WEARABLE TECHNOLOGY FOR DESIGN AND SAFETY EVALUATION OF RIDER
ACCELERATION EXPOSURE ON ZIP LINE ATTRACTIONS

by

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BSc Computer Science,

Concentrations in Software Engineering and Human-Computer Interaction,

University of Calgary, 2017

A Major Research Project

presented to Ryerson University

in partial fulfilment of the

requirements for the degree of

Master of Digital Media

in the program of

Yeates School of Graduate Studies, Digital Media

Toronto, Ontario, Canada, 2018

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Shelly-Ginelle Sicat

Abstract

Wearable Technology for Design and Safety Evaluation of Rider Acceleration Exposure on Zip Line Attractions

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Master of Digital Media, 2018

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Aerial adventure attractions are intended to produce exhilarating sensations at significant elevation, speed, and acceleration, all while maintaining the safety of the participant. While Zip Line designers and owners can refer to international standards addressing many safety requirements, the measurement and assessment of acceleration exposures of the Zip Line rider has not been standardized. My major research project (MRP) considers the design and validation protocol for wearable sensor technology to collect acceleration and g-force exposure of a Zip Line rider. Introducing the combination of systematic design and quantitative analysis to wearable technology architectures requires considerable thought taking into account existing ride standards, biomechanics, ergonomics and the need for data accuracy. The primary objectives are two-fold, 1) contribute a test protocol that will evaluate the reliability and validity of the proposed system, and 2) take a step forward towards implementing a consistent process to capture acceleration exposure on Zip Line attractions. We contribute a test protocol that will evaluate the reliability and validity of the proposed system.

Acknowledgements

There are many individuals who have contributed to the successful completion of this major research project, of which I extend my sincere gratitude towards.

To my dedicated supervisors, Kathryn Woodcock, and Alex Ferworn, for their exceptional support, unwavering guidance, and unconditional care throughout the program. Not only was it a pleasure to work and learn alongside them, but it was also humbling to see how much passion and wisdom they have in their expertise. They will forever be my inspiration and mentors.

Additional thanks to all collaborators and stakeholders that made this project possible. Alan Black, adbForensics for his insightful discussions on Zip Line safety standards and methodology. Jimmy Tran, N-CART Laboratory on technical architecture and insight on sensor placement and programming. Rob Sheridan, Blue Mountain; Randy Richards, Treetop Eco-Adventure Park; Jamie Barrow, Vail Resorts; for accommodating data collection visits and providing insight of Zip Line safety procedures.

This research was supported in part by scholarship grants from Ryerson University Yeates School of Graduate Studies and Technical Standards and Safety Authority (TSSA).

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1. Introduction

From exhilarating heights soaring across the mountains or complex terrains, Zip Lines are a popular activity choice for adrenaline seekers. Starting at heights of over 30 ft, and traveling well over 1,000 ft, a rider glides to the bottom at speeds averaging 100 km/h (Schilling, 2016). Securely contained within a properly fitted harness, riders wear a helmet but are otherwise unconfined, allowing them to experience a sensation of free flying in various postures, specific to each Zip Line. As a method to discover new vantage points within the rainforest to an activity commercialized for public leisure, there now exists hundreds of Zip Lines in many countries with a variety of intriguing features (Schilling, 2016). An increase of exposure presents more opportunities for occurrence of even rare events such as malfunction and other injury mechanisms.

As a rider would be physically exposed to grave injury in the event of structural or equipment failure, international standards establish requirements for safe operation (notably ASTM F2959 Standard Practice for Aerial Adventure Courses and Association of Challenge Course Technology Standards). An estimated 16,850 nonfatal Zip Line injuries were treated in U.S. emergency departments between 1997 and 2012, and nearly 70 per cent of those injuries occurred during the last four years of that span (Edwards et al., 2015). The majority have been falls (77 per cent) and collisions (13 per cent), including those with trees and other structures used to anchor Zip Lines (Edwards et al., 2015).

An additional potential mechanism of injury is associated with abrupt deceleration on arrival at the braking system at the end of the Zip Line. Upon encountering the brake system, the free body of the harnessed rider suspended from the trolley typically behaves like a pendulum due to momentum and gravity, with some amount of flailing of the whole body or segments of

the body upon abrupt deceleration, potentially compounded by the posture or movement of the rider. Although standards have established limits for acceleration exposure for amusement device riders (ASTM F2291), the Standard Amusement Ride Characterization (SARC) test described in ASTM F2137 (and its counterparts in other standards systems) is based on a rider seated in a ride vehicle. The SARC test protocol describes the specifications of testing ballast weight, transducer location, gravity consideration, and test documentation practices. Little is known about the levels of acceleration experienced by Zip Line riders, nor is there a standard practice for acquiring acceleration measurements in a reliable manner.

This paper describes a design requirements model for measurement of Zip Line acceleration using wearable technology. Wearable devices integrating accelerometer sensors are commonly used for analyzing sport and health performance (Chambers et al., 2015; Beanland et al., 2013;2014; Yamamoto et al, 2017; Kwee-Meier et al., 2016). Wearable computing has evolved greatly over recent years, with emerging systems that are active, intuitive, and virtually invisible (Adapa et al., 2018; Anliker et al., 2004). The method of developing wearable architecture enables users to discover beyond human capability, visualizing data from a pulse sensor or detecting movement as we currently see in fitness monitors. However, wearable technology to capture acceleration of Zip Line users is a novel application.

