Objective Classification of Dynamic Balance Using a Single Wearable Sensor

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Keywords: Dynamic Balance, Inertial Measurement Unit, Y Balance Test, Fatigue, Lumbar.

Abstract: The Y Balance Test (YBT) is one of the most commonly used dynamic balance assessments in clinical and research settings. This study sought to investigate the ability of a single lumbar inertial measurement unit (IMU) to discriminate between the three YBT reach directions, and between pre and post-fatigue balance performance during the YBT. Fifteen subjects (age: 23±4, weight: 67.5±8, height: 175±8, BMI: 22±2) were fitted with a lumbar IMU. Three YBTs were performed on the dominant leg at 0, 10 and 20 minutes. A modified Wingate fatiguing intervention was conducted to introduce a balance deficit. This was followed immediately by three post-fatigue YBTs. Features were extracted from the IMU, and used to train and evaluate the random-forest classifiers. Reach direction classification achieved an accuracy of 97.80%, sensitivity of 97.86±0.89% and specificity of 98.90±0.56%. "Normal" and "abnormal" balance performance, as influenced by fatigue, was classified with an accuracy of 61.90%-71.43%, sensitivity of 61.90%-69.04% and specificity of 61.90%-78.57% depending on which reach direction was chosen. These results demonstrate that a single lumbar IMU is capable of accurately distinguishing between the different YBT reach directions and can classify between pre and post-fatigue balance with moderate levels of accuracy.

1 INTRODUCTION

Dynamic balance requires the maintenance of equilibrium during tasks that involve movement of the centre of mass outside of the base of support (Gribble et al., 2012). The Star Excursion Balance Test (SEBT) is one of the most commonly used dynamic balance assessment tools (Holden et al., 2016, Doherty et al., 2016, Gribble et al., 2012, Smith et al., 2015). It assesses many facets of the sensorimotor spectrum, including strength, proprioception and dynamic balance, closely mimicking the functional demands required for optimal sports performance. The SEBT requires the individual to maintain their balance, while reaching as far as possible in eight directions (Gribble et al., 2012).

Large bodies of research have demonstrated dynamic balance deficits, as measured by the SEBT, between control and pathological groups with conditions such as acute ankle injuries (Doherty et al., 2015), chronic ankle instability (Doherty et al., 2016) and anterior cruciate ligament injuries (Herrington et al., 2009). Additionally, researchers have attempted to establish the role these assessments play in the detection of risk factors that may predispose individuals to lower limb injuries (Gribble et al., 2015, Plisky et al., 2006). Despite this, there are a number of limitations to the SEBT which should be considered. These include the non-standard stance surface, the lack of a definite starting point reference, the time consuming nature of completing eight reach directions and the requirements of the assessor to visually monitor the stance foot, while marking the maximal reach distance (Gribble et al., 2012, Plisky et al., 2009). In an attempt to address some of these limitations, improve the reliability and the uptake of dynamic balance tests in clinical practice, the redundancy of five of the eight reach directions was demonstrated. This resulted in the development of the commercially available Y Balance Test (YBT) (functionalmovement.com, Danville, VA) which incorporates the anterior (ANT), posteromedial (PM) and posterolateral (PL) reach directions of the SEBT (Plisky et al., 2009).

Johnston, W., O'Reilly, M., Dolan, K., Reid, N., Coughlan, G. and Caulfield, B.
Objective Classification of Dynamic Balance Using a Single Wearable Sensor.
DOI: 10.5220/0006079400150024
In *Proceedings of the 4th International Congress on Sport Sciences Research and Technology Support (icSPORTS 2016)*, pages 15-24
ISBN: 978-989-758-205-9

While the YBT does address some of these aforementioned limitations, there are a number of challenges which continue to restrict its use in clinical practice. Firstly, while research has shown that these assessments are capable of demonstrating statistically significant differences in reach distances between groups (Plisky et al., 2006, Gribble et al., 2015, Doherty et al., 2016, Doherty et al., 2015, Herrington et al., 2009), it has been difficult to determine clinically relevant cut off points. Plisky and colleagues (2006) and Smith and colleagues (2015) reported that a right/left asymmetry of greater than 4cm on the ANT reach direction of the SEBT and YBT respectively is associated with an increased risk of a lower limb injury. While Gribble and colleagues (2015) reported that a reduced ANT reach distance, in combination with high BMI, is associated with increased risk of lower limb injury. Schaefer and colleagues (2012) reported that the minimally detectable change for normalised reach distances ranged from 4.9-5.4% for the different reach directions, while Munro et al (2010) showed that the smallest detectable difference ranged from 6.87-8.15% of leg length depending on the reach direction. While these thresholds provide guidance for clinicians on the reach distances that can be considered clinically relevant, they are population specific, and only provide a small amount of clinically relevant information. Another is the time consuming nature of the YBT testing protocol, which requires the individual to complete 4 practice trials followed by 3 recorded trials in order to obtain a reliable and repeatable score (Gribble et al., 2012).

