

Exploring Amateur Performance in Athletic Tests Using Wearable Sensors

Stephen Mitchell
Engineering
James Madison University
Harrisonburg, VA
mitchess@dukes.jmu.edu

Jason Forsyth
Engineering
James Madison University
Harrisonburg, VA
forsy2jb@jmu.edu

Michael S. Thompson
Electrical and Computer Engineering
Bucknell University
Lewisburg, PA
mst008@bucknell.edu

Abstract—The growing market for sports analytics has spurred more interest than ever in quantifying athletic performance. This trend, alongside the proliferation of new wearable technologies, has expanded the possibilities for both professional and amateur athletes to instrument themselves and collect meaningful data. The reactive strength index (RSI) can be used to communicate this kind of data by presenting a person’s ability for rapid movement. A user study was conducted in which young adults of amateur athletic status performed a jumping exercise to assess the feasibility of using a commercial off-the-shelf inertial measurement unit (IMU) to measure this metric compared to the usual method of using a force plate. Results suggest that the measurement of meaningful RSI improvements is possible using inexpensive IMUs with comparable results to costly force plates.

Index Terms—Biomedical monitoring, Wearable sensors

I. INTRODUCTION

As athletics becomes increasingly data-driven, new methods for assessing player performance are created and previous methods are refined to be more accessible to amateur athletes. One such indicator of athletic performance is the Reactive Strength Index (RSI), which is a measurement of a player’s capacity for fast, explosive movement [1]. To measure RSI a participant exerts a rapid force over a short period in the form of a jumping exercise in which the height of the jump and the time on the ground is measured and used to compute the RSI. This metric gives coaches and trainers deeper insights into the changes in their athlete’s endurance and fatigue from exercise and allows assessment of training program effectiveness. The standard way to measure this metric is by using a force plate to accurately measure when an athlete has started a jump and landed again. However, the high cost of this equipment makes the RSI prohibitively expensive to calculate for many amateur athletes and lower-budget sports programs. An alternative approach to calculating this value is through the data provided by inertial measurement units (IMUs).

The benefit of this method is that IMUs are inexpensive compared to force plates, however, the data is considerably noisier due to the sensor’s attachment to the person performing the exercise, posing a challenge for calculating the exact points a participant lands or takes off from the ground. We developed an algorithm to find these points based on accelerometer data captured from IMUs placed on a participant’s foot while

performing a drop jump off a raised platform. A user study was conducted to measure the RSI in amateurs in comparison to the same metric measured on a force plate. Results indicate that effective measurement of the RSI through IMUs is possible for modest performance gains, however further analysis of the variation in error between participants is necessary to understand the reasons for the differences in RSI between the force plate and IMU data. This study differentiates itself from previous research by: (1) calculating the RSI using IMUs through the use of off-the-shelf hardware as opposed to custom-built components, (2) participants being of amateur status as opposed to athletes, and (3) utilizing a moving average detection approach to identify take-off time rather than bandpass filters and hardcoded “time on ground” logic [2].

The remainder of the paper is organized as follows: Section II will discuss how RSI is used in exercise science and what increases in RSI values might indicate meaningful physiological change. Section III discusses the challenges associated with calculating the RSI from our sensors and provides an algorithm for doing so. Section IV outlines a user study to collect simultaneous force plate and inertial measurement data during drop jump exercises. Results from this study will be presented in Section V with discussions of the applicability of our approach to measuring increased RSI performance. Finally, we conclude with a summary and look towards future work in Section VI.

II. BACKGROUND AND MOTIVATION

A. The Reactive Strength Index and Drop Jumps

RSI is a common physiological measurement that assesses an athlete’s ability to perform “explosive” and quick movements. These quick actions are frequent in sports such as basketball, soccer, and rugby that require the athlete to make sudden, but strong, movements during competition. RSI can be measured in several ways but is commonly performed as the measure of a person’s contact time with the ground and the height of the jump that they achieve [1], [3]. This measure is reliable in a variety of settings but can also be influenced by participants jumping technique [4] and by the commands provided during the jumping activity [5]. In our work, the particular commands and form of the jump as less important,