In studies that analyze acceleration, data acquired using a tri-axial accelerometer is often supplemented with a GPS sensor and concurrently recorded digital video footage. This way, data recorded from the sensors can be compared with a visual recording, to analyze the correlation or causation. The type of accelerometers used varied. Accelerometers on the market range in price, customization and specification. Therefore, depending on the device's acceleration magnitude and frequency recorded, will determine the appropriate sensor to use.

Despite the frequent use of body-worn accelerometers, some sources report challenges regarding sensor displacement, number of sensors and signal accuracy. For example, sensor deployments are subject to variations introduced by the normal use of the accessories into which they are embedded (Banos et al., 2014). Sensors may also change position dynamically due to loose attachments, e.g., when integrated into baggy clothes (Harms et al., 2008). As a consequence, data acquired can drastically drift from the intended activity observed (Banos et al., 2014). Methods to minimize sensor displacement often involve the use of multi-sensor configurations to counteract the variations (Banos et al., 2014; Davila et al., 2017). Placement of the sensors should consider the biomechanics required to perform the desired motion or activity for more accurate results (Amasay, 2010).

We envision the development of a method of acquiring acceleration data from garments worn by Zip Line riders which are capable of capturing the full nine degrees of freedom of movement of riders as they encounter a Zip Line braking system. Data acquired in this way will inform the assessment of the Zip Line acceleration exposure. Further, by embedding this data within a context-aware, proactive, and intelligent interface, the data may be used in real time by designer/engineers, owner/operators and regulatory inspectors in support of their roles. This paper refers to a device that could be used in design analysis, testing during the commissioning stage to verify that the Zip Line as built has the intended characteristics, and periodically to verify that the characteristics have been maintained.

2. Related literature

2.1 Acceleration safety testing in amusement rides and devices

Impacts involving the human body are a common phenomenon of life. As Mckenney (1970) describes it, “from the buttock’s slap which is often used to start the breathing of a newborn baby, to the fatal fall, which may occur at practically any age, impact may be said to be part of human experience from birth to death”. However, with the adoption of mechanical devices within multiple industries such as the military, aerospace and amusement parks, impact hazards have increased both in number and magnitude (Mckenney, 1970; Pfister et al, 2009).

Amusement rides are unique in that they are deliberately designed to create the illusion of danger and expose users to a variety of motions (Eager et al., 2016; BIAA, 2003). For example, Zip Line riders are purposely subjected to elevated acceleration where the magnitude, duration and rate of change of the acceleration. These variables are increased to enhance the sensory stimulation but are also limited to ensure ride safety (Eager, 2013). Despite the intention to entertain and thrill, effects of elevated accelerations do not all lead to pleasure. If a ride was inadequately designed or faulty, it would result in discomfort or even harm to the health of its’ passengers (Eager et al., 2016).

With the progressive adoption of mechanized entertainment, safety standards are required to address acceleration limits. Safety testing is performed for different purposes throughout the design and use lifecycle of a product. The complexity of this process involves multiple parties - inspector/auditor, designer/manufacturer, owner/operator, and any authority having jurisdiction (ADJ) (Personal communication, Gonzales to Woodcock 27 April 2018). The dynamic structure allows for an evolution of solutions brought through collaboration between self-organizing, cross-functional teams to utilize appropriate practices for their context (Personal communication,

Gonzales to Woodcock 27 April 2018). Ultimately, each party works together to ensure safety regulations are met.

Acceleration experienced by the rider is determined not only by the speed and acceleration of the movement of the passenger carrying unit, but also by the seating position of the rider within it. Typically, tri-axial accelerometer measurements are made during a normal operating cycle with accelerometer placement and vehicle loading (BIAA, 2003). A SARC test is used to specify a standard coordinate system to measure acceleration in terms of Gx (eyes front/back), Gy (eyes right/left) and Gz (eyes down/up) (ASTM F2137). Reference to the positive and negative acceleration limits help to analyze what is tolerable given the duration of the ride. As the duration increases, magnitude tolerance decreases. This is due to the fact that: a) blood flow in the body is time dependent and it takes a few seconds for the blood to be reduced or increased in the head and b) fatigue can become a factor (BIAA, 2003).

Specific measurement placement includes cases for which riders ride while seated, standing or lying down. For example, “for a ride or device in which riders ride while seated, the accelerometer shall be mounted at a location between 12 and 16 in above the seat level and between 2.5 and 5 in. fore of the upper torso” (ASTM 2137). A minimum of two consecutive test data records from one transducer mounting location is required to establish a repeatable measure for test configuration and the acquired test data. Test documentation for all rides or devices that incorporate significant random, non-repeatable, motion is excepted from this requirement. The raw data recorded is then required to be post-processed, with a 4-pole, single-pass, Butterworth low-pass filter using a corner frequency (F_n) of 5 Hz (ASTM 2137). Such requirements serve to eliminate noise and impact accelerations less than 200 ms.

While we may presume that the acceleration limits of F2291 are valid for maximum tolerable exposure of a rider from his or her frame of reference, we have no method of reliably determining what the actual exposure is for a rider on a Zip Line. For example, to suspend a SARC-instrumented dummy within a harness is unlikely to indicate the acceleration experienced by a rider in different foreseeable postures achievable through voluntary/involuntary body movements. Consequences of avoiding analysis of acceleration limits may result in serious injuries, e.g., brain injury/aneurysm, or aggravating blood pressure/cardiac, etc (BIAA, 2003). This gap informs the goal of the project, to measure the acceleration experienced in a realistic Zip Line exposure.