An additional strategy which has been employed to improve the accuracy and objectivity of the SEBT and YBT is the use of marker based motion analysis and force platform systems, providing information on the control of movement and balance strategy employed during the task (Coughlan et al., 2012, Fullam et al., 2014, Doherty et al., 2015). However, these methods have a number of major limitations, restricting their application in clinical practice. Firstly, the set-up is time intensive and requires training, increasing the overall testing time and limiting the number of clinicians with the experience required to use the systems with efficacy. The systems are expensive (> €100,000). They are commonly not accessible outside of a laboratory environment. The application of markers may hinder natural movement during dynamic tasks (Bonnechère et al., 2014, Ahmadi et al., 2014). The data recorded from such systems also requires extensive processing and analysis, which is time consuming.

In recent times, there has been a shift away from traditional motion capture systems towards unobtrusive systems that incorporate inertial measurement units (IMUs) (Ahmadi et al., 2014). Such systems address some of the aforementioned limitations of traditional motion capture, as they allow for inexpensive, accessible quantification of human movement, in an unconstrained environment (Giggins et al., 2013). These IMU systems have been used in the objective quantification of a range of activities, from static balance tasks (King et al., 2014, Alberts et al., 2015, Furman et al., 2013), to dynamic tasks such as the squat (O'Reilly et al., 2015) and single leg squat (Whelan et al., 2015), walking (Zijlstra and Hof, 2003, Yang et al., 2013) and running (Lee et al., 2010). Early work investigating the use of IMUs in balance assessment has shown that a static balance assessment, instrumented with an IMU mounted on the lumbar spine, was not as effective as the traditional subjectively scored assessment in identifying balance deficits post-concussion (Furman et al., 2013). More recently, King et al (2014) demonstrated improved levels of sensitivity and specificity from the instrumented balance error scoring system (BESS). It is likely that the conflicting results are due to the different quantified variables selected in the two studies. King et al (2014) utilised root mean squared acceleration, whereas Furman et al (2013) used sway path length, which may not be capable of detecting subtle changes in balance, when measured using a lumbar mounted IMU. While these initial studies have demonstrated the ability of IMUs to detect differences in static balance between groups, there is a paucity of evidence surrounding their ability to classify dynamic balance performance during tasks such as the YBT.

Previous research has established the effect various forms of muscle fatigue such as high intensity intermittent exercise (Whyte et al., 2015), lower limb functional exercises (Gribble et al., 2009) and isolated muscle fatigue (Gribble and Hertel, 2004, Gribble et al., 2009) have on dynamic balance. The combined physiological effects of central and peripheral fatigue mechanisms may result in changes to the integration of sensorimotor information from the balance subsystems, leading to decreased balance performance. Therefore, this research sets out to evaluate the ability of a single lumbar mounted IMU to objectively quantify dynamic balance performance. It is hypothesised that a single IMU system has the potential to accurately differentiate the three reach directions (ANT, PM and PL) and distinguish "normal" and "abnormal" balance as influenced by fatigue.

2 METHODS

2.1 Subjects

Fifteen healthy participants aged between 18 and 40 (age: 23±4, weight: 67.5±8, height: 175±8, BMI: 22±2) who actively participate in sport were recruited from the wider university population. Participants were excluded from the study if they suffered from chronic ankle instability, had sustained a lower limb injury in the last six months, had vestibular, visual or balance impairment, cardiovascular disease, any neurological disease, or answered yes to any questions on the PAR-Q (Warburton et al., 2011). Ethical approval was obtained from the University Human Research Ethics Committee and all participants provided informed consent prior to participating in the study.