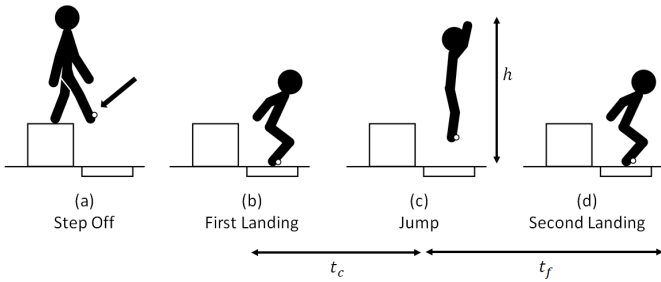


Fig. 1: Steps performed in a drop jump with measurements of time of contact (t_c), time of flight (t_f), and jump height (h). A body-worn accelerometer is indicated with an arrow and an in-ground force plate is shown upon which the user lands.

as we are simply measuring the relative accuracy between an in-ground force plate and a body-worn accelerometer.

RSI measurements are typically taken during a “drop jump” exercise. The exercise begins by having a participant step off from an elevated platform, land on the ground, and quickly execute a vertical jump in place. The elements of this drop jump can be seen in Figure 1. Several metrics are calculated from this jump including jump height, power output, and ground contact time. A “good” drop jump is one in which the participant achieves a high vertical jump while minimizing the time in contact with the ground.

To measure the RSI of a participant performing a jump exercise, the height (h) of the person’s jump is divided by the time in which the participant is in contact with the ground (t_c). In the context of a drop-jump, t_c begins when the participant initially touches the ground from stepping off a raised platform and ends once both of the participant’s feet have completely left the ground. The height of the jump comes from the maximum distance in meters from the ground to the lowest part of the participant’s feet between the first and second landing points. Alternatively, if the height of the jump (h) cannot be measured, it can be derived using the time of flight (t_f) of the person’s jump using $h = \frac{gt_f^2}{8}$ [2], [3], [6]. From these parameters, RSI can be expressed solely in terms of the time of flight (t_f), time of contact (t_c), and gravitational acceleration (g) as shown in Equation 1 below:

$$RSI = \frac{h}{t_c} = \frac{gt_f^2}{8t_c} \quad (1)$$

In Section III-A we will discuss in greater detail how these parameters can be found using a force plate and wearable IMU as proposed in our study.

B. Measuring Meaningful Change in RSI

RSI as a performance metric has been used in a variety of situations to assess an athlete’s improvement based upon exercise conditioning. Some examples include training improvements in youth soccer [7], [8], college athletes [9], and professional basketball players [5]. As our proposed system is intended to record improvement in athlete performance, it is important to know how significant these changes are in

TABLE I: Observed improvement in RSI measures for various athletic populations under training conditions.

Study Population	Meaningful RSI Gains
Male Youth Soccer (13 y.o.) [8]	1.1 ± 0.5 to 1.5 ± 0.5
Male Youth Soccer (12 - 15 y.o.) [7]	0.91 ± 0.24 to 1.01 ± 0.26
Professional Rugby Athletes [11]	1.8 to 2.0
Professional Rugby Athletes [11]	2.0 to 2.4

terms of RSI and whether our system is sufficiently sensitive to detect these changes. As a starting point, RSI measurements can vary over a range of athletic populations. In particular, youth athletes exhibit RSI values between (1.0 - 1.5) [7], [8], trained athletes between (1.5 - 2.0) [1], [9], [10], and professional athletes between (2.0 - 2.5) [5], [11]. Thus, at a coarse level, RSI ranges between 1.0 and 2.5 over a wide spectrum of athletic performance.

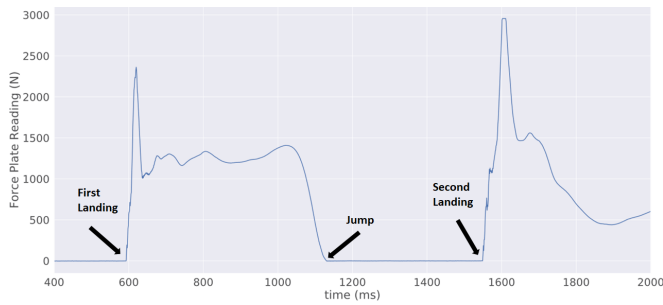
Examining these RSI ranges further, it is important to determine what are the athletically significant changes within each population. Over short training sessions of several weeks, an athlete is unlikely to show RSI changes that move them from a youth athlete ($RSI \approx 1.0$) to a professional one ($RSI \approx 2.0$), however, modest gains within RSI bands should be observable. Thus, our system should be able to identify the “smallest worthwhile change” that is of benefit to the athlete [11].