2.2 Human behavior on amusement rides

In addition to prevention of rider ejection due to the acceleration of the ride, many amusement rides limit human posture and behaviour through user instructions and various restraint and containment systems particularly where self-extraction could lead to serious injuries. Additional positioning devices, such as handrails, may be provided to increase subjective sense of security and a structure that can be used to brace against the ride's forces. Despite these provisions, most sources report that the majority of rider injuries on amusement rides involve situationally inappropriate rider behaviour (Stenzler, 2016; Woodcock, 2007). While most attractions provide posted safety information, riders may not perceive the information as personally applicable (Sarkisian, 2008). In addition, inappropriate actions may be intuitive reactions to sudden stimuli, rather than risk-taking decisions. Each rider has his or her own risk tolerance, and individual risk tolerance, as well as risk perception, affects behaviour (Wilde, 1989).

Unsafe actions may be produced by an effort to reduce sensation and increase security and comfort, e.g., grabbing for something to hold, and grasping the Zip Line cable instead of the trolley, as easily as by intentions to increase sensation and sense of thrill, e.g., twisting into a posture that increases disorientation and conceals view of safety equipment. Each of these postures could affect the acceleration of the body torso in relation to the point of attachment upon braking, as well as the acceleration of the head and extremities in relation to the torso. While the acceleration on a roller coaster is predominantly determined by the acceleration of the ride vehicle, this is not the case on a Zip Line. The approach to measuring effective acceleration of the rider's body must allow foreseeable variety of voluntary/involuntary postures and unconscious movement as well as swinging and flailing movement produced by momentum of unrestrained body segments.

3. System requirements

To measure acceleration during use of a Zip Line that accounts for a realistic range of foreseeable postures and voluntary/involuntary body movements, the accelerometers must be mounted on a body that will be exposed to the movement profile of the Zip Line.

Anthropomorphic manikins (“crash test dummies”) or ballast containers (torso-shaped water bottles) or sandbags are often used in the SARC test. However, the object’s speed and hence the momentum to be counteracted by the brake deceleration is affected by the aerodynamics of the dummy shape and material. Static objects such as manikins, containers, and sandbags have limited positioning. Although a human rider can introduce difficulties in achieving repeatability and consistency due to differences in the way humans respond to changing forces, (BIAA, 2003), in the case of Zip Lines, capturing the effect on acceleration of these different responses is of the utmost relevance. Therefore, the design must be wearable by a human rider, as well as attachable to a static object.

Second, the accelerometers must be capable of capturing the swing (pitch-X and roll-Y) and rotation (yaw-Z) as well as the deceleration of the trolley. The body parts close to the trolley will decelerate similarly to the trolley, but the more remote body parts will experience different acceleration as momentum causes them to continue to travel, and swing. To address sensor displacement, a well-fitted structured garment with fixed pockets will further secure placement.

To collect data to describe this movement pattern, accelerometers must be positioned at critical points. The preliminary proposal is to capture acceleration at the head, base of the neck, shoulder, centre of mass (COM), and heart. The most damaging injuries occur in the head and upper extremities (Pfister, 2005; Pielles, 2017). Therefore, placement on the head and the base of the neck can help analyze the *roll* (*Y*). As the rider can turn freely over the duration, *yaw*

(rotation around Z) can then be detected by placing accelerometers on the shoulder. This will determine the angle of the rider as they approach the braking mechanism, indicating the appropriate accelerometer-duration limit to compare results with. To analyze the pendulum effect, namely at the COM placement, will be dependent on the type of harness used. The position with respect to the rider's body will vary as the adult harness has the connection point located at the navel and for children it is located closer to the chest. Finally, the heart level placement will be used for comparability with exposure limits based on the SARC test. Each individual accelerometer indicates the acceleration at its corresponding point. Deriving motion capture by the synchronized system of accelerometers will describe the degree of whole-body swing (X-Y) and rotation (Z). Different acceleration at different points on the body presents potential for strain and soft-tissue injury or concussion.

Additionally, we will use digital camera video footage to supplement data obtained from the instrumented garment. The use of five cameras, one attached to a head strap to record the test participant's point-of-view (POV), two at the top platform, and two at the bottom platform will observe the rider's initial and final position. Data recorded from the sensors can be compared with the visual recording, to further observe the correlation or causation between the two.

Although these requirements describe the overall concept of the wearable, an iterative design approach will be required.

3.4 Garment specification

The garment is split into two components, a vest and head wear. The vest houses the shoulder, heart and COM sensors while the headpiece houses the head and neck sensors, as

shown in Figure 1. Given the above requirements, the garment's main priority is to address sensor displacement while ensuring flexibility for body shape and size of a test participant.

The base of the vest is made up of a tactical vest waistcoat, as commonly used in field combat training. The material is made of a sturdy 600D oxford fabric and insulated with foam boards, maximizing wear-resisting material to endure long time use. The surface of the vest is covered with hook and loop (H&L) tape allowing it to accommodate a wide range of body shapes and sizes. Additionally, the shoulder and waist include modular plastic buckles, and a durable H&L tape strap system.

