# Binary Classification of Running Fatigue using a Single Inertial Measurement Unit

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# Binary Classification of Running Fatigue using a Single Inertial Measurement Unit

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***Abstract*— The popularity of running has increased in recent years. A rise in the incidence of running-related overuse musculoskeletal injuries has occurred parallel to this. This study investigates the capability of using data from a single inertial measurement unit (IMU) to differentiate between running form in a non-fatigued and fatigued state. Data was captured from an IMU placed on the lumbar spine, right shank and left shank in 21 recreational runners (10 male, 11 female) during separate 400m running trials. The trials were performed prior to and following a fatiguing protocol. Following stride segmentation, IMU signal features were extracted from the labelled (non-fatigued vs fatigued) sensor data and used to train both a Global and Personalised classifier for each individual IMU location. A single IMU on the Lumbar spine displayed 75% accuracy, 73% sensitivity and 77% specificity when using a Global Classifier. A single IMU on the Right Shank displayed 100% accuracy, 100% sensitivity and 100% specificity when using a Personalised Classifier. These results indicate that a single IMU has the potential to differentiate between non-fatigued and fatigued running states with a high level of accuracy.**

## I. Introduction

The popularity of running has increased over the past few decades [1]. This has correlated with a rise in the rate of running-related overuse musculoskeletal injuries [2], with incidence ranging from 19% to 78% among studies with follow-up periods between 1 week and 18 months [3, 4].

There are many biomechanical factors that may contribute to sustaining a running related injury. These include pelvic tilt, hip excursion, heel-strike foot pattern, vertical oscillation (bounce), and under-flexed knees [3]. Biomechanical aberrations such as this can lead to running injuries such as plantar fasciopathy, Achilles tendinopathy, calf pain, medial tibial stress syndrome, patellofemoral pain (PFP), iliotibial band syndrome (ITBS), and tendinopathy [3].

Detecting these technique faults requires expert analysis and training. All of these faults can be simultaneously present while running in an exhausted state and may become further pronounced. Therefore, it is important that runners recognise when they are fatigued and are experiencing altered running 'form'. However, being able to objectively measure when this has occurred is challenging and runners are left to rely on subjective perception of their running form during the activity itself. Objective assessment of running technique is usually performed within a laboratory setting. However, these assessments often use expensive equipment, are time intensive and the application of markers may hinder normal functional movement patterns [5]. Moreover, laboratory assessment is hampered by space constraints.

In an attempt to overcome these issues wearable IMUs have seen increased attention. These sensors allow for a simple and effective processing and analysis of the movement biomechanics in real-time. They offer the potential for low cost, objective biomechanical analysis in an unconstrained environment [6]. There has been a rapid growth in their popularity in recent years with commercial products such as FitbitTM and JawboneTM utilising them for exercise monitoring and activity tracking [7, 8].

In this study we seek to determine the capability of IMUs to detect changes in a runner's non-fatigued and fatigued state. This may allow for the progression or degradation of an athletes running form to be naturally assessed in their usual sporting environment. With the recent development of more accurate and relatively inexpensive IMUs, combined with improved algorithms to more accurately determine sensor orientation, velocities and displacements, it has become feasible to deploy wearable body sensor networks in training sessions. Early detection of deteriorating form throughout the stages of a run may help athletes avoid injury by imposing personal limits on their physical stress. Forewarning to an abnormal or injury causing movement strategy would prove beneficial in early diagnosis and preventative treatment for athletes. A single IMU will ensure that the system is cost effective, not cumbersome and is less likely to cause harm to the wearer or to opponents during contact sports [5].