Table I provides data from several studies examining the effectiveness of various exercise regimes and the impact on the athlete’s RSI value. RSI gains reported are those considered statistically significant that showed improvement in the athlete’s performance. Examining these meaningful changes in athletic performance, it can be seen that significant changes in RSI values range from deltas of (0.1 to 0.5). Thus, our system should be capable of distinguishing measurements of at least changes in RSI at 0.1 levels to be applicable in the widest application range.

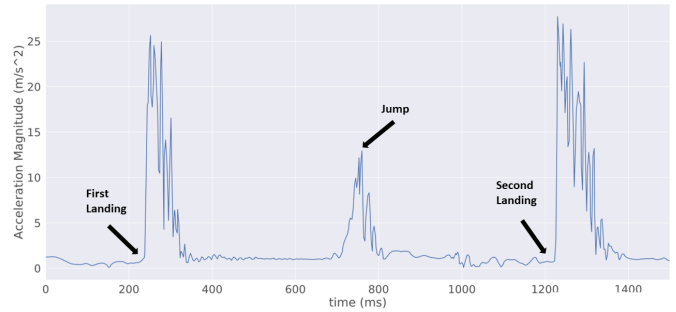
C. Comparison With Existing Technologies and Approaches

Our proposed system is not the first to measure athlete performance without the use of a force plate and several products exist in the market to do so. Products such as OptoJump [12] provide mobile light-based platforms to measure contact timing and jump height, while other wearable products such as the Pushband [13] use similar IMU-based approaches. While these systems can be an accurate measure of RSI performance [14], it may be prohibitive for certain populations as the units cost between \$450 - \$2000. Less expensive, but also accurate options are available through several smartphone apps such as MyJump [15] and What’s My Vert [16]. However, these camera-based approaches are unable to provide force-time metrics related to jumping performance as they are not direct measures of the athlete’s motion [14]. Specifically, these camera systems may be unable to measure the RSI index [17] that is more commonly used in high-level athletes.

Overall, our approach provides a balance of cost, mobility, and measurement accuracy that would be appropriate for a range of users. The inertial measurement unit utilized is low-



(a) In-ground force plate



(b) Body-worn accelerometer

Fig. 2: Comparison of Drop Jump data collected from force plate in (a) and body worn accelerometer in (b).

cost (\$75 [18]) and provides direct force measurements that are appropriate for traditional and modified RSI measurements. Section V will discuss in further detail the accuracy trade-offs in our system as compared to the “gold standard” force plate measurement and custom-hardware approaches [2].

III. METHODOLOGY AND APPROACH

In this section, we describe the challenges of identifying RSI parameters of time of flight (t_f) and time of contact (t_c) in force plate and inertial measurement unit data. Additionally, we provide an algorithm for automatically determining those points within recorded data streams.

A. Measuring RSI with Force Plates and IMUs

Figure 2 shows sensor measurements from a single drop jump exercise with readings from an in-ground force plate in Figure 2a and a body-worn IMU in Figure 2b. As described in Section II-A, the reactive strength index can be calculated by determining the time of contact (t_c) a person has with the ground between landing and executing a vertical jump, and by the time of flight (t_f) during that vertical jump. These parameters, t_f and t_c , must be extracted from each data stream to calculate the appropriate RSI value.

Examining the force plate data in Figure 2a, the sensor reports a measurement in Newtons (N) that is the force applied to the plate. In the context of the drop jump exercise, the force plate is the small box in the lower part of Figure 1. Identifying the points at which a participant is in contact with the plate are found by finding when the force plate measures any positive amount of force on its surface, seen in the first landing and second landing arrows of Figure 2a. This indicates that the participant has applied some amount of force to the plate and they have therefore made solid contact with its surface. So long as this force is sustained in any amount, the participant is considered to be in continuous contact with the plate. When the participant jumps, force is steadily released from the plate as the user accelerates their body upwards. Once the force reading on the plate has returned to zero, this indicates that the participant is no longer applying any amount of force to the plate and is therefore no longer in contact with its surface. This can be seen at the point indicated by the jump arrow in Figure 2a.

