, (Chawla, 2005; He and Garcia, 2009). The use of a personalised classifier may also allow for the development of a universal classifier in the future. All labelled data collected for personalised classifier development could be stored and used to build the large data set necessary to improve universal classifiers. The main disadvantage associated with a personalised classifier is that data must be collected and labelled from individual patients. This means practitioners must monitor exercise technique in real time or use post hoc video analysis and label appropriately, which may prove time consuming. However, since practitioners often monitor exercise biomechanics prior to independent exercise completion, it may fit into clinical practice smoothly. In an effort to streamline this process, the authors have recently developed a tablet application that enables clinicians to simultaneously capture video and IMU data from a person exercising. The application automatically splits video and IMU data into reps, allows efficient repetition labelling and can automatically build personalised classifiers.

In conclusion, the deadlift is important in rehabilitation and strength and conditioning. Accurate deadlift biomechanics quantification is important to reduce injury risk and ensure goals are achieved. The work presented in this paper indicates that an IMU system can classify acceptable and aberrant deadlift biomechanics with good to excellent overall accuracy, sensitivity and specificity using a personalised classifier. Furthermore a personalised classification system is far better at identifying specific naturally occurring deadlift deviations. The results presented in this work are comparable with current research in the area. However, most of this research has been carried out using universal classifiers and identifying induced deviations. While a universal classifier may allow for less end user interaction, it is difficult to classify naturally occurring deviations from acceptable deadlift biomechanics using this technique. As a result, the use of a personalised classifier may be more appropriate for identifying aberrant deadlift biomechanics.

Conflict of interest statement

All authors of this article would like to state that there are no known conflicts of interest that could have biased or influenced the presented article.

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