The base of the headpiece utilizes a leather suede lined cap, as commonly used in aviation. The structure is sturdy and shaped snugly for the head. Given that Zip Line riders have to wear safety helmets, we chose a base that is thin, comfortable and snug to wear underneath. A H&L tape strap is mounted along the back of the head where the head and neck sensors will be attached.

Figure 1. Wearable architecture prototype

For both components, we created custom-made pockets out of polyester material lined with fusible interfacing to tightly house the sensors, as shown in Figure 2. Each pocket-front utilized a mesh fabric to allow the test participants and administrators to visually check if the accelerometers were turned on and in the correct position before and after launch. A number of 1-inch H&L tape straps were kept on the vest in case the accelerometers needed extra reinforcement. Depending on the Zip Line harness used, the strap aimed to tighten the attachment onto the desired location, e.g. the COM accelerometer pocket needed to be attached directly onto the Zip Line Harness which experiences the most movement - latching, unlatching, and swinging during the Zip Line visit. The straps are can then be easily transportable with the test participant during set-up.

Figure 2. A close-up look at the custom pocket holders for the sensors.

3.4 Accelerometer specification

The human activity monitor (HAM) accelerometers used were supplied by Gulf Coast Data Concepts, of which included one HAM-IMU-alt, and four HAM-IMU models. The HAM is a self-recording data logger available with several sensor variants. The form factor is 2.21L x 1.55W x 0.60H inch weighing at 0.9oz, keeping it compact and light-weight. Data from the digital sensors are time stamped using a real time clock and stored to a microSD card in simple text format. When connected via the USB to a personal computer, the HAM appears as a standard mass storage device containing the comma delimited data files and the user setup file. The HAM includes an internal 250mAh lithium-polymer rechargeable battery, which will recharge using USB power. Each accelerometer is easily activated with a portable magnet head. Pass a magnet near the top of the HAM enclosure to activate the logger. The magnetic switch minimizes inadvertent disabling of the logger. Logging will start about 3-5 seconds after activation and orange LED will blink as data is written to the flash memory. To stop recording, hold a magnet near the enclosure top for about 3 seconds. The orange and blue LEDs will begin to blink rapidly for 2 seconds and then turn off. Remove the magnet and the HAM turns off.

The default recorded sample rate is set to 50 Hz and the file size approximately records 15-minute intervals. Both the IMU-alt and IMU record All three sensors, acceleration, gyroscope, and magnetometer, are reported in addition to the quaternion solutions. While the IMU-alt also has the additional feature to record high precision barometric pressure sensor. The accelerometer is set to 16g range and the gyroscope is set to the default 2000 °/sec. The logger will activate using the magnetic on/off switch. However, each accelerometer can be customized through the config.txt file found in the storage unit. The user is able to program selectable sample rates, change the time stamp and turn on or off the sensor variants available.

For the purposes of our project, we are most interested in the accelerometer sensor data. Therefore, we chose to modify the default settings to record a 200 Hz sample rate. Utilizing the maximum Hz rate ensures we collect as much frequency possible and thus will be able to smoothen the data during post processing. The data gathered by the gyroscope, magnetometer, and quaternions will be utilized to supplement the acceleration analysis, considering the position and direction the test participant is in. The sensor orientation present on the IMU and IMU+Alt does not confide with conventional axis orientation. To maintain consistency with the calculated quaternion solutions, the axis' point in the following directions as shown in Figure 4, 5 and Table 1 is noted. When the accelerometers are placed within their corresponding pockets, the orientation of each differ from the other.

Table 1. Sensor orientation on the wearable architecture

Direction	Axis (Head, Neck, Shoulder, Heart)	Axis (Centre of Mass - Harness)
Front	Z+	Y+
Back	Z-	Y-
Right	X+	X+
Left	X-	X-
Top	Y-	Z+
Bottom	Y+	Z-

Figure 3. Sensor orientation

Figure 4. Sensor orientation of each sensor location.

3.5 Predictive model

As the Zip Line rider launches from the top platform, the acceleration experienced is predicted to gradually increase and plateau as the acceleration is sustained. Depending on the test participant's position at the arrival at the brake mechanism, the axis at the front of the accelerometers would then cause a rapid positive acceleration. This acceleration recorded should be the maximum acceleration found. For example, a test participant facing forwards, will experience a positive acceleration spike on Z, proceeding with negative acceleration as they swing backwards. The trailing forces may bounce as they gradually maintain their position and are safely detached from the Zip Line. Based on the wearable specification above, we can begin to predict the results to come:

- **H1.** Duration from Zip Line start to upon arrival at the brake mechanism will gradually increase acceleration and eventually plateau as it reaches an equilibrium.

- **H2.** Test participants will encounter the highest acceleration upon contact at the brake mechanism. This will be reflected on the front axis based on the position of the user.

4. Validation Protocol

A test instrument and sensor placement must produce reliable data for commissioning tests and periodic inspections. While the proposed device design has incorporated several performance requirements, a prototype must be tested to evaluate the reliability and validity of its data. This validation protocol will collect acceleration data with a variety of different human participants, equipment, structure and methods. By analyzing the results, we will report a method to determine the most appropriate setup for analyzing the task.

4.1 Venue description

Considering the dynamic characteristics may be affected by local attributes of the venue, descriptive data will be collected about the structures and operational practices. Each Zip Line resort has unique features and structures. Obtaining the specifications of the rides, information about current safety inspection processes and understanding the challenges faced during said processes should be noted as shown in Table 1.