When analyzing data measured by an accelerometer attached to the participant performing the drop jump, additional challenges were present in identifying the take-off and landing points. Unlike a force plate, there is no way to directly measure the force being applied to the ground through just accelerometer data. After stepping off the raised platform, the participant makes contact with the ground. This impact creates a large spike in the reading of the accelerometer due to the sudden deceleration of the participant’s body. A similar reading occurs after the participant lands from jumping. These two points typically create the largest change in acceleration across the data set and can therefore be used to estimate when the participant has landed. Examples of these large impulses can be seen in the data pointed to by the first landing and second landing arrows of Figure 2b.

After identifying the two landing points the period between these landings is either how long the participant is on the ground or in the air. While landing points are characterized by large deceleration, the acceleration produced by the participant jumping is less dramatic and the data tends to be noisier as the participant’s body moves to recover from the initial landing and the participant prepares themselves to jump. The takeoff point for this study was estimated to be the point at which the acceleration was greatest between landing points, seen at the point indicated by the jump arrow in Figure 2b. This point was chosen as the estimation because it corresponds with the fact that the largest acceleration of the participant’s feet should occur immediately as the participant leaves the ground, and that the small amounts of acceleration previous to this point are just indicative of the participant readying themselves to jump.

B. Algorithms for Identifying Time of Contact and Time of Flight

The design of an algorithm to find the landing, jumping, and second landing points from force plate data was relatively straightforward due to the low-noise nature of the data and the direct measurement of force being applied by the participant. The algorithm first established a baseline from the first few seconds of data to be used as a comparison for an increase in force. This value was not always zero due to the calibration of the force plate and therefore had to be accounted for. The

algorithm then used that established baseline as a threshold to find the first landing point. Once the force measured by the plate increased above the threshold, the first landing point could be marked and the measurement for the time of contact with the ground (t_c) could begin. The algorithm then searched for when the measured force returned to the set threshold to mark when the participant had fully left the plate. At this point, the time of contact with the ground ended and the time of flight (t_f) began. Similarly to finding the first landing point, we found the next point at which the force measured was above the set threshold after the takeoff point and used that as the second landing point, ending the time of flight.

The algorithm designed to find the landing points and jumping points based on accelerometer data required more intensive logic to find the points among the greater amounts of noise. Additionally, empirical methods were devised to find patterns in the accelerometer data that best represented when the participant took off from the ground. To find landing points, a derivative was taken of the raw accelerometer data and the two highest points of the resulting data were taken to be the initial and final landing points. These points represented the greatest momentary change in acceleration of the sensors and therefore accurately represented the landing points. After identifying the landing points, the take-off points for the jump were examined. It was empirically determined through internal trials that the best representation of this take-off point could be found by taking a moving average over the entire data set and then finding the maximum point on the resulting data that fell between the two established landing points. The timestamp of the initial landing point subtracted from the timestamp of the takeoff point yielded the time of contact with the ground. The timestamp of the takeoff point subtracted from the timestamp of the final landing point yielded the time of flight.

After the time of contact with the ground and time of flight were calculated the RSI value was calculated following the equations in Section II-A.

IV. USER STUDY AND EXPERIMENTAL DESIGN

A user study was conducted to test the efficacy of our approach in measuring the RSI for amateur participants described in Section III. 11 healthy young adults were recruited and the study was conducted in the James Madison University Animal Motion Lab. Participants were asked to wear athletic footwear and were given instructions on how to attach the IMU to the shoe on their dominant foot. A commercially available IMU (Mbientlab MetaMotionR) [18] was used to measure accelerometer data and an in-ground force plate (AMTI Force Plate) was used to measure force plate data. Participants were asked for basic biometric data about their height and weight as well as questions about their relative athletic ability.