2.2 Measures

2.2.1 Y-Balance Test

The YBT is an instrumented alternative to the SEBT, capable of measuring dynamic postural control. The YBT utilises three of the eight original SEBT reach directions (ANT, PM and PL) and was developed in order to provide a more objective reach distance measurement, allowing for more accurate results, collected in a less time consuming manner. The YBT has been reported to demonstrate excellent intra-tester (0.85-0.89) and inter-tester (0.97-1.00) reliability (Plisky et al., 2009). The YBT requires participants to stand on one leg, with their hands on their hips, and slide a block as far as possible in the three specified directions, with the contralateral limb, before returning to bilateral stance. A fail is recorded if the participant (1) uses the block for support, (2) raises the stance heel from the platform, (3) makes ground contact, (4) kicks the block forward to gain extra distance or (5) removes one or both hands from the hips during the task. The reach distances are then normalised against the participant's leg length using the formula:

$$\begin{gathered} Normalised\ Reach\ Distance = \\ (Reach\ Distance)\ /\ (Leg\ Length) \end{gathered} \tag{1}$$

Leg length is obtained by the same investigator for each study participant by measuring the distance from the anterior-superior iliac spine to the most distal aspect of the medial malleolus (Gribble and Hertel, 2003). The average YBT reach distances scores used for analysis were obtained by finding the mean of the three normalised maximal YBT scores in each reach direction. The YBT testing protocol was developed and conducted according to the guidelines outlined by Gribble and colleagues (2012).

2.2.2 Modified Wingate Test

The Wingate test is traditionally used in the measurement of peak anaerobic power and anaerobic capacity (Smith and Hill, 1991). A modified version of the extended Wingate test protocol employed by Carey and Richardson (2003) was used during this study in order to maximally fatigue participants. The modified test requires participants to cycle at maximal intensity for 60 seconds, rather than the traditional 30 second protocol. The cycle ergometer resistance is set to *0*.075 g·kg-1 as per previously published methods (Kraemer et al., 2000, Laurent et al., 2007). Prior to commencement of the Wingate test, participants completed a 5-minute warm-up cycling at 50-60 RPM, which included 3 x 5 second sprints. Following the 5-minute warm-up, participants commenced cycling at a cadence of 50-60 RPM for 30 seconds. At the end of the 30 second period, the 60 second Wingate test commenced, and participants were encouraged to maintain a maximal effort for the duration of the 60 seconds in order to ensure maximal fatigue.

2.2.3 Inertial Measurement Unit

A Shimmer3 IMU (Shimmer, Dublin, Ireland) was mounted at the level of the fourth lumbar vertebra (Figure 1). The IMU was calibrated and configured to stream tri-axial accelerometer (±2 g), gyroscope (±500 ◦/s) and magnetometer (±1 gauss) data at 102.4 Hz via Bluetooth to an Android tablet, using Multi-Shimmer sync software (Shimmer, Dublin, Ireland). These data acquisition parameters were chosen based on previous work carried out by our research group

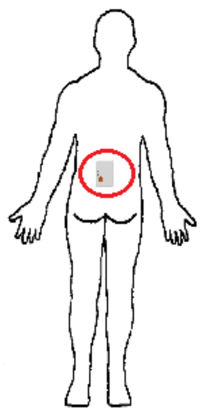

Figure 1: Illustrates the mounting location of the Lumbar IMU.

investigating the use of IMUs in the evaluation of exercise technique during similar movements, such as the single leg squat (O'Reilly et al., 2015).

2.3 Procedure

On arrival to the performance laboratory, the experimental protocol was explained to the participants, and individuals completed 4 practice trials in each direction, on their dominant leg (all right leg dominant). Leg dominance was obtained by asking the participants which leg they would use to kick a ball (Wilkins et al., 2004). Following completion of the practice trials, each participant was fitted with the IMU as described above. Participants then completed three recorded YBT in each direction (randomised order) on the dominant limb. This was repeated at 0, 10 and 20-minutes in order to provide a pre-fatigue baseline measurement of dynamic balance. YBT maximal reach distances and IMU data were collected for each YBT attempt. If a participant failed to complete the test as described above, the individual reach direction was repeated, and an annotation was recorded in the IMU data to denote a failed and repeated reach direction.

Following the baseline assessment, participants completed the modified Wingate protocol in order to elicit maximal anaerobic fatigue. Immediately following the Wingate protocol, participants completed the YBT to capture the reduced dynamic balance performance elicited by maximal anaerobic fatigue.