## II. Methods

The primary objective of this study was to determine the capability of a single IMU to differentiate between an athletes running form in a non-fatigued and fatigued state. The secondary objective was to examine the discriminative capability of a single IMU trialled at three different mounting locations, the Lumbar Spine, the Right Shank and the Left Shank during a non-fatigued and fatigued run

### *A. Participants*

21 recreationally active participants (10 males, 11 females, age: 24.6 ± 1.9 years, height: 174.2 ± 10.4 cm and body mass: 72.1 ± 10 kg) were recruited for the study. Subjects were free of chronic musculoskeletal pathology and had no lower limb injury that would impair their running

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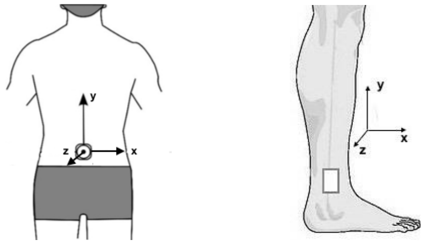

Figure 1: Location & Orientation of the Lumbar & Shank mounted IMU.

performance. Each participant signed a consent form and completed a physical activity readiness questionnaire (PAR-Q) prior to completing the study. The study protocol was reviewed and approved by the human research ethics committee in University College Dublin.

### B. *Experimental Protocol*

A pilot study was carried out to identify an appropriate sampling rate and the required ranges for the accelerometer, gyroscope and magnetometer on the IMUs (SHIMMER, Shimmer research, Dublin, Ireland). In the pilot study data were collected at 256Hz. On arrival, the testing protocol was explained to the participant and informed consent was obtained. Testing took place on an outdoor conventional track commonly used by runners. Participants completed a 5 minute warm up including light jogging and stretching of the major muscle groups. Next, IMUs were secured to the participant at the following three locations; both shanks 2cms above the lateral malleolus and on the 5th lumbar spinous process (Figure 1).

Data were acquired from each IMU placed on the participant during separate 400m running trials that were performed prior to and following a fatiguing intervention. The participants firstly ran 400m with a natural pace matching their training 5km running speed (non-fatigued state). The Beep Test or Pacer Test protocol [9] was then used to induce fatigue [10]. Participants reported their perceived level of exertion using the Borg scale at each progressive level of the beep test. The Borg RPE is a scale for Rating of Perceived Exertion (RPE). It is a tool for estimating effort, exertion, breathlessness, and fatigue during physical work [11]. When a subject could no longer match the pace to reach the next level or when a Borg rating of 18 or higher was reported the test was terminated. A subsequent 400m run was completed within 30 seconds of completing the Beep test (fatigued state).

### C. *Data Analysis*

IMU Processing: Shimmer3 IMUs (Shimmer, Dublin, Ireland) firmware and configuration settings were set using Consensys™ software (Shimmer, Dublin, Ireland) to a sampling frequency of 256 samples/s, tri-axial accelerometer (± 8 g), gyroscope (± 1000 °/s) and magnetometer (± 4 Ga) to replicate those used in recently published research [12]. Each IMU was calibrated for these specific sensor ranges using the Shimmer 9DoF Calibration application (www.shimmersensing.com/shop/shimmer-9dof-calibration).

Signal Processing: Signal processing and classification analyses were completed using MATLAB 2016b (The MathWorks, Natwick, USA). The accelerometer x, y, z, gyroscope x, y, z and magnetometer x, y, z signals were first low pass filtered at fc = 5 Hz using a Butterworth filter of order n = 5 [13]. Seven additional signals were computed, comprising of Euler; Pitch, Roll and Yaw and Quaternion W, X, Y, Z, using built in algorithms on board the Shimmer IMUs. This resulted in a total of 16 signals. Grouping the vectors of the accelerometer, gyroscopic, magnetometer, Euler and quaternions signals results in a total of 31 possible signal combinations ($C(5, r)$ $where\ r = 1{:}5$).

Stride Segmentation: An adaptive algorithm based on recent similar work, for the lumbar mounted IMU [14] and for the shank sensors [15], was used to segment stride repetitions using successive heel strikes [6]. Over a 10 second sample, ≈14 strides were captured and labelled as either a non-fatigued or fatigued state sample. This results in a total of 584 extracted stride repetitions which were labelled accordingly (292 non-fatigued, 292 fatigued). Segmented strides are shown for non-fatigued (Blue) and fatigued (Red) for two sample signals in Figure 2 and 3. Notice both an overall change in the signal plot between the two states as well as increased stride variability during the fatigued state.

