Measuring the Effect of Lower Extremity Fatigue on Basketball Shooting

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It is well understood that fatigue hinders athletic performance. Past work has studied fatigue and its effect on the upper body during shooting in basketball. However, little work has been done to analyze the impact of fatigue on the lower extremities during this activity. Using ECG, EMG, accelerometer, and PZT respiration data, we attempted to determine whether such an impact exists. With this data, we were able to identify muscle imbalances and found that better shooters had more balance, consistent leg muscle activation, and consistent vertical acceleration during shots. Though our experimental process did not seem to induce fatigue as intended, our findings offer avenues for future iterations of research in the lower extremities for basketball shooting.

Additional Key Words and Phrases: Basketball, Fatigue, EMG, Accelerometer, ECG, Shooting

ACM Reference Format:
David Williams and Pranav Datta. 2024. Measuring the Effect of Lower Extremity Fatigue on Basketball Shooting. 1, 1 (May 2024), 9 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 BACKGROUND

In physically demanding sports like basketball, it is widely known that fatigue can negatively affect performance. However, measuring fatigue and its effect on athletic performance has proven difficult to measure explicitly [15]. In the limited amount of literature, several ways to measure fatigue have been proposed with varying levels of success [10]. One relatively common successful method is the countermovement jump test, which measures the force a player is capable of applying when jumping straight up. This test, while it can demonstrate fatigue, requires a high load force plate, so it can only be used after an activity is done [16][9]. Other studies have looked at the effect of fatigue during activity, also with varying success. Some looked at the changing kinematics in the shooting arm due to fatigue, measuring no significant difference for the change in rotation but a significant difference for the change in velocity [17][13]. Another study targeted fatiguing lower back muscles, finding decreased field goal percentages and an overall change in shooting kinematics [14]. There is still a gap in knowledge on the effect of fatigue on basketball performance, specifically measuring lower body fatigue during activity and translating that to an impact on performance.

We measured fatigue and its effects by detecting differences in leg muscle activation, acceleration, heart rate variability, and respiratory rate throughout an entire session of basketball shooting. We used an EMG sensor on the vastus lateralis in the left and right leg, an accelerometer in the lower back, an ECG sensor, and a respiratory band to take these measurements. This solution provides access to data in a setting that has previously not been explored. While there is data on leg force from fatigue, they are not taken during activity and the connection to basketball shooting is not

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measured. Considering the importance of leg power and balance while shooting, we predicted that fatigue in the legs would have a significant effect on shot percentage, which had not been directly examined before.

2 METHODOLOGY

2.1 Participants

The study comprised 7 male Georgia Tech students of roughly equal height and weight with varying athletic experience. All participants had participated in team or individual sports at the high school level and had some history of playing basketball in an organized or "pick-up" fashion. The study required that each participant had a relatively practiced and consistent shooting motion, but no requirement on the average proficiency of this shooting motion was made. Additionally, no physical conditioning baseline was made, so participants were in various cardio fitness levels. Given the physical nature of the experiment, each participant was asked to provide informed consent about their involvement in the study.

2.2 Equipment

The BITalino (r)evolution kit was used to acquire the EMG, accelerometer, ECG, and respiration signals [5]. Each sensor connects to a microcontroller which itself connects to any Windows, Andriod, iOS, Linux, or macOS device via Bluetooth through the OpenSignals (r)evolution application [6]. The recording of the signal data is controlled through this application and can be exported into a .txt file for analysis using the biosignalsnotebooks Python module [2].

The electromyography (EMG) sensor measures the electrical current of muscles during contraction through electrodes attached to the surface of the skin [18]. The BITalino sensor outputs these currents as noisy raw signals which can then be filtered, processed, and unit-converted to electric voltage in millivolts over time. Features of this signal, such as amplitude and frequency, can be used to measure events such as muscle activation and imbalance.

The BITalino accelerometer measures acceleration in one direction [1]. The raw signals can be filtered and converted to g's over time, and information such as jump height, speed, force, and airtime can be calculated using these signals.