2.4 Data Analysis

Nine signals were collected from the IMU; accelerometer *x, y, z,* gyroscope *x, y, z* and magnetometer *x, y, z*. Data were analysed using MATLAB (2012, The MathWorks, Natwick, USA). To ensure the data analysed applied to each participant's movement and in order to eliminate unwanted high-frequency noise, the nine signals were low pass filtered with an 8^{th} order Butterworth filter with a 20Hz cut-off. Nine additional signals were then calculated. The 3-D orientation of the IMU was computed using the gradient descent algorithm developed by (Madgwick et al., 2011). The resulting W, X, Y and Z quaternion values 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 planes respectively. The magnitude of acceleration was also computed using the vector magnitude of accelerometer *x, y, z*. The magnitude of acceleration describes the total acceleration of the IMU in any direction. This is the sum of the magnitude of inertial acceleration of the lumbar spine and acceleration due to gravity. Additionally, the magnitude of rotational velocity was computed using the vector magnitude of the gyroscopes *x, y* and *z*.

Each reach direction from each completed YBT was extracted from the IMU data and resampled to a length of 1000 samples; this was undertaken to minimise the influence of the speed of repetition performance on signal feature calculations. It ensures the computed features related to differences in movement patterns and not the participant's exercise tempo. Descriptive features were computed in order to characterise the pattern of each of the eighteen signals as the YBT was completed. These features were namely 'Mean', 'RMS', 'Standard Deviation', 'Kurtosis', 'Median', 'Skewness', ' Range', 'Variance', 'Max', 'Index of Max', 'Min', 'Index of Min', 'Energy', '25th Percentile', '75th Percentile', 'Level Crossing Rate' and' Fractal Dimension' (Katz and George, 1985) . This resulted in 17 features for each of the 18 available signals producing a total of 306 features. These features were then used to develop and evaluate a classifier for the automated detection of reach direction in the YBT and a separate classifier for the detection of pre-fatigue or fatigued YBT performance. The random-forests method was employed to perform classification of reach direction and for the detection of fatigued YBT performance (Breiman, 2001). This technique was chosen as it has been shown to produce superior accuracy, sensitivity and specificity scores in analysing exercise technique with IMUs in comparison to the Naïve-Bayes and Radial-basis function network techniques (Mitchell et al., 2015). Four hundred decision trees were used in each random-forest classifier.

The quality of the exercise classification system was established using leave-one-subject-out-cross-validation (LOSOCV) and the random-forests classifier with four hundred trees (Fushiki, 2011). Each participant's data corresponds to one fold of the cross validation. At each fold, one participant's data is held out as test data while the random forests classifier is trained with all other participants' data. The held out data is used to assess the classifier's ability to correctly categorise unseen data. The use of LOSOCV ensures that there is no biasing of the classifiers, meaning the test subjects data is completely unseen by the classifier prior to testing. Previous research by Taylor et al (2010) has shown that not employing this method of testing can skew results significantly. In our system, each individual reach direction was classified.

The scores used to measure the quality of classification were total accuracy, average sensitivity and average specificity. Accuracy is the number of correctly classified observations divided by the total number of observations completed; this is calculated as the sum of the true positives (TP) and true negatives (TN) divided by the sum of the true positives, false positives (FP), true negatives and false negatives (FN):

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{2}$$

The sensitivity and specificity were calculated for each of the reach directions, sequentially treating each label as the 'positive' class, and then the mean and standard deviation across the five values was taken. Sensitivity and specificity were computed using formulas 3 and 4 below:

$$Sensitivity = \frac{TP}{TP+FN} \tag{3}$$

$$Specificity = \frac{TN}{TN+FP} \tag{4}$$

Sensitivity measures the effectiveness of a classifier at identifying a desired label, while specificity measures the classifiers ability to detect negative labels. In the detection of fatigued balance, single sensitivity and specificity scores were calculated, treating pre-fatigued balance as the positive class and fatigued balance as the negative class.

In reviewing the accuracy, sensitivity and specificity scores produced by each classifier, 90% or over was considered an excellent 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. These values were chosen by the authors after reviewing existing literature on identifying exercises with IMUs. In reviewing such literature, an existing accepted standard for a good, moderate or poor classifier could not be found. Therefore, the above system was agreed on by the authors to facilitate interpretation of our range of results.