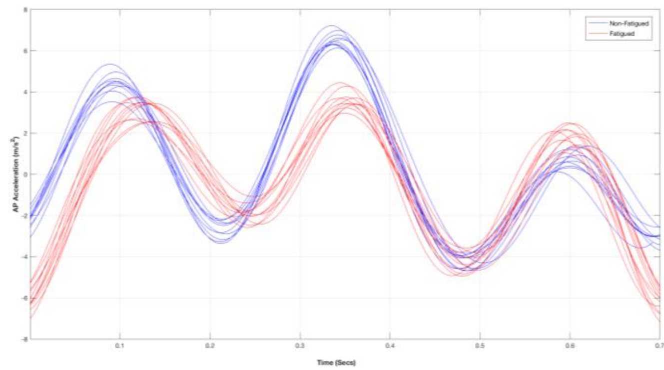

Figure 2: Sample Anterior-Posterior Acceleration Signal over 10 Strides during the Non-Fatigued (Blue) & Fatigued (Red) Run from the Lumbar Mounted IMU.

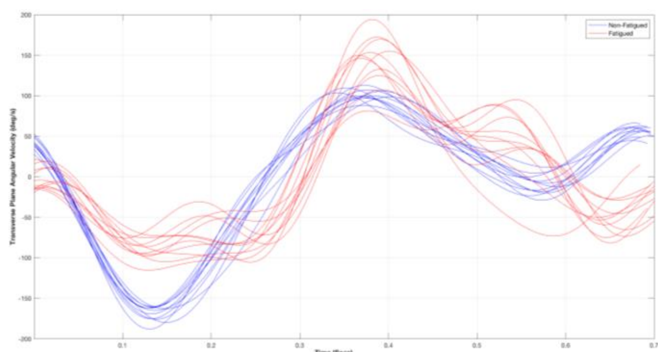

Figure 3 Sample Transverse Plane Angular Velocity Signal over 10 Strides during the Non-Fatigued (Blue) & Fatigued (Red) Run from the Shank Mounted IMU.

Classification: Sixteen time-domain and frequency-domain descriptive features were computed in order to describe the pattern of each of the sixteen IMU signals over each stride repetition. The features computed follow those used in recent similar work [16]. Signal features were then ranked using a Wilcoxon Rank Sum Test, in ascending order, by their statistical significance according to P value. The top 20 ranked discriminative signal features ($P \leq 0.05$) between the non-fatigued and fatigue stride pattern were then extracted.

TABLE 1: THE 15 SIGNAL COMBINATIONS AND PERFORMANCE MEASURES ACHIEVED USING RANDOM FOREST GLOBAL CLASSIFICATION FOR THE LUMBAR, RIGHT AND LEFT SHANK MOUNTED IMU. HIGHLIGHTED IN BOLD IS THE SIGNAL COMBINATION WITH THE HIGHEST F1 SCORE ACHIEVED AT THAT LOCATION.

