Automatically Detecting Asymmetric Running using Time and Frequency Domain Features

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***Abstract*—Human motion analysis technologies have been widely employed to identify injury determining factors and provide objective and quantitative feedback to athletes to help prevent injury. However, most of these technologies are: expensive, restricted to laboratory environments, and can require significant post processing. This reduces their ecological validity, adoption and usefulness. In this paper, we present a novel wearable inertial sensor framework to accurately distinguish between symmetrical and asymmetrical running patterns in an unconstrained environment. The framework can automatically classify symmetry/asymmetry using Short Time Fourier Transform (STFT) and other time domain features in conjunction with a customized Random Forest classifier. The accuracy of the designed framework is up to 94% using 3-D accelerometer and 3-D gyroscope data from a sensor node attached on the upper back of a subject. The upper back inertial sensors data were then down-sampled by a factor of 4 to simulate utilizing low-cost inertial sensors whilst also facilitating a decrease of the computational cost to achieve near real-time application. We conclude that the proposed framework can potentially pave the way for employing low-cost sensors, such as those used in smartphones, attached on the upper back to provide injury related and performance feedback in real-time in unconstrained environments.**

***Keywords*— Activity classification; Machine learning; Wearable sensors; Inertial sensors; Injury prevention**

I. Introduction

It is estimated that up to 70% of both competitive and recreational runners sustain overuse injuries during any 1-year period [1]. These injuries are associated with the high impact load and impact acceleration produced against the body each time the foot strikes the ground [2]. Some of these injuries are unilateral, suggesting that inter-limb loading asymmetry may be a causative factor [3]. Indeed, inter-limb symmetry during functional tasks, including running, offers a means of screening for predisposition to injury, as well as assessing the effectiveness of injury rehabilitation [3][4]. Traditionally, this assessment of asymmetry has been undertaken in a laboratory environment using multi-camera motion analysis systems (e.g. Vicon, UK) combined with a force-plate embedded in the ground (e.g. AMTI, USA) to determine loading using inverse dynamics [5]. While some studies have reported asymmetry to be a causative factor [6], others have failed to find such an association [7]. The contrast in findings may reflect current methodological issues with data capture.

One major challenge to understanding the role of asymmetry is the limited number of studies that have been undertaken due to the cost of the aforementioned biomechanical analysis systems (in excess of 50,000 Euro), as well as the small number of bilateral foot strikes examined (usually less than 10) because of the long processing time required (up to 20 minutes per foot strike). Similarly, these constraints subsequently limit the routine assessment of running asymmetry by clinicians (e.g. athletics therapists and trainers, physiotherapists). With the advent of Micro-Electro-Mechanical Systems (MEMS), there has been a rapid growth in the development of wearable inertial sensors to monitor various human activities [8][9]. Such sensors are relatively cheap, allow the collection of a very large number of foot strikes in natural running environments, and the data gathered requires extremely short post-processing times (potentially less than a second). To date only a few studies (e.g. [10]) appear to have attempted to quantify impact acceleration asymmetry during running (using 5 foot strikes per participant). Clearly, more studies are required in this area. In addition, from an applied perspective an asymmetry monitoring system would ideally be able to report if a runner was asymmetrical or not. Such information would be extremely useful to a clinician, or in fact to a runner who self-monitors his/her predisposition to injury. This is different from simply reporting the magnitude of asymmetries, because overall asymmetry may be due to a combination of aspects of loading (e.g. peak impact acceleration, time to peak impact, etc.), not simply an individual component. Indeed, Exell et al. [11] demonstrated that a composite score of asymmetry that incorporates numerous signal components was more effective at quantifying overall asymmetry due to inter-subject variability in the individual components that were asymmetrical (note: impact acceleration was not assessed). Finally, uptake, wearability and ultimately user-adherence will be heavily influenced by the cost of the system, the number of sensors required to accurately identify asymmetry and battery life. The main aims of the present study were:

- To determine if machine based learning techniques could accurately identify a condition of induced asymmetry.
- To determine the influence of sensor numbers, sensor location, and sampling frequency on the accuracy of asymmetry identification.