3 RESULTS

ICC values for the three normalised reach directions ranged from 0.976 – 0.986, indicating excellent test-retest reliability across the pre-fatigue measures. Due to the excellent ICC scores observed, the final pre-fatigue measure was considered representative of the pre-fatigue state, and was used in the comparison pre and post-fatigue. The SEM ranged from 0.792-1.48 for the three YBT reach directions. The average decrease in YBT reach distances following the fatigue protocol was 2.65 ± 4.91 (ANT), 2.44 ± 3.06 (PM) and 3.57 ± 4.27 (PL). Paired samples t-tests demonstrated statistically significant differences ($p < 0.05$) between the final pre-fatigue YBT measurement and the first post-fatigue measurement in all reach directions (Table 1).

Table 1: Comparison of ICC, SEM and paired sample t-tests for the YBT normalised Reach Direction for all three directions. The level of significance was set to $p < 0.05$ and statistically significant values were denoted with an*.

Reliability Analysis Pre01, Pre02 & Pre03			Level of Significance (p Values) for Post-hoc Paired t-test
Reach Distance	**ICC**	**SEM**	**Pre03 vs Post01**
ANT	0.986	0.792	0.049*
PM	0.976	1.482	0.008*
PM	0.978	1.134	0.006*

The classification algorithm for a single lumbar mounted IMU was capable of differentiating the three reach directions in the pre-fatigue baseline measures with an accuracy of 97.80%, Sensitivity of 97.86 ± 0.89% and specificity of 98.90 ± 0.56%. Figure 2 presents a confusion matrix that illustrates the exact percentage of reach direction repetitions that were classified correctly and incorrectly. The rows represent the actual reach direction recorded and the columns show the classifier's predicted reach direction.

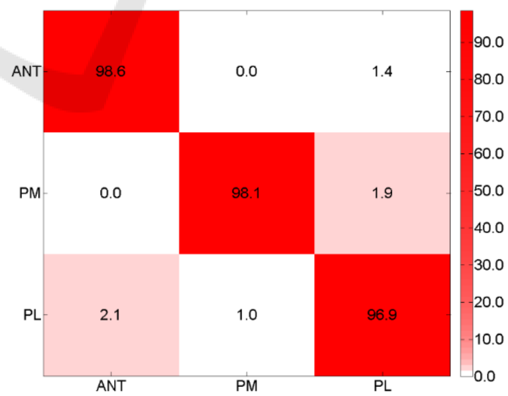

Figure 2: A confusion matrix showing multi-class classification results for the three reach directions. The percentage of reach direction attempts classified correctly are marked in bold.

A single lumbar mounted IMU was capable of discriminating pre and post-fatigue balance performance with an accuracy of 61.90%-71.43%, sensitivity of 61.90%-69.04% and specificity of 61.90%-78.57% depending on which reach direction was chosen (Table 3). When all reach directions were considered together, balance performance was classified with an accuracy of 70.24%, sensitivity of 64.28% and specificity of 76.19%.

Table 2: The accuracy, sensitivity and specificity results of the classification algorithm in the detection of baseline and fatigued dynamic balance.

	ANT	PM	PL	All Directions
Accuracy	61.90	71.43	70.24	70.40
Sensitivity	61.90	69.04	61.90	64.28
Specificity	61.90	73.80	78.57	76.19

4 DISCUSSION

The purpose of this study was to determine if data derived from a single lumbar mounted IMU is capable of accurately differentiating the individual reach directions of the YBT, and classifying pre and post-fatigue dynamic balance performance.

The traditional normalised YBT reach distance results presented demonstrate that the modified Wingate protocol had a detrimental effect on the participant's dynamic balance. The ICC values for the pre-fatigue baseline assessments presented suggest that the normalised YBT reach distance scores for each reach direction possess excellent test-retest reliability. The paired sampled t-test results (Table 1) demonstrate that there was a statistically significant difference between the final pre-fatigue measurement and the post-fatigue measurements, suggesting that the fatigue intervention had a detrimental effect on the YBT reach distances for all three reach directions. Additionally, the SEM results for all reach directions was smaller than the average decrease in reach distance between the final pre-fatigue and the post-fatigue measurement, indicating that the fatigue intervention had a negative effect on reach distance scores. When the SEM is viewed in conjunction with the ICC, it allows us to be sure that any deviation from the baseline is as a result of the fatiguing intervention, and not a consequence of natural biological variation.