Table 2. Venue description data

Topic	Data to be collected
Customers	Attendance and seasonality of operation
Zip Line(s) at venue	Tabulation of each Zip Line and its parameters: elevation, length, intended speed and duration of transit.
Safety procedures, general	Description of nature and frequency of safety inspection
Safety procedures, for acceleration	Description of current process/practice/equipment used, if any, to measure acceleration.
Subjective assessment of acceleration	Operator perception of circumstances of variation in acceleration, if any, for each Zip Line.
Objective assessment of acceleration	Typical and maximum acceleration recorded, if available, for each Zip Line.

4.2 Procedure for data capture

The validation procedure followed is described in the next paragraph. When we refer to the “test subject” we mean either human rider or a simulant. We refer to a “test administrator” who is a qualified individual who is responsible for conducting a safe, effective and meaningful test using the instruments previously described.

The test subject was fitted with the instrumented garment and typical harness and helmet involved for safety protection. The garment was tested to ensure that its instruments are in order. Additionally, the POV camera was mounted on the test participant’s helmet utilizing a head strap. Subjects donned the garment before the beginning of the ride. A check for sensor placement was conducted once the garment was being worn. The test administrator then prepared the test subject to ride the Zip Line, latching the harness onto the trolley. Before departing, the test administrator took note of the initial position of the test subject and the tri-axial accelerometers. More specifically, addressing the direction of the three axes involved. Two cameras were attached to the top platform to capture the test subject’s initial position for additional reference. The test subject then proceeded to ride the Zip Line, approached the end of the ride, encountered the Zip Line braking system and stopped. The test administrator observed the final position of sensors before unlatching the test subject. Two cameras were attached at the bottom platform to capture the final position of the test subject for additional reference. The test participant commuted back up to the Zip Line top platform to repeat the process.

Figure 5. Wearable architecture setup. Blue indicates accelerometer placement. Orange indicates camera placement.

4.3 Filtering procedure

Each accelerometer logger consistently records 15 min interval .csv files, turning off for a second and shortly proceeding to record the next interval until it is turned off. To fully filter and analyze the data recorded, we concatenated all data files corresponding to each anatomical location. The combined data was then filtered with a “4-pole, single pass, Butterworth low pass filter using a corner frequency (F_n) of 5 Hz”, as required by ASTM F2291 and F2137.

Additionally, the Invensense MPU-9250 embedded within the HAM-imu and HAM accelerometers reports data using a 16-bit value, or 65536 counts. To convert the raw data to “g” units and “degree-seconds”, accelerometer data was divided by 2048 and gyroscope data was divided by 65.536. Raw versus filtered data is then shown in Figure 7. For the full Python program details and code, please refer to Appendix I.

Figure 6. Raw versus filtered data.

4.4 Post-processing the video footage

Each visit was made up of three main phases - *setup*, *runs*, and *transits*. As each accelerometer was *ON* for the full duration of the Zip Line visit, we analyzed the supplementary video recordings to extract each phase duration. Utilizing Final Cut Pro X video editor, we compiled the POV, initial back, initial side, final front, and final side video footage into one clip. This process was done by matching the audio and visual cues to ensure the timing was close to accurate and the desired view was shown. Including a timestamp at the bottom of the clip then helped to record the durations into an excel sheet.

The start time for each accelerometer was different. Therefore, to extract the *setup* duration, we marked the time the test participant turned *ON* the corresponding accelerometer

(*ON start*) to the time the test participant reached the beginning of their first run (*run start*).

Subtracting the *ON start* and *run start* time intervals then determined how long the test participant took to start their first run. The *run* duration was split up into *run to brake* and *brake swing* durations. *Run to brake* begins once the test participant launched from the top platform to the point when the Zip Line trolley meets the brake mechanism. The *brake swing* then captures the g-force and maximum impact experienced. By separating the two components, we are able to hyper focus on the acceleration experienced at arrival at the brake mechanism. Lastly, the *transit* duration begins are run end to when the next run begins.

Table 3. Video Duration Data from Zip Line Visit 4

Start Time (Setup Duration)		0:16:05					
Start Time Head		0:02:02	0:14:03				
Start Time Neck		0:01:47	0:14:18				
Start Time Shoulder		0:02:23	0:13:42				
Start Time Heart		0:02:23	0:13:42				
Start Time COM		0:02:11	0:13:54				
Visit	Run	Run Start	Brake Start	Run End	Run to Brake Duration	Brake Swing Duration	Transit Duration
4	1	0:16:05	0:16:18	0:16:19	0:00:13	0:00:01	0:05:08
4	2	0:21:27	0:21:41	0:21:42	0:00:14	0:00:02	0:04:53
4	3	0:26:34	0:26:46	0:26:47	0:00:12	0:00:01	0:04:41
4	4	0:31:27	0:31:40	0:31:41	0:00:13	0:00:02	0:04:42
4	5	0:36:22	0:36:34	0:36:35	0:00:12	0:00:01	0:04:50
4	6	0:41:24	0:41:37	0:41:38	0:00:13	0:00:01	0:06:52
4	7	0:48:29	0:48:42	0:48:43	0:00:13	0:00:01	

After compiling the video footage, the following durations were recorded, example as shown in Table 3. By timestamping each phase, as recorded from the video footage, we estimated similar time intervals within the accelerometer data. For every minute, there exists

3000 samples (or rows) generated, consequently 500 samples per second and 5 samples per millisecond. Depending on the duration of the phase, we would then extract the equivalent number of samples of the data. For example, *Run to Brake* duration of 13 second will be equivalent to $500 * 13 = 6500$ rows.