The present study examines both impact acceleration and segment angular velocity. Given that virtually all musculoskeletal injuries are caused by relative excessive force/loading, the assessment of impact accelerations provides a valuable insight into the predisposition to injury ($F = ma$) [12]. Segment angular velocities on the other hand are used to determine the magnitude of impact accelerations [12]. A challenge in examining if a system is capable of accurately classifying those with asymmetry is to identify *a priori* such a cohort of participants. Indeed, the literature does not agree on what quantifies overall asymmetry. An accepted methodological approach in examining asymmetry is to externally induce changes in unilateral loading and segment motion [13]. We achieved this by requiring participants to run with one foot shod and one foot unshod (i.e. barefoot).

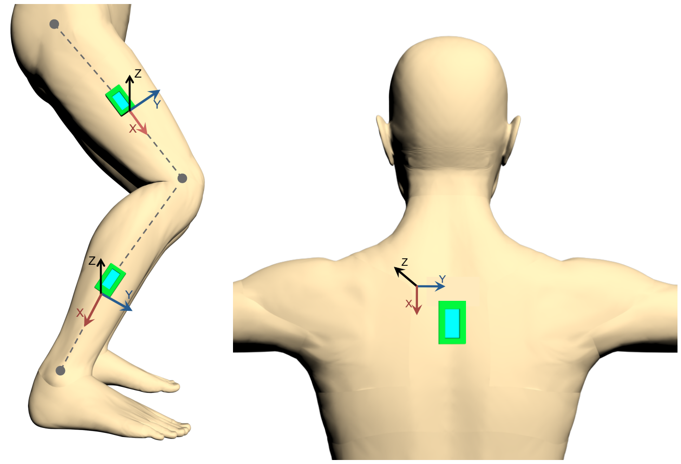
II. Data Collection

A. Participants

Twenty-one healthy male participants were recruited [age: 33±13 years; height $179.5 \pm 13.5m$; mass $69.5 \pm 19.1kg$], who had no gait impairments, no history of significant trauma to the lower extremities, and were experienced treadmill runners. All participants indicated right leg dominance and ran with a heal strike pattern. The University Institutional Ethics Review Board approved all procedures, and all participants gave informed consent.

B. Experimental Procedures

Participants wore shorts, a tight Lycra vest and their own running shoes. Five inertial Shimmer3 sensors [Shimmer, Ireland] were attached to the body. Two sensors were attached to the tibia bilaterally ($10cm$ inferior to the knee joint center), two to the femur bilaterally ($15cm$ superior to the knee joint center), and one to the upper back (approximately at $T2$). The sensor placement on tibia, thigh and upper back are shown in Figure 1. The X axis of the sensors were aligned visually with the longitudinal axis of the body segment. The tibia and femoral sensors were attached using double-sided tape and velcro straps with some elasticity in the fabric so as not to impede natural movement, while the upper back sensor was placed in the custom sewn pocket of a tightly worn Lycra vest. For each sensor data were recorded to an internal SD card at 1024 frames per second. A physical event was used to synchronize sensor data streams; this involved performing 5 vertical jumps with relatively straight legs to produce large acceleration spikes evident in the accelerometer data stream. In a post processing step, peak alignment was automatically performed and all data streams were cropped to two seconds before the first vertical jump landing.
Participants ran on a treadmill (Trotter 645; Cybex, USA) for the two testing conditions, separated by 30 seconds: bilaterally shod and unilaterally shod (right/dominant leg shoe and sock were removed). The latter condition was utilized to experimentally impose asymmetry. Prior to sensor application participants ran on the treadmill for a 3 minute warm-up and then determined their self-selected training speed. For each subsequent test condition, participants ran for 1 minute at their warm-up speed and then for 3 minutes at $1km/h$ below their self-selected training speed; pilot testing indicated that participants could run comfortably wearing one shoe at this speed. Data were captured during the last 1.5 minutes of the training speed run without the knowledge of the participant. The order of testing conditions was randomized.