| **Signal Combinations** | **Lumbar** | | | | **Right Shank** | | | | **Left Shank** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Acc. (%)*** | ***Sens. (%)*** | ***Spec. (%)*** | ***F1 Score (%)*** | ***Acc. (%)*** | ***Sens. (%)*** | ***Spec. (%)*** | ***F1 Score (%)*** | ***Acc. (%)*** | ***Sens. (%)*** | ***Spec. (%)*** | ***F1 Score (%)*** |
| *Accel.* | *55* | *57* | *54* | *55.5* | *62* | *65* | *58* | *61.3* | *46* | *51* | *42* | *46.1* |
| *Gyro.* | *59* | *57* | *61* | *58.9* | *47* | *32* | *62* | *42.2* | *46* | *48* | *44* | *45.9* |
| *Mag.* | *54* | *57* | *52* | *54.4* | *59* | *51* | *68* | *58.3* | *67* | *69* | *65* | *66.9* |
| *Euler* | *66* | *60* | *72* | *65.5* | *54* | *54* | *54* | *54.0* | *45* | *42* | *49* | *45.2* |
| *Accel.,Gyro.* | *64* | *67* | *60* | *63.3* | *59* | *58* | *60* | *59.0* | *48* | *52* | *44* | *47.7* |
| *Accel.,Mag.* | *57* | *56* | *59* | *57.5* | *62* | *66* | *58* | *61.7* | *62* | *63* | *62* | *62.5* |
| *Accel.,Euler.* | *65* | *57* | *72* | *63.6* | *55* | *58* | *53* | *55.4* | *45* | *44* | *46* | *45.0* |
| *Gyro.,Mag.* | *53* | *50* | *56* | *52.8* | *50* | *53* | *47* | *49.8* | *57* | *58* | *55* | *56.5* |
| *Gyro.,Euler.* | *65* | *62* | *69* | *65.3* | *54* | *53* | *56* | *54.5* | *50* | *59* | *41* | *48.4* |
| *Mag.,Euler* | *61* | *61* | *61* | *61.0* | *54* | *52* | *55* | *53.5* | *65* | *65* | *65* | *65.0* |
| *Accel.,Gyro.,Mag.* | *57* | *58* | *56* | *57.0* | *56* | *54* | *59* | *56.4* | *63* | *63* | *63* | *63.0* |
| *Accel.,Gyro,Euler* | *68* | *59* | *77* | *66.8* | *65* | *69* | *61* | *64.8* | *41* | *44* | *46* | *45.0* |
| *Accel.,Mag.,Euler* | *70* | *66* | *74* | *69.8* | *67* | *68* | *66* | *67.0* | **67** | **71** | **64** | **67.3** |
| *Gyro.,Mag.,Euler.* | *66* | *67* | *65* | *66.0* | *53* | *50* | *58* | *53.7* | *58* | *60* | *56* | *57.9* |
| *Accel.,Gyro.,Mag.,Euler* | **75** | **73** | **77** | **74.9** | **70** | **75** | **65** | **69.6** | *60* | *58* | *62* | *59.9* |

The Random-Forests method was firstly employed to perform classification [17]. A total of 128 trees were used for each classifier, decided as an appropriate value to balance system efficiency and accuracy. Binary classification was used to establish how effectively each individual IMU could distinguish between a non-fatigued and a fatigued running state.

Global classification was evaluated using leave-one-subject-out-cross-validation, LOSOCV [18] for each of the possible thirty-one combinations of IMU signals. Combinations which contained Quaternion Signal features were subsequently disregarded due to early trends which showed inaccurate results when included. The remaining 15 possible signal combinations (Table 1) for the Lumbar, Right Shank and Left Shank respectively were used for classification and ranked based on greater Accuracy, Sensitivity and Specificity measures and resulting F1 score, computed according to the below formulae.

$$1 . Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$2 . Sensitivity = \frac{TP}{TP + FN}$$

$$3 . Specicificity = \frac{TN}{TN + FP}$$

$$4 . F1\ Score = 2\left(\frac{Sensitivity\ x\ Specificity}{Sensitivity + Specificity}\right)$$

The quality of the Personalised exercise classification systems was established using K-Fold cross validation with 10 folds [18]. The Global Classification performance of the Random Forest classifier was also tested against three other machine learning algorithms; Support Vector Machine (SVM), K-Nearest Neighbors (KNN) and Naïve Bayes using the top performing signal combination for each location [19].

## III. RESULTS

Table 1 presents the 15 possible signal combinations tested. Accuracy, Sensitivity, Specificity and F1-score percentages achieved for each subset of signals are given using Random Forest LOSOCV for the Lumbar, Right Shank and Left Shank mounted IMU respectively. The F1 score metric is included for comparing each combination as the accuracy score may be skewed by imbalances in the training/test data sets. The best performing combination for each location is marked in bold text.

Table 2 presents the Accuracy, Sensitivity, Specificity and F1-score percentages achieved for the Lumbar, Right Shank and Left Shank mounted IMU when using K-Fold cross validation personalised classification. A mean value along with the standard deviation is given for the 21 total participants. SVM, KNN and Naïve Bayes were also computed showing inferior or equivalent classification quality.

Table 3 presents a comparison of classification scores using the previously extracted best performing combination of signal features and used to train and evaluate the four following classification algorithms: Random Forests, SVM, KNN and Naïve Bayes. 128 trees were used for random forests classification. The parameters of the SVM and KNN data sets were left as their default values as defined in MATLAB.