The electrocardiogram (ECG) sensor measures the change in electrical impulse across the heart in millivolts over time through electrodes attached at various locations on a person's body. After filtering the raw signals, a pattern is revealed where the first P wave shows the atria of the heart contracting and relaxing, the QRS complex shows how the electrical signal passes to the ventricles, and the T wave shows the ventricles contracting and relaxing. These patterns can be processed to determine heart rate, variability, and rhythm [11].

The piezoelectric respiration (PZT) sensor is a chest band that measures its displacement to determine volume changes in the torso during respiration [7]. The raw signals can be processed to deduce respiration rate, cycle, and amplitude.

2.3 Experimental Design

The experiments were performed at the Georgia Tech Campus Recreation Center basketball courts. Each participant was fitted with EMG sensors on their left and right vastus lateralis muscle, an accelerometer to the top of a BITalino microcontroller which was attached to the participant's waistband, ECG sensors connected to the participant's left and right pectoral muscle and lower left rib, and PZT respiration sensor around the participant's lower chest (Fig. 1). An iPhone was placed near the half-court line to record each participant's shots. Participants were given 5-10 minutes to warm up and adjust to the various sensors attached to them. After this period, we started recording the BITalino sensor data using the OpenSignals application and started the experimental task.

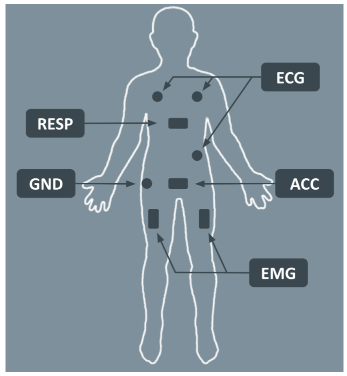

Fig. 1. Placement of sensors on each participant.

The task started with an initial jump where the participants jumped as high as they could. They then shot the basketball from the top of the 3-point arc 10 times, running from the shot location to the opposite baseline after each shot (Fig. 2). After the 10 shots, the participants were asked to jump as high as they could again. This process was repeated 3 times for a total of 40 shots and 5 jumps over 10-11 minutes.

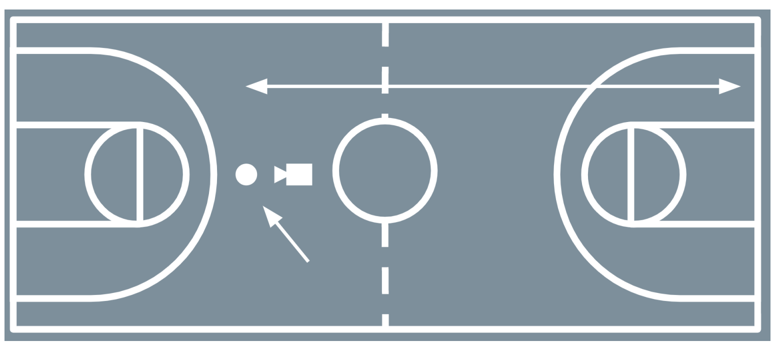

Fig. 2. Diagram of experiment protocol.

2.4 Data Processing

The videos of the experiment were post-processed to determine the time points for each of the shots and jumps as well as the shot outcomes. This and the data exported from the OpenSignals application were uploaded to Google Colab for analysis. The time points were verified and adjusted if necessary by layering the EMG data from each leg and finding local regions where peaks simultaneously occurred, indicating a shot or a jump.

A low-pass filter was used on the raw accelerometer data to eliminate noise [4]. The data was then unit-converted to g's and plotted alongside the jump and shot times (Fig. 3) [8]. The maximum and minimum acceleration in a 1.5-second window after these time points were analyzed.

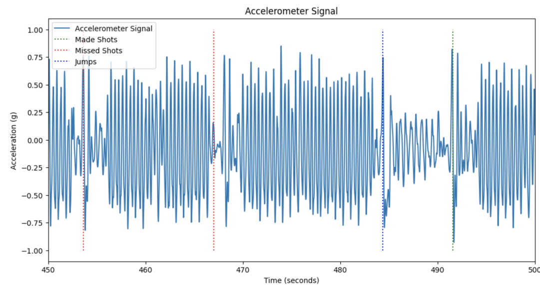

Fig. 3. Filtered accelerometer signal plotted alongside jump and shot times.