(a) Thigh and tibia sensor placement

(b) Back sensor placement

Fig. 1: Placement of inertial sensors on thigh, tibia and upper back is illustrated.

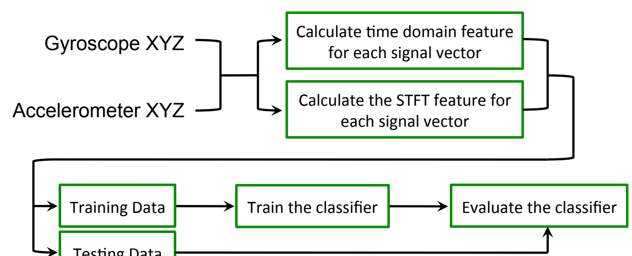
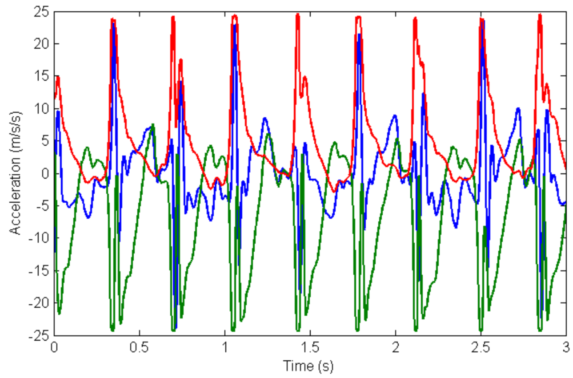


Fig. 2: Overview of the model creation process

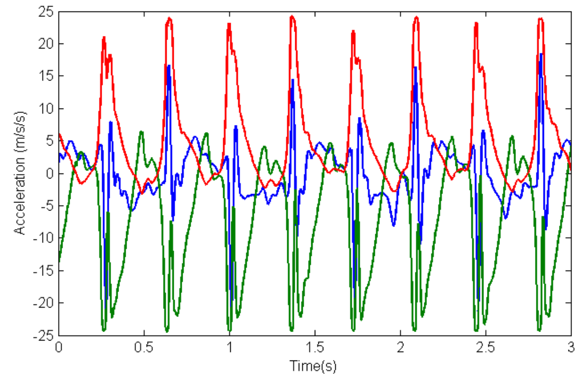
III. Proposed Framework

Machine learning is a branch of artificial intelligence that creates algorithms that can learn from data. In this work machine learning techniques were utilized in order to accurately distinguish between symmetrical and asymmetrical running. Machine learning techniques have been successful applied to health and human performance classification problems such as detecting sleep apnea, assessing an athlete's activities in an outdoor training environment and providing real-time feedback on performance during training sessions [14][15][16].

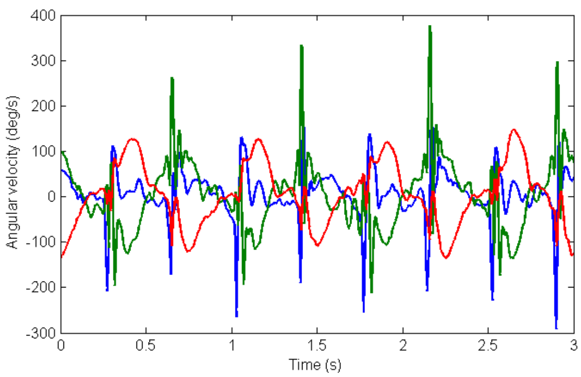
Figure 2 illustrates the machine learning process employed to create our classification models. Time and frequency domain information is extracted from gyroscopic and accelerometer data from the participants. Classification models can be created and tested from this extracted data. The data collected in section II was split up into different 3 second windows using a sliding window with 50% overlap. Figure 3 illustrates examples of these data windows from each sensor for both asymmetric and symmetric running. Feature extraction on sliding windows with 50% overlap has demonstrated success in past works [17][18]. 1349 examples of asymmetrical running