TABLE 2: PERSONALISED CLASSIFICATION PERFORMANCE MEASURES USING RANDOM FOREST LOOCV CLASSIFICATION FOR THE LUMBAR, RIGHT AND LEFT SHANK MOUNTED IMU.

| **Personalised Classification ( $\bar{x}$ (SD) )** | | | | |
|---|---|---|---|---|
| **IMU Sensor Location** | ***Acc. (%)*** | ***Sens. (%)*** | ***Spec. (%)*** | ***F1 Score (%)*** |
| *Lumbar* | *89 (6)* | *88 (7)* | *89 (6)* | *89* |
| *Right Shank* | *100 (0)* | *100 (0)* | *100 (0)* | *100* |
| *Left Shank* | *99 (2)* | *99 (3)* | *99 (2)* | *99* |

TABLE 3: GLOBAL CLASSIFICATION METHOD COMPARISON FOR ACCURACY, SENSITIVITY, SPECIFICITY AND F1 SCORE ACROSS EACH OF THE 3 IMU LOCATIONS.

| IMU Global Classifier Comparison | | | | | |
|---|---|---|---|---|---|
| **IMU Location** | **Classifier** | ***Acc. (%)*** | ***Sens. (%)*** | ***Spec. (%)*** | ***F1 Score (%)*** |
| *Lumbar* | *Random Forest* | ***75*** | ***73*** | ***77*** | **75** |
| | *SVM* | *68* | *70* | *64* | 67 |
| | *KNN* | *62* | *60* | *63* | 62 |
| | *Naïve Bayes* | *61* | *73* | *49* | 59 |
| *Right Shank* | *Random Forest* | ***70*** | ***75*** | ***65*** | **70** |
| | *SVM* | *66* | *68* | *64* | 66 |
| | *KNN* | *53* | *59* | *47* | 52 |
| | *Naïve Bayes* | *56* | *58* | *54* | 56 |
| *Left Shank* | *Random Forest* | ***67*** | ***71*** | ***64*** | **67** |
| | *SVM* | *66* | *62* | *72* | 67 |
| | *KNN* | *50* | *54* | *46* | 50 |
| | *Naïve Bayes* | *48* | *77* | *20* | 32 |

## IV. DISCUSSION

The purpose of this study was to determine if a single IMU system could classify running form between a non-fatigued and fatigued state.

Using global classification, our results showed that a single Lumbar, Right Shank or Left Shank mounted IMU is capable of distinguishing between a non-fatigued and a fatigued run with 75%, 70%, and 67% accuracy respectively. Overall results from Table 1 suggests that extracting features from the complete set of IMU signals (Accelerometer, Gyroscopic, Magnetometer and Euler) appears superior than using subsets of these signals based on the 31 combinations tested (Top 15 Shown). The extra computational overhead in this case proves beneficial towards increasing performance measures.

Results from our personalised random forest classifier (Table 2) indicate that a single Lumbar, Right Shank and Left Shank mounted IMU is capable of distinguishing between a non-fatigued and a fatigued run with 89%, 99%, and 100% accuracy respectively. In addition to producing higher levels of overall classification accuracy, personalised classifiers are more computationally efficient than global classifiers as they require less training data and memory. Disadvantages related to a personalised classifier is that data sets must be gathered and labelled from individual end users. Therefore, they are less efficient than a global classifier's "set up and go" approach.

Table 3 shows comparable results between four different global classification methods using the best ranked signal combination for each location. The Random Forest LOSOCV classification algorithm lead to optimal performance measures with an F1 score of 75%, 70% and 67% for the Lumbar, Right Shank and Left Shank mounted IMU respectively, outperforming the SVM (67, 66 67%), KNN (62, 52 50%) and Naïve Bayes (59, 56 32%) algorithms. In all cases, utilising only the best ranked signal features as selected using a Wilcoxon Rank Sum Test, which showed a high level of consistency between the non-fatigued and fatigued state, lead to improved performance measures.