We used the implementation of the Burst detection algorithm using the Teager Kaiser Energy Operator from the biosignalsnotebooks Python library on the EMG data [12]. This function detects muscle activation periods and identifies the start and end of these periods using the increase and decrease of electric potential [3]. This data was plotted alongside the jump and shot times to identify regions of muscle imbalance and the change in muscle activation strength over time (Fig. 4). For each leg's EMG data, the maximum activation in a 1.5-second window after these time points was analyzed.

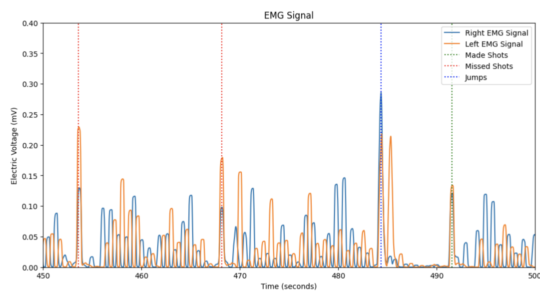

Fig. 4. Filtered EMG signal plotted alongside jump and shot times.

A low-pass filter and a moving average were applied to the PZT respiration data to reduce noise [4]. A peak detection algorithm was then applied to determine the respiration rate and its change throughout the experiment (Fig. 5) [3].

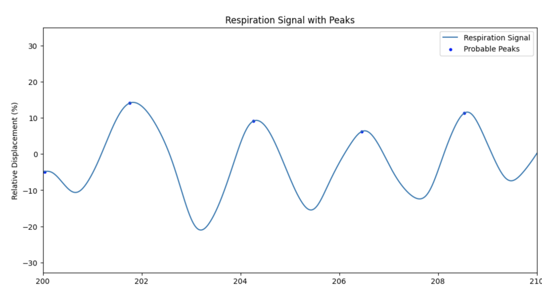

Fig. 5. Filtered PZT respiration signal with peaks.

A band-pass was applied to the raw ECG data to keep frequencies within a certain range. The data was further processed using differentiation, integration, and moving windows to eliminate further noise until a discernible heartbeat pattern could be seen. A peak detection algorithm was then applied to determine the participant's heart rate (Fig. 6). A tachogram was also created to see the change in cardiac cycle over time (Fig. 7) [3].

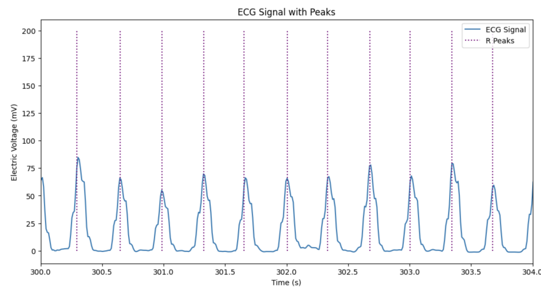

Fig. 6. Filtered ECG signal with peaks.

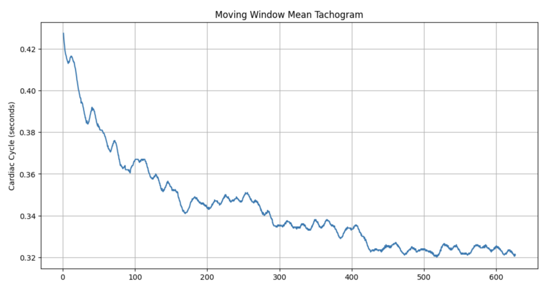

Fig. 7. Tachogram.

3 RESULTS

One trend we found with all signals was the presence of lots of noise. This is likely due to hardware and the environment in which we collected data. Due to the volume of data collected, we were unable to manually correct for false positive or false negative peaks identified, making some signals from certain subjects difficult to work with.