The results presented in this paper support previously published ones indicating that dynamic balance is heavily influenced by isolated muscle fatigue (Gribble et al., 2004, Gribble et al., 2009), lower limb fatiguing exercises (Gribble et al., 2009), treadmill running (Wright et al., 2013) and high intensity intermittent exercise protocols (Whyte et al., 2015). Whyte and colleagues (2015) investigated the effect of high intensity intermittent exercise on dynamic balance, as measured by the SEBT. It was reported that the percentage reduction in SEBT reach distance, for the ANT, PM and PL directions were marginally lower than those presented in our study. Importantly, these differences may be a result of the different fatiguing interventions influencing the sensorimotor system to different extents (Whyte et al., 2015). Additionally, different methods of dynamic balance assessments were utilised in the two studies. Whyte and colleagues (2005) used the SEBT, whereas the YBT was implemented in our study, potentially explaining the difference in the magnitude of change (Coughlan et al., 2012). These past findings, combined with the results from this study, demonstrate that at a group level, the fatigue intervention had a negative effect on dynamic balance.

The IMU classification system was capable of differentiating individual YBT reach directions with excellent levels of accuracy, sensitivity and specificity. The confusion matrix (Figure 2) illustrates the percentage of the reach directions classified correctly and incorrectly, indicating where the confusion occurred. The ANT reach direction was classified with the greatest success rate of 99%, followed by PM (98%), and then PL (97%). These results may be expected as the three reach directions utilise different strategies to complete a maximal reach. The ANT reach direction involves a single planar movement which incorporates a single leg squat type movement, while the individual reaches outside of their base of support. In contrast, the PM and PL movements involve multi-planar movements, requiring the individual to enter a single leg squat, while rotating at the pelvis and trunk in order to achieve a maximal reach distance. Indeed, previous research conducted by Kang and colleagues (2015) investigating trunk, pelvic and lower limb kinematic strategies utilised during the YBT. The results presented by their group demonstrate that the ANT reach direction requires a largely different strategy to the PM and PL directions. The ANT direction requires minimal trunk and pelvic kinematic movements, with 1° trunk extension, 4° trunk ipsilateral flexion, 9° anterior pelvic tilt, and 1° of pelvic ipsilateral rotation. The majority of the movement strategies stem from sagittal plane movements at the hip (30° flexion), knee (62° flexion) and ankle (39° dorsiflexion). In contrast, the PM and PL reach directions require large changes in trunk and pelvic kinematics, with the PM reach direction requiring 43° trunk flexion, 21° trunk ipsilateral flexion, 39° anterior pelvic tilt and 0° of pelvic contralateral rotation, and the PL reach direction requiring 48° trunk flexion, 16° trunk contralateral flexion, 38° anterior pelvic tilt and 11° of pelvic contralateral rotation. These results clarify the similarities and differences between the movement strategies utilised during each reach direction, contextualising how the classification algorithm was capable of classifying the individual reach directions with such high degrees of accuracy.

The YBT reach direction classification results presented in this study are in line with previously published IMU exercise identification results which range between 85-95% depending on the exercises and IMU setups (Giggins et al., 2014, Pernek et al., 2015, Chang et al., 2007). Giggins and colleagues (2014) demonstrated that a single IMU location could differentiate between seven basic rehabilitation exercises with an accuracy of between 93-95% depending on the mounting location. Additionally, Pernek and colleagues (2015) reported that a single IMU system can correctly identity upper limb free weight exercises with 85% accuracy. This is significant as the excellent levels of accuracy (98%) presented in this study were achieved using just 252 observations. In contrast, the exercise classification work presented above used a greater number of observations to train the classifiers, with Giggins et al (2014) utilising 3940 observations and Pernek et al (2015) using 440 observations per exercise.

The lumbar IMU classification algorithm was capable of differentiating dynamic balance performance, as influence by fatigue, with and accuracy of between 62% and 71%, depending on the reach direction (Table 3). The PM reach direction demonstrated the highest classification accuracy (72%), followed by the PL (70%) and then the ANT (62%) reach direction. When all reach directions were considered together, the classification algorithm was able to differentiate normal and abnormal balance with an accuracy of 70%.