The superior performance of both individual shank mounted IMUs during personalised classification (Accuracy ≈ 99%) when compared to the Lumbar Mounted IMU (Accuracy = 89%) is possibly due to a higher intra-subject variability, between a non-fatigued and fatigued state, for the outputted shank mounted IMU signals than for the lumbar mounted IMU sensor position. For global classification the lumbar mounted IMU outperforms the shank mounted IMUs possibly due to the inter-subject variability between fatigued/non fatigued states at the lumbar spine exceeding the inter-subject variability at the shank due to greater variation in running styles at this position.

The growing availability of IMU's has led to numerous researchers exploring the capability of sensors to monitor running performance and injury prevention. While several researchers have analysed running performance using IMUs [5, 20-22], to the authors' knowledge none have assessed the capability of a single IMU in detecting changes in running form between a non-fatigued and fatigued state. It is difficult to make direct comparisons with previous research, as there is a large variance in sensor position, features investigated and classification methods. One similar study has described the capability of IMUs in classifying symmetrical and asymmetrical running styles using a single sensor worn on the upper back with up to 94% overall accuracy [5]. However, this was artificially induced during treadmill running achieved by requiring participants to run with one foot shod and one foot unshod (i.e. barefoot) as opposed to detection of fatigue onset. In this instance, taking into account the large deviations between separate strides and major shift in form that would exist due to one foot shod running, it may be expected to achieve this level of accuracy. The current study was conducted on an outdoor conventional track that may result in greater natural variability in pacing and lead to lower initial performance measures. The presence of asymmetrical stride patterns at the onset of fatigue is only one factor of running biomechanics that may be altered. Understanding further changes in intrinsic factors such as stride length, vertical oscillation and ground reaction forces between the non-fatigued and fatigued state will assist in extracting meaningful spatial and temporal features [23].

Eskofier, et al. [24] demonstrated the potential of pattern classification methods in detecting perceived running fatigue using biomechanical as well as physiological features from several body sensors data to a high level of accuracy. In this case, 20% of participant's datasets forced exclusion, as this sample of forefoot striking runners lacked a heel compression signal which provided the top performing classification features for their classification system. The study acknowledges the possibility of incorporating movement signals from inertial measurement sensors like accelerometers or gyroscopes to further enhance the fatigue classification ability of a body sensor network.

It is important to note that fatigue was induced deliberately by the beep test in this study and treated as a binary variable for classification purposes. This may be considered an unnatural way of fatiguing during an athlete's run as opposed to a more natural progressive decline in running economy over increasing time/distance [23]. However, a multi-stage shuttle run test has been shown to be a valid estimator of maximum oxygen consumption and race performance over 10km [25]. In addition, the incremental test ensures a gradual rise in work rate and heart rate and is highly reliable [9].

Future work will examine possible correlations that may exist between specific signal features and increasing levels of fatigue utilising a more gradual, continuous approach rather than binary classification. Improved global classifiers may be developed by collecting a large data set of personalised labelled data. The age range of participants in further studies must also be increased to address any age-dependent factors in running techniques or postures which may exist. This data could be gathered and stored by practitioners, sports scientists and S&C coaches. This advancement could also lead to the possibility of including this classification technology into everyday electronic devices like smartphones. It is hoped to further improve and develop this system to classify running fatigue with a single IMU. It is envisaged that a smartphone app may have the ability to provide accurate, real-time feedback of running technique and possible subsequent breakdown for all levels of running, reducing fatigue related injury risk.

## V. Conclusion

In this study, we demonstrated the potential of wearable technology to detect changes in running technique. We demonstrated that a single IMU can classify between a non-fatigued and fatigued run using both personalised and global classifiers. The results of this study imply that a single IMU sensor may have the potential to reduce the risk of running related injuries associated with fatigue to a high level of accuracy and may be improved through further understanding of detectable kinematic and kinetic changes between the non-fatigued and fatigued state. To fulfil this potential, future research could consider assessing other common running related biomechanical deviations that may increase injury risk at the onset of fatigue and examine threshold values that may be able to further discriminate between the non-fatigued and fatigued running form. This research can potentially progress towards live feedback of ones running economy beyond the constraints of a laboratory setting using inexpensive sensor technology.

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