Upon extracting the runs from the batch, we eliminated noise in the data and could properly start our analysis.

5. Results

Analyzing the curve found among the run intervals, we did not clearly see the gradual growth over the *Run Start to Brake* duration, therefore **H1** is not satisfied. Instead the acceleration was relatively maintained throughout the *Run Start to Brake* duration. Additionally, as the test participant encountered the brake mechanism, a consistent jolt in the data was expressed, followed by a bounce effect along the eyes-up-and-down axis.

Regarding **H2**, among the sensor locations, the positive exposure recorded reached 2.06 G on the neck, and negative exposure of -2.01 G on the COM as shown on Figure 8. While the minimum and maximum values recorded are tolerable, in comparison to acceleration limits express in F2291, further investigation involving the rotational values draw interesting results. During each run, the test participant launched from the platform, face forward with sensors in their initial positions. As the participant rode the Zip Line to the bottom platform, they experienced a number of gradual turns. Therefore, this presents three cases based on the final position when encountering the brake mechanism: frontwards (initial position), backwards, or sideways.

Figure 7. Maximum and minimum acceleration exposure recorded on each sensor.

Referring to the results shown in Appendix II, III, IV, there exists a number of similarities and differences among the cases. Overall, the pattern for each sensor remained consistent. The head and neck maintain similar rapid spike structure, alternatively the shoulder and heart experience a spike and plateau pattern, and lastly the COM experiences a relatively scattered pattern. What differentiates the cases from one another is which axis' spike and whether it is positive or negative acceleration experienced. If the test participant was able to rotate themselves back to their initial position, before the brake mechanism, we call this the forward case (Results shown in Appendix II). The initial spike caused the X, Y and Z axis to positively spike for the head and neck and negative spikes on the Z axis occur on the shoulder, heart and COM. The opposite occurs, if the test participant arrives backwards (Results shown in Appendix III). A negative spike is presented on the Z axis on the head and neck sensor. Alternatively, test participants also commonly arrived along the left side (Results shown in Appendix IV). A negative spike is found on the X and Z axis on all sensors, while the Y axis is positive on the head, neck, and COM, but negative on shoulder and heart.

Collectively, we have gathered consistent patterns and values of acceleration exposure on Zip Line attractions.

6. Discussion

Summarized, we contribute a validation protocol that will evaluate the reliability and validity of a wearable architecture system used to measure acceleration of a Zip Line rider. Although this study provides a model for exploration, there exists a number of assumptions and areas for improvement which require investigation in future research.

Our design is intended to be wearable by a human rider, as well as attachable to a static object. Based on existing injury reports and perceived biomechanics used during this activity, we assume that the accelerometer placements chosen is the most ideal. However, to collect data and investigate the acceleration recorded, the initial placements may or may not suffice. Additional sensors to detect the rider's position may be an avenue to explore.

For the visits recorded over the duration of this research, the test administrators were also the Zip Line operators. Considering they were not part of the research team, there existed limited familiarity with the technical aspects of the wearable architecture. Future studies are recommended to use a team of two to three researchers. This would include a test participant, top platform test administrator, and a bottom platform test administrator. The test participant would follow the validation protocol procedure as mentioned above with additional responsibility to talk to the camera as they swing and turn on the Zip Line. Each test administrator would manually record the *setup* time for each accelerometer and *run* start and end timestamps and also talk to the test participant POV camera as the time is recorded. The research team could use this data to compare with the video footage as another indicator for time.

In our study, we only analyzed the front axis among three cases: frontward, backward and sideway arrival. We had not considered that axis rotation as the test participant swings upwards.

Future studies will need to consider the quaternion values recorded and how that affected the acceleration results.

Our iterative exploration successfully performed an extensive study on the dynamic range of subjects, and venue architectures. Conclusively, the validation protocol provides a systematic foundation for the development for wearable system catered to design and safety evaluation.

Appendix I - Post Processing Data Jupyter Notebook

Team Zip-G-Force Data Filters

Post processing for acceleration data

1. Import data analysis libraries
2. Import and store the data as "RAW DATA"
3. Run the aliased data through a post processing filter and store data as "BUTTERWORTH FILTERED DATA"
 - The F2137 filter is a butterworth 4 pole
4. The InvenSense MPU-9250 reports accelerometer data using a 16-bit value, or 65536 counts. To convert the raw data to "g" units and "degree-seconds", accelerometer data is divided by 2048 and gyroscope data is divided by 65.536. Store final data as "MANIPULATED DATA"
5. Using the video duration data (estimated values), extract the runs from the combined data.
 - Duration to trim until start of first run
 - Run duration
 - Run to brake duration
 - Transit duration
 - Repeat