Participants were instructed to step onto a 43 centimeter raised platform positioned next to the force plate and were given a demonstration of how to step off and perform a drop jump. Emphasis was placed on remaining still before and after the jump had been performed to minimize the noise generated on the accelerometer. The participant was asked to practice

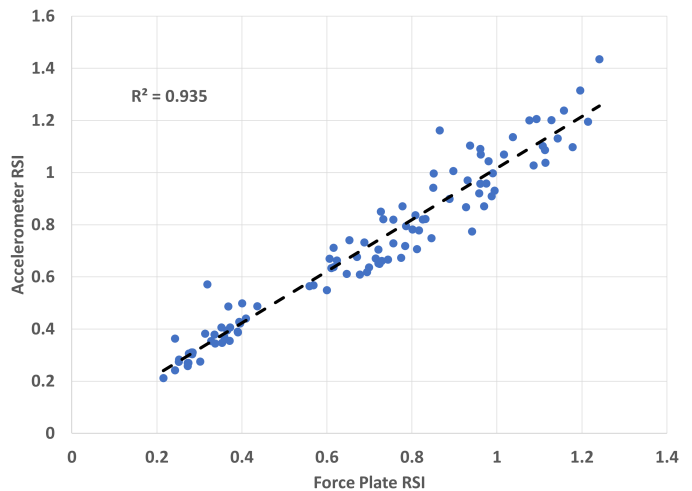


Fig. 3: RSI values as measured from the force plate and body worn accelerometer. Pearson's Correlation coefficient between two measures is found at $R^2 = 0.935$

the exercise as many times as they needed to feel comfortable with the process and so that the participant's form could be corrected if steps were performed incorrectly. Once the participant said they felt comfortable with the exercise and it was determined that the drop jump was being performed correctly, the participant was asked to start on top of the raised platform.

An iPad paired with the IMU collected accelerometer data at 800Hz across three axes and software on the biomechanics lab computer captured force plate data at 1000Hz. Data recording began before the user received instructions to jump. After the participant landed, jumped, and landed for a second time, recording on the force plate was stopped and it was decided whether or not the trial should be repeated. If the participant stumbled, stepped off the force plate, or otherwise performed a jump that did not fit the form of a drop jump, the trial was marked as errant and not used during data analysis. This process was repeated as many times as necessary until ten correctly performed trials were conducted for each participant. Breaks were given every five trials. After ten trials were successfully recorded, data collection was stopped and the sensor was removed from the participant's shoe.

V. RESULTS AND DISCUSSION

Following the user study described in Section IV, data was collected from 11 participants who performed a total of 102 jumps. One participant was excluded from the study due to their inability to correctly perform the drop jump exercises. Two additional jumps are reported, beyond the expected 100, as the participant unintentionally performed extra jumps. For each drop jump performed, the RSI from the force plate and IMU was calculated following the methods in Section IV. These two data sets are plotted against each other in Figure 3 to determine the correlation (R^2) between the two measurements. Overall, the measurements between the two systems are highly correlated with $R^2 = 0.935$. A high correlation between the

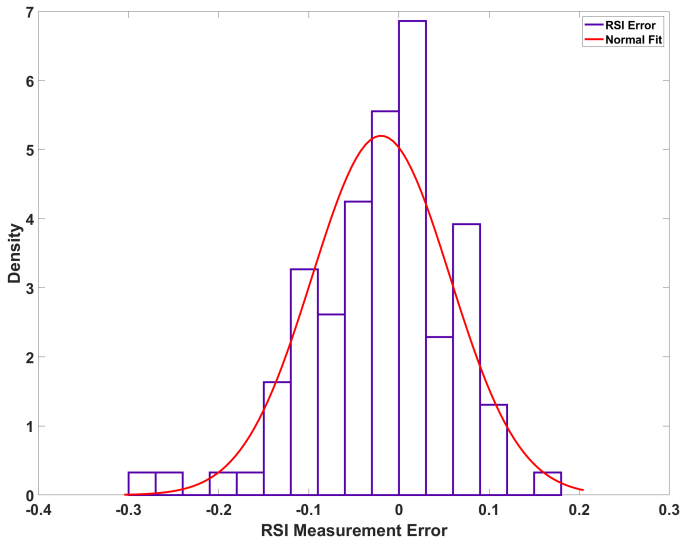


Fig. 4: Distribution of measurement error with fitted normal distribution

two measures was expected as both the IMU and force plate measured the same physical phenomenon.