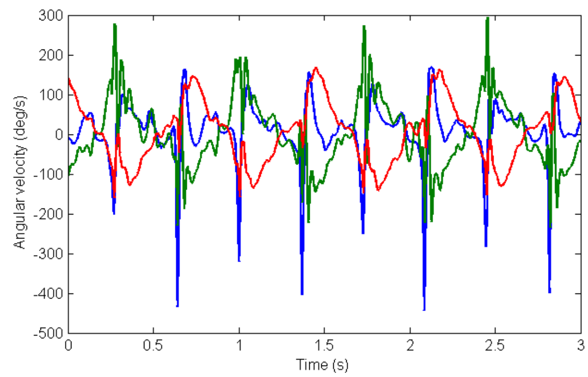
(a) Raw Accelerometer Data for Asymmetric Running



(b) Raw Accelerometer Data for Symmetric Running



(c) Raw Gyroscopic Data for Asymmetric Running



(d) Raw Gyroscopic Data for Symmetric Running

Fig. 3: Examples of raw data from each sensor for both running styles

and 1498 examples of symmetrical running were created. The 21 participants ran symmetrically for a slightly longer duration on average during the symmetrical running condition resulting in a higher number of symmetrical running examples. In this work three different classifiers from different families were investigated to ascertain which classifier could best distinguish between the two running conditions. The classifiers employed were Random Forest (RF), Naive Bayes (NB) and Radial Basis Function (RBF) Network. The RF classifier operates by building a multitude of decision trees with each having a vote. The forest then chooses the class which has the most votes. The RF classifier has been successfully used in recognizing human movement [19] and therefore was chosen to be investigated as part of this work. The NB classifier is a Bayesian classifier which has been used in a wide array of classification problems since the 1990s [20][21]. Finally an artificial neural network classifier called the RBF Network was also employed. These types of classifiers are based on the properties of biological neural systems that are well equipped for handling large amounts of input data.

In this work, features are extracted from the raw accelerometer and gyroscopic data (from all 3 axes) and fed into the classifiers. Time and frequency domain features are compared to see which performs better at distinguishing between the two running conditions before both domains are fused to extract discriminative features from both domains. The time domain features extracted are listed below and are calculated for each sensor axis.

- Average value
- Standard Deviation
- Time between peaks over 60% of the mean
- Number of peaks over 60% of the mean
- Sum of all values
- Absolute sum of all values

Time domain features have been used extensively to automatically detect different user activities [22][23]. 60% of the mean was used to detect peak in order to eliminate much of the peak noise from low value data without employing a computationally intense filter.

Frequency-domain features can be derived from the coefficients of time-frequency transforms, like the Short Time Frequency Transform (STFT). Frequency-domain entropy is helpful in discriminating features that differ in complexity [24]. For instance, the asymmetrical running entropy could be different than the symmetrical running entropy due to the particular foot impacts with the ground occurring during

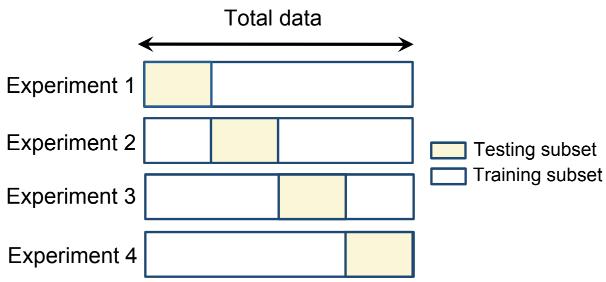


Fig. 4: K-Fold Cross Validation

the latter activity, which results in generating different frequency signatures. Therefore, the coefficients of the Short-Time Fourier Transform (STFT) are used to compute the frequency-domain entropy [25].