Import Libraries

```
In [69]: #Imports
import pandas as pd
import numpy as np
import glob, os

#For filtering and plotting graphs
import matplotlib.pyplot as plt
import plotly.plotly as py
import plotly.graph_objs as go
from scipy.signal import butter, lfilter, freqz
from math import pi

#Ignore warning
import warnings
warnings.filterwarnings("ignore")
```



```

In [70]: #Static Variables
colnames_HAM_IMU = ['Time',
                    'Ax', 'Ay', 'Az',
                    'Gx', 'Gy', 'Gz',
                    'Qw', 'Qx', 'Qy', 'Qz',
                    'Mx', 'My', 'Mz', 'T',
                    'Date Time']

colnames_HAM_IMU_ALT = ['Time',
                        'Ax', 'Ay', 'Az',
                        'Gx', 'Gy', 'Gz',
                        'Qw', 'Qx', 'Qy', 'Qz',
                        'Mx', 'My', 'Mz', 'P', 'T',
                        'Date Time']

files = glob.glob('DATA-*')

#Filepaths
ttea_v1_head = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/061518 - Treetop Eco Adventure/Accelerations/1 - Head/'
ttea_v1_neck = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/061518 - Treetop Eco Adventure/Accelerations/2 - Neck C7/'
ttea_v1_shoulder = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/061518 - Treetop Eco Adventure/Accelerations/3 - Left Shoulder/'
ttea_v1_heart = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/061518 - Treetop Eco Adventure/Accelerations/4 - Heart/'
ttea_v1_com = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/061518 - Treetop Eco Adventure/Accelerations/5 - COM Harness/'

bmfp_v2_head = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/061918 - Blue Mountain/Accelerations/1 - Head/'
bmfp_v2_neck = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/061918 - Blue Mountain/Accelerations/2 - Neck C7/'
bmfp_v2_shoulder = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/061918 - Blue Mountain/Accelerations/3 - Left Shoulder/'
bmfp_v2_heart = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/061918 - Blue Mountain/Accelerations/4 - Heart/'
bmfp_v2_com = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/061918 - Blue Mountain/Accelerations/5 - COM Harness/'

bmfp_v3_head = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/062018 - Blue Mountain/Accelerations/1 - Head/'
bmfp_v3_neck = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/062018 - Blue Mountain/Accelerations/2 - Neck C7/'
bmfp_v3_shoulder = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/062018 - Blue Mountain/Accelerations/3 - Left Shoulder/'
bmfp_v3_heart = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/062018 - Blue Mountain/Accelerations/4 - Heart/'
bmfp_v3_com = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/062018 - Blue Mountain/Accelerations/5 - COM Harness/'

bmfp_v4_head = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/062118 - Blue Mountain/Accelerations/1 - Head/'
bmfp_v4_neck = '/Users/shellyginelle/Documents/GitHub/zipline-acceleration-analysis/062118 - Blue Mountain/Accelerations/2 - Neck C7/'

```

```

on-analysis/062118 - Blue Mountain/Accelerations/2 - Neck C7/'
bmfp_v4_shoulder = '/Users/shellyginelle/Documents/GitHub/zipline-accele
ration-analysis/062118 - Blue Mountain/Accelerations/3 - Left Shoulder/'
bmfp_v4_heart = '/Users/shellyginelle/Documents/GitHub/zipline-acceleratio
n-analysis/062118 - Blue Mountain/Accelerations/4 - Heart/'
bmfp_v4_com = '/Users/shellyginelle/Documents/GitHub/zipline-acceleratio
n-analysis/062118 - Blue Mountain/Accelerations/5 - COM Harness/'

#For debugging purposes - Checkpoint
#Check if file path exists. In the following code, you will need to subs
titute the corresponding file path.
os.path.exists('/Users/shellyginelle/Data/1 - Head/DATA-001.csv')
os.path.exists(bmfp_v4_head)

```

Out[70]: True

Import Data

Every .CSV file records for 15 mins. The idea is to concatenate all .CSV files for each specific accelerometer positions then chop the sections into set of events:

1. On Zip Line
 - Start
 - Arrival at Brake Mechanism
2. Offloading - Figure out the time it took for you to get back onto the Zip Line of choice

```

In [71]: '''
1. Read all HEAD data files
'''
head_raw_dir = os.chdir(bmfp_v4_head)
head_results = pd.DataFrame([], columns=colnames_HAM_IMU)

for counter, file in enumerate(files):
    head_df = pd.read_csv(file, skiprows=[0,1,2,3,4,5,6,7], sep=',', nam
es=colnames_HAM_IMU, engine='python')
    #Append the results into one dataframe
    head_results = head_results.append(head_df)

#Save the results into a separate combined .csv
head_results.to_csv(bmfp_v4_head + 'COMBINED_HEAD_DATA.csv')

#Read combined data, rename columns and print data
head_raw_df = pd.read_csv(bmfp_v4_head + 'COMBINED_HEAD_DATA.csv',
                           skiprows=[0], sep=',', names=colnames_HAM_IMU,
                           header=None, engine='python')

#print combined dataframe
#head_raw_df

```

```

In [72]: '''
2. Read all NECK C7 data files
'''
neck_raw_dir = os.chdir(bmfp_v4_neck)
neck_results = pd.DataFrame([], columns=colnames_HAM_IMU)

for counter, file in enumerate(files):
    neck_df = pd.read_csv(file, skiprows=[0,1,2,3,4,5,6,7], sep=',', names=colnames_HAM_IMU, engine='python')
    #Append the results into one dataframe
    neck_results = neck_results.append(neck_df)

#Save the results into a separate combined .csv
neck_results.to_csv(bmfp_v4_neck + 'COMBINED_NECK_DATA.csv')

#Read combined data, rename columns and print data
neck_raw_df = pd.read_csv(bmfp_v4_neck + 'COMBINED_NECK_DATA.csv',
                           skiprows=[0], sep=',', names=colnames_HAM_IMU, header=
None, engine='python')

#print combined dataframe
#neck_raw_df