These results would be expected, because as we previously discussed above, the three reach directions require different levels of movement strategy complexity. The ANT reach direction presented with the lowest degree of classification accuracy. The ANT reach direction is the least complex movement, predominantly requires sagittal plane movement of the stance limb (Kang et al., 2015). It may be that the ANT reach direction movement does not sufficiently challenge the sensorimotor system in all individuals to elicit a balance deficit large enough to be consistently detected by the lumbar mounted IMU. In contrast, the higher degree of accuracy observed in the detection of abnormal balance during the PM and PL reach directions are expected as these movements require the individual to implement a more complex multi-planar movement strategy. Both the PM and PL reach directions require the individual to reach outside of their base of support while utilising their trunk as a mobile counter-lever, involving a combination of complex multi-planar movements occurring at the trunk, pelvis, hips, knee and ankle (Kang et al., 2015, Fullam et al., 2014, Doherty et al., 2016). This complex multi-planar movement may more comprehensively challenge the integration of the sensorimotor subsystems, resulting in more pronounced strategy changes following the introduction of a balance deficit, thus leading to differences in the IMU data.

To the best of the authors knowledge this is the first research study that has attempted to classify dynamic balance performance using an IMU. Previous research has investigated the ability of single and multiple IMUs to detect technique breakdown during compound lower limb exercises such as the squat (O'Reilly et al., 2015) and single leg squat (Whelan et al., 2015). Lower limb exercises such as the single leg squat incorporate many of the requirements involved during the YBT reach directions, such as maintaining one’s balance while executing a dynamic task on a single leg. Whelan and colleagues (2015) reported that a single lumbar based IMU mounted on the lumbar spine was capable of classifying correct and incorrect single leg squat technique with an accuracy of 92%. While the classification accuracy presented by Whelan and colleagues is higher than that of the YBT balance performance classification presented in our study, it is probable that the YBT classification performance would be greatly improved by increasing the number of observations used to train and test the classifier.

The results presented in this paper demonstrate the potential of a single lumbar mounted IMU to automatically classify YBT reach direction and balance performance. This lays the groundwork for the development of an accurate dynamic balance performance classification system that can provide accessible, in depth, clinically relevant information, surrounding an individual’s dynamic balance, outside of the constraints of a laboratory. Future work will allow us to detect changes in movement and balance strategy during the YBT, characterising the dynamic balance defects. This would provide clinicians with more in depth information which can be used to comprehensively and objectively assess the integration of the sensorimotor subsystems, in an accessible manner. This has the potential to provide information in areas such as lower limb injuries, identification of lower limb injury risk factors, assessment of the motor function domain post-concussion, as well as balance training in strength and conditioning and rehabilitation.

A number of limitations to the study must be acknowledged. The sample size and resultant number of observations that could be used to train and evaluate the classification algorithms were relatively small, potentially resulting in decreased levels of accuracy. It can be expected that as the number of participants and observations are increased, there will be a resultant increase in the accuracy of the balance performance identification. Secondly, no gold standard motion capture system was employed in this study. However, YBT reach directions are commonly accepted as the standard in clinical balance assessments, and each participant was educated and supervised by a Chartered Physiotherapist throughout the duration of the study.

Extensive future work is required to improve the classification results presented in this paper. Firstly, a greater number of participants is required to increase the size of the data set in order to establish a normative dataset. Additionally, a classification system with improved accuracy, sensitivity and specificity will be developed. This may be achieved through investigating the effectiveness of a single IMU located at different anatomical positions, collecting a larger data set to allow for more training data for the classification algorithms and the identification of new features to input into the classifiers which enable further distinction of normal and abnormal balance. Novel classification techniques for IMU data may also be employed such as the application of deep learning on the data. This will also require a larger data set to be collected.

5 CONCLUSION

To conclude, the results presented in this paper demonstrate that a lumbar mounted IMU is capable of accurately distinguishing the three YBT reach directions, as well as classifying balance performance as influenced by a maximal anaerobic fatigue. This work lays the foundations for the development of a single IMU system, that can accurately differentiate the YBT reach directions, as well as detect changes in balance strategy, characterising and classifying dynamic balance performance.

ACKNOWLEDGMENTS

This study was funded by the Science Foundation of Ireland (12/RC/2289).

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