When asked to rate their fatigue on a scale of 1-10 after completing the study, subjects answered in the range of 4-6, indicating they felt tired but may not have reached the intended level of fatigue.

3.1 PZT Respiration

For Respiration, we found no significant increase in breathing rate or breathing rate variance across the study. Subjects stayed around 30 breaths per minute for the duration of the experiment, indicating they were exercising but not straining themselves too hard.

3.2 ECG

From our ECG data, we found that subjects' heart rate did increase over the course of the study, as would be characteristic of exercise, but heart rate variability did not increase significantly (p>0.05) (Fig. 7). For heart rate increase, this simply indicates the subject is exercising so there is little insight to be drawn. The lack of heart rate variability is indicative that subjects did not experience fatigue while undergoing this study.

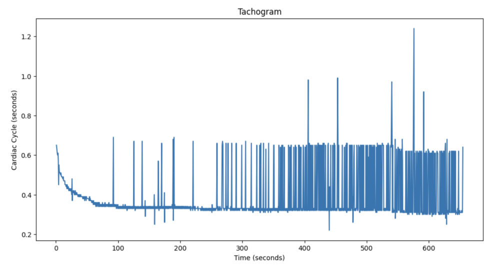

Fig. 8. Bimodal Tachogram.

ECG uniquely had a lot of noise, especially in the latter half of the study. This could be due to subjects beginning to sweat, causing the leads to slip. The outcome of this excess noise was a lack of reliable data in peak detection, with a common occurrence being a tachogram that almost appeared bimodal (Fig. 8). Not every subject suffered from this noise, but a tachogram with this trend did occur often enough to be worth mentioning.

3.3 Accelerometer

From our accelerometer data, we found the most significant insights by looking at the variance of the minimum and maximum acceleration achieved during the shots. The minimum acceleration is directly related to the velocity, displacement, and the amount of force generated during the beginning of the shot since the shooter starts from a standstill and takes the same amount of time descending on each shot, according to our analysis of the video corroborated by the EMG data as described above. Similarly, the maximum acceleration is directly related to the same metrics, but on the ascension of the shot. On streaks (3 or more made shots in a row), we saw evidence that the minimum and maximum acceleration stayed consistent (within .05 g's) on each shot. In contrast, when a participant missed a similar number of shots in a row, either the minimum or maximum acceleration would vary by up to .2 g's (Fig. 9). This trend is worth exploring more in a dedicated study, but there is preliminary evidence from multiple subjects of this study.

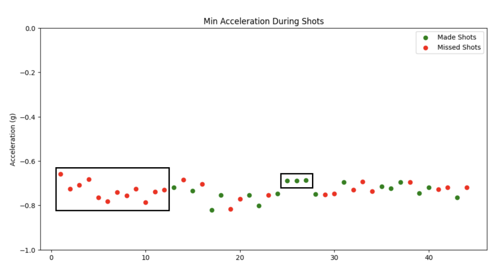

Fig. 9. Trends in make streaks versus miss streaks.

We did not see any significant change (p>0.05) in the mean/median of minimum or maximum acceleration values over the number of shots taken or jumps for any participant. Additionally, we did not see a significant difference (p>0.05) in mean/median of acceleration values for misses versus makes. However, we found that made shots had less variance in maximum acceleration compared to missed shots (Fig. 10). On average, made shots varied by 0.133 g's while missed shots varied by 0.2 g's. We did not find a similar trend for the variance of minimum acceleration, as made shots for our participants varied by 0.175 g's while missed shots varied by 0.183 g's on average.

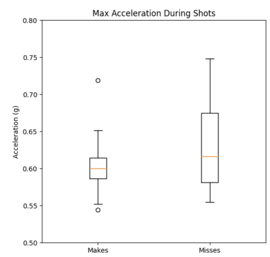

Fig. 10. Accelerometer make versus miss.