In addition to measures of correlation, the measurement error comparing the calculated RSI values was determined. For this error, the force plate RSI value was taken to be the “true” measure as the force plate more clearly indicates the time of flight and time of contact parameters, relative to the IMU. The distribution of these errors was found to be normal through a χ^2 goodness of fit test. A plot of the measurement errors is shown in Figure 4 with a fitted normal distribution. Across all jumps, the mean error μ was -0.0198 with a standard deviation σ of 0.767 . These results provide a 95% confidence interval ($\mu \pm 1.96 * \sigma$) for our error of $(-0.169, 0.129)$.

Having these results, we can now return to the central question of whether our low-cost accelerometer is an effective replacement for an in-ground force plate. Overall, our results are reliable in replicating the force plate measures as we achieve a high correlation ($R^2 = 0.935$), and our measurement error is in line with existing estimations of IMU and force plate RSI measurement errors of $(-0.16, 0.16)$ [19] and $(-0.11, 0.12)$ [2]. However, no measurement system is without error and by examining the 95% confidence interval, our approach would be able to detect RSI changes larger than 0.169 . Examining, Table I, this approach would be suitable for several studies [7], [11], but it would be unable to detect more minute changes observed in other studies [8].

Examining our work further, we encountered similar challenges identifying the take-off points in the jump from accelerometer data [2]. There is potential for improved RSI results if a method can be developed for measuring this point with greater accuracy. A dedicated IMU could be placed at a participant’s hip to detect changes in the participant’s center of gravity or the use of gyroscope as well as accelerometer data to detect changes in a person’s foot as it is related to when they jump are potential points that could be further explored.

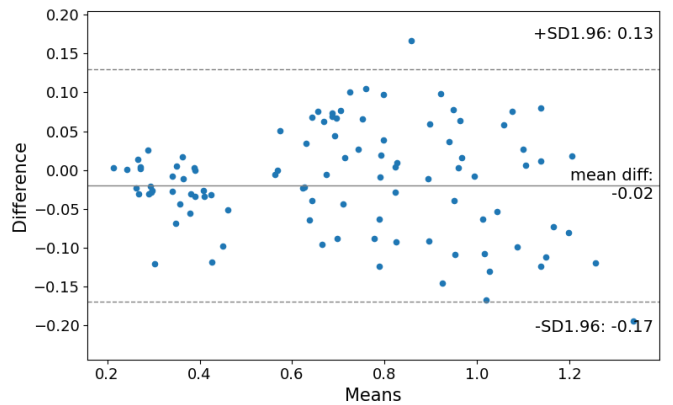


Fig. 5: Bland-Altman plot showing the mean RSI value measured for a jump between the accelerometer and force plate on the horizontal axis. The vertical axis show the difference in those two measurements for a single jump. 95% confidence intervals are provided on the measurements.

Another interesting point of note is the similarity to previous work that the smaller the RSI, the more accurate that the RSI can be calculated from IMU data [2]. This is exemplified in the Bland-Altman plot seen in Figure 5 where the average RSI measurement from the IMU and force plate is plotted on the x-axis, and the difference between these two measures is on the y-axis. As the RSI of the data increases across the x-axis, and thus a stronger jump is performed, the greater the spread of the points and therefore the larger error. The IMU measurements may have more “noise” as the person is performing a more energetic jump, and thus the take-off and landing points are more difficult to identify. Potentially, different analysis techniques could be applied based upon the reaction time of the participant [20] to more accurately capture their performance.

VI. CONCLUSIONS

The feasibility of tracking improvement in athletic ability with commercial off-the-shelf hardware presents the possibility of reducing data inequity between large, well-funded sports programs and amateur athletics by making performance metrics more accessible. The user study conducted and methodology defined showcases one such method of achieving this goal. Our results show that these IMUs are effective in measuring RSI changes that reflect moderate to extreme RSI improvements of at least 0.2 . The study also shows the potential for increased precision of results if further research is done into a better prediction of takeoff points. A greater collection of participant biometric data could also aid in the grouping and reasoning behind differences in error between participants. Overall, the study presents positive results towards increasing the accessibility of performance metrics with the possibility of further improvement.

ACKNOWLEDGMENTS

The authors would like to thank Dr. Roshna Wunderlich and the JMU Animal Motion Laboratory. Funding for this work is provided by the JMU CISE Faculty Development Grant and the CISE Mini Grant.

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