Standard Fourier analysis cannot provide simultaneous time and frequency localization whereas this is a useful feature of the STFT. STFT is a well known technique in signal processing to analyze non-stationary signals. STFT segments the signal into narrow time intervals and calculates the Fourier transform of each segment.The STFT has been used with success for extracting discriminative features from physiological data and can be seen in Equation 1. In this equation, $x[n]$ and ω are the time-series signal and the analysis window, respectively. Yen et al. in [26] states that a wide enough STFT window gives good frequency resolution and therefore this value was set to 1.5 seconds in our experiments. Narrow windows provide good time domain information however those features are already extracted in our scheme. Mannini et al. in [24] achieved a high level of accuracy when using the STFT to compute the frequency-domain entropy while trying to identify a number of everyday activities. In the present work, the DC component and energy of the signal are also extracted as Mannini does in [24].

$$STFT\{x[n]\} \equiv X[m,\omega] = \Sigma_{-\infty}^{\infty} x[n]\omega[n-m]e^{-j\omega} \quad (1)$$

The energy of each signal $x[n]$ was calculated as:

$$E = \sum_{n} |x[n]|^2. \quad (2)$$

IV. Results

All results presented in the present work are calculated using K-fold cross validation. The main advantage of this approach is that all the examples in the dataset are eventually used for both training and testing. Figure 4 illustrates the K-Fold cross validation approach when K is set to four. For each fold the accuracy of the model is calculated using the allocated test and train data. Once each fold has been completed the overall accuracy of the system is calculated as the mean of all the folds. This approach provides a better judgment on how the model will perform on unknown data than simply splitting the data into test and train segments [27]. In this work K is set to ten, which is common across the literature in this area [28][29].

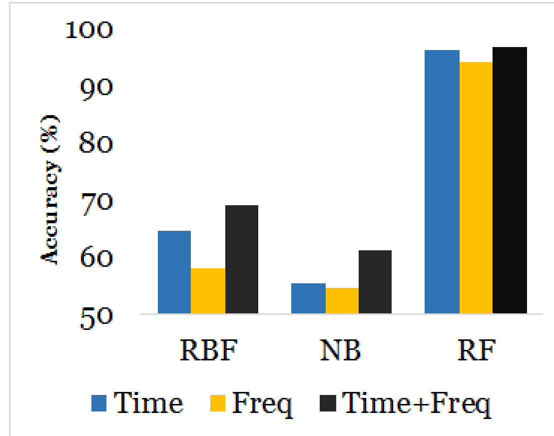


Fig. 5: Comparison of different classifiers and feature extractions methods

A. Feature Extraction Methods

Figure 5 illustrates the classification accuracy attained by each of the classifiers for the three feature extraction methods using data from all five (i.e left/right tibia, left/right thigh and the upper back) sensors. Time and frequency domain features are compared individually before fusing the extraction methods. The RF outperforms the other two classifiers by a significant margin for all three feature extraction methods. It can also be observed from Figure 5 that fusing the two approaches gives a better result than either individually. Utilizing a RF classifier with fused time and frequency features achieves an accuracy score of 97%.

B. Different combinations of sensors

In this section, we investigated whether we could employ a smaller number of sensors to classify symmetrical and asymmetrical running. The advantages of reducing the number of sensors to monitor and classify various activities are as follows [30]:

- The entire activity classification system would be cheaper and less prone to set up/synchronization error.
- Lower computational cost as fewer features need to be extracted for classification, potentially enabling real-time feedback.
- This can address the very typical scenario where end-users may only have access to, or only be able/willing to wear, a small number of sensors.

Figure 6 illustrates the classification results obtained utilizing one or more sensors placed on different parts of the body. Investigating the performance of different combinations of sensors allows the classification framework to be optimized. Redundant sensors can be identified and removed from the sensor framework. This reduces cost and makes the system less invasive. The different combinations of fused sensor data examined:

- C1: Two Thigh and Two Shank Sensors

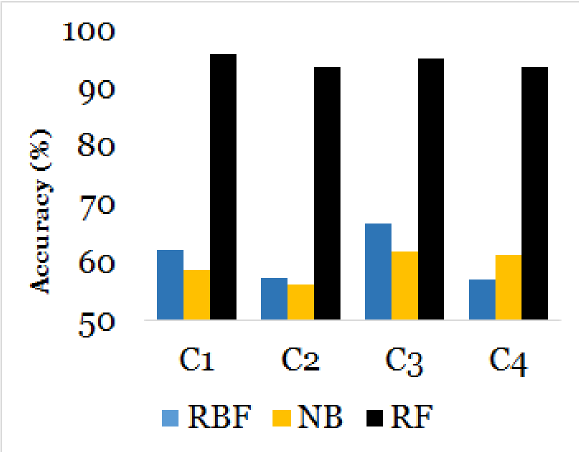


Fig. 6: Comparison of different sensor combinations

	Precision	Recall	F-Measure
Asymmetric	0.941	0.927	0.934
Symmetric	0.934	0.948	0.941

TABLE I: Precision, recall and F1 scores using one sensor on the upper back

- C2: Two Thigh Sensors
- C3: Two Shank Sensors
- C4: Upper Back Sensor

Placing sensors on the shanks and thighs combined gives a classification accuracy of 96%. This is only 1% lower than using all five sensors. Similar accuracy results are achieved with sensors only placed on either the shanks, the thighs or only the upper back. For example, using only data from the sensor placed on the upper back gives an accuracy result of 94%. The precision, recall and F1 score can be seen in Table I. Therefore using more than one sensor in this framework only adds a relatively minor increase in accuracy. A sensor placed in the upper back is more desirable as it is less likely to cause harm to the wearer or to opponents during contact sports. For instance, in professional rugby union a device incorporating a GPS and accelerometer is only allowed to be placed between the shoulder blades during matches [31].

C. Sensor with a low sample rate

In section IV-B, it was shown that it is feasible to accurately distinguish between symmetrical and asymmetrical running employing only the upper back sensor. In a further attempt to reduce the cost of the system and the amount of computation required at each window to obtain real-time feedback, the inertial sensor data were down-sampled from $1024Hz$ to as low as $256Hz$, effectively reducing the computation time by a factor of 4. Down sampling can simulate the output of inertial sensor systems manufactured to lower specification.

Smartphones today often have accelerometers and gyroscopes embedded within them however due to size constraints they are generally only able to capture data at a lower sampling rate than custom inertial sensors. Downsampling the data capture rate to $256Hz$ emulates the performance of modern smartphones [32]. Smartphone placement on the body is important for safety of the user and the phone [33] hence only the sensor data from the upper back was used. Using a Random Forest classifier in conjunction with the fused feature extraction method already mentioned, a classification result of 90.3% was achieved. It takes approximately 2ms to classify all sensor data using the aforementioned method on an Intel Core i7 CPU.

V. Conclusion

In this paper, we described a novel body worn inertial sensor framework capable of automatically classifying symmetrical and asymmetrical running styles. Twenty one healthy subjects participated in the experiment and synchronized data was collected from five sensors attached on the left/right tibia, left/right thigh and the upper back of each participant. We investigated a number of features from both the time domain and the frequency domain as an input for the classifier. After investigating a number of different families of classifiers, we found best performance using the Random Forest as it surpassed other classifiers in terms of accuracy and speed. Using all five sensors, our technique is capable of classifying symmetrical and asymmetrical running patterns successfully with up to 97% overall accuracy in less than $2ms$. We also showed that reducing the number of sensor nodes does not significantly degrade the overall accuracy. In fact, our framework can reach up to 94% accuracy by only employing the data from the upper back sensor. In a further attempt to reduce the cost of the system and the amount of computation at each window, we down sampled the upper back sensor from $1024Hz$ to $256Hz$. The effect of down sampling was used to simulate low cost inertial sensors (e.g. sensors embedded in smartphones) and achieve real-time application. It is envisaged that smartphones can potentially be utilized to provide accurate, real-time feedback during running and in an unconstrained environment to help prevent injury in outdoor environments.

VI. Future work

While removing one shoe provides an effective means of imposing asymmetry, future research should examine if the same rate of effective classification is evident in patients, such as those with unilateral anterior cruciate ligament injury, using both retrospective and prospective study designs.

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