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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