3.4 EMG

By looking at the difference in maximum EMG activation between each leg, we could detect muscle imbalances for each shot (Fig. 11). Two of our participants had significant muscle imbalances, with one favoring their left leg on most shots while the other favored their right. For the participant that had higher EMG activation values for their left leg, we found that the activation in their right leg varied by far less (0.15 mV) than their left (0.35 mV). Interestingly, we learned that this subject with high muscle imbalance tore the ACL in their left leg, indicating this imbalance could have some relation to injury. Muscle imbalance in athletes with prior injuries is an insight we would like to explore further in a future study.

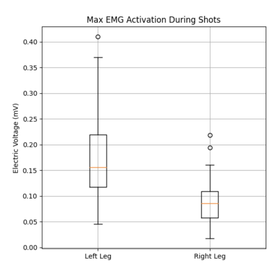

Fig. 11. EMG with muscle imbalance.

When comparing makes versus misses, the maximum combined EMG activation and the difference between the left and right leg were the trends we decided to focus on (Fig. 12). Similar to the trend seen in the accelerometer data, we found no significant difference in the maximum EMG activation for makes versus misses (p>0.05) or the difference between left and right EMG for makes versus misses (p>0.05). From visual inspection, there does seem to be a slightly lower variance for made shots when looking at maximum EMG activation, but this would need to be explored in another study. Overall, there is little that we could find from EMG when comparing the makes and misses of a single subject.

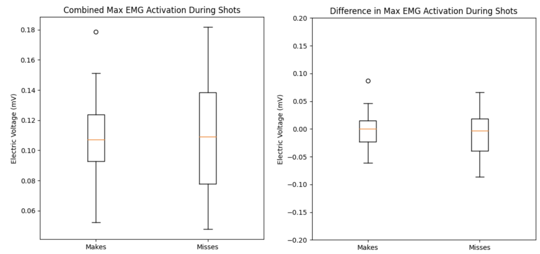

Fig. 12. Combined max EMG activation (left) and EMG activation difference (right).

4 DISCUSSION

Based on our results, it appeared that our experiment did not induce the desired fatigue. This is likely because our protocol focused primarily on shooting and jogging. Other essential movements present in basketball, such as sprinting, shuffling, and jumping were not entirely captured. An improved study would incorporate these actions to make the experiment more representative of the physical load experienced by basketball players and hopefully cause lower extremity fatigue as intended. Additionally, our experiments attempted to condense the activity of a typical basketball game into 10-11 minutes to make the time commitment for our participants as minimal as possible. A longer study, or one that takes place during an actual basketball game, would better reflect the physical load experienced by players.

Our study also comprised participants who were all amateurs at the sport. As a result, they lacked the hours of practice in developing a refined shooting motion that an experienced basketball player would have. Therefore, it was unclear whether changes in muscle activation or acceleration were due to fatigue or lack of shooting experience. A study comprising solely basketball players would reduce the likelihood of the participants changing their shooting motion throughout the experiment, which is something that may have affected our data. Our participants also had to overcome the wires, sensors, and microcontroller that were attached to them. Though the warm-up period was intended to help our participants get acclimated to shooting and running with these sensors, even minute adjustments to a shooting motion as a result of these sensors could be the reason why some participants made fewer shots than they would have otherwise. Condensing the sensors into a less obtrusive wearable such as a pair of compression shorts would eliminate any interference that would cause a participant to change their shooting motion during the study. It would also be more practical if such a device were to be used in an actual basketball context.

Our original intention was to identify the effect of fatigue on a person's basketball shooting specifically in the lower extremities. The goal was to propose a wearable using a minimal amount of sensors that may be used, for example, to identify a point of fatigue in a player where it starts to affect their shooting form and accuracy. The player's playing time could be regulated based on their lower extremity fatigue and its effect on their performance. In our results, whether that is because of the faults in our study or because there isn't an impact of fatigue on the lower extremities during basketball shooting, we did not find such an effect. Based on the sensors we found to provide the most data, future iterations of this study may pivot to instead looking at the lower extremity influences of made shots compared to missed shots using EMG sensors placed on more leg muscles and accelerometers. A future iteration may also look at identifying changes in muscle activation during shooting before and after injury, which could influence correction and assist a player in recovery.

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Received 11 April 2024