```

```

In [73]: '''
3. Read all SHOULDER data files
'''
shoulder_raw_dir = os.chdir(bmfp_v4_shoulder)
shoulder_results = pd.DataFrame([], columns=colnames_HAM_IMU_ALT)

for counter, file in enumerate(files):
    shoulder_df = pd.read_csv(file, skiprows=[0,1,2,3,4,5,6,7,8], sep=
',', names=colnames_HAM_IMU_ALT, engine='python')
    #Append the results into one dataframe
    shoulder_results = shoulder_results.append(shoulder_df)

#Save the results into a separate combined .csv
shoulder_results.to_csv(bmfp_v4_shoulder + 'COMBINED_SHOULDER_DATA.csv')

#Read combined data, rename columns and print data
shoulder_raw_df = pd.read_csv(bmfp_v4_shoulder + 'COMBINED_SHOULDER_DATA.csv',
                               skiprows=[0], sep=',', names=colnames_HAM_IMU_ALT, header=
None, engine='python')

#print combined dataframe
#shoulder_raw_df

```

```

In [74]: '''
4. Read all HEART data files
'''
heart_raw_dir = os.chdir(bmfp_v4_heart)
heart_results = pd.DataFrame([], columns=colnames_HAM_IMU_ALT)

for counter, file in enumerate(files):
    heart_df = pd.read_csv(file, skiprows=[0,1,2,3,4,5,6,7,8], sep=',',
names=colnames_HAM_IMU_ALT, engine='python')
    #Append the results into one dataframe
    heart_results = heart_results.append(heart_df)

#Save the results into a separate combined .csv
heart_results.to_csv(bmfp_v4_heart + 'COMBINED_HEART_DATA.csv')

#Read combined data, rename columns and print data
heart_raw_df = pd.read_csv(bmfp_v4_heart + 'COMBINED_HEART_DATA.csv',
                           skiprows=[0], sep=',', names=colnames_HAM_IMU_ALT, head
er=None, engine='python')

#print combined dataframe
#heart_raw_df

```

```

In [75]: '''
5. Read all COM Harness data files
'''
com_raw_dir = os.chdir(bmfp_v4_com)
com_results = pd.DataFrame([], columns=colnames_HAM_IMU)

for counter, file in enumerate(files):
    com_df = pd.read_csv(file, skiprows=[0,1,2,3,4,5,6,7], sep=',', name
s=colnames_HAM_IMU, engine='python')
    #Append the results into one dataframe
    com_results = com_results.append(com_df)

#Save the results into a separate combined .csv
com_results.to_csv(bmfp_v4_com + 'COMBINED_COM_DATA.csv')

#Read combined data, rename columns and print data
com_raw_df = pd.read_csv(bmfp_v4_com + 'COMBINED_COM_DATA.csv',
                           skiprows=[0], sep=',', names=colnames_HAM_IMU, header=N
one, engine='python')

#print combined dataframe
#com_raw_df

```

```

In [76]: #Create temp df so we don't alter the raw data values, will need for plo
ts later
head_raw_temp_df = head_raw_df
neck_raw_temp_df = neck_raw_df
shoulder_raw_temp_df = shoulder_raw_df
heart_raw_temp_df = heart_raw_df
com_raw_temp_df = com_raw_df

```

Filter Data

```
In [77]: #Run the aliased data through a post processing butterworth filter, save
         results as post processed data - pp
         '''
         head_pp_df
         neck_pp_df
         shoulder_pp_df
         heart_pp_df
         com_pp_df
         '''

def butter_lowpass(cutoff, fs, order=5):
    nyq = 0.5 * fs #The Nyquist frequency is half the sampling rate.
    normal_cutoff = cutoff / nyq
    b, a = butter(order, normal_cutoff, btype='low', analog=False)
    return b, a

def butter_lowpass_filter(data, cutoff, fs, order=5):
    b, a = butter_lowpass(cutoff, fs, order=order)
    y = lfilter(b, a, data)
    return y

# Filter requirements.
order = 6
fs = 200.0      # sample rate, Hz mpu_SampleRate
cutoff = 5.0    # desired cutoff frequency of the filter, Hz

# Get the filter coefficients so we can check its frequency response.
b, a = butter_lowpass(cutoff, fs, order)

# Plot the frequency response.
w, h = freqz(b, a, worN=8000)
plt.subplot(2, 1, 1)
plt.plot(0.5*fs*w/np.pi, np.abs(h), 'b')
plt.plot(cutoff, 0.5*np.sqrt(2), 'ko')
plt.axvline(cutoff, color='k')
plt.xlim(0, 0.5*fs)
plt.title("Lowpass Filter Frequency Response")
plt.xlabel('Frequency [Hz]')
plt.grid()
```

```

In [78]: # Demonstrate the use of the filter.
# First make some data to be filtered.
T = 5.0 # seconds
n = int(T * fs) # total number of samples
t = np.linspace(0, T, n, endpoint=False)
# "Noisy" data. We want to recover the 1.2 Hz signal from this.
data = np.sin(1.2*2*np.pi*t) + 1.5*np.cos(9*2*np.pi*t) + 0.5*np.sin(12.0
*2*np.pi*t)

# Filter the data, and plot both the original and filtered signals.
y = butter_lowpass_filter(data, cutoff, fs, order)

plt.subplot(2, 1, 2)
plt.plot(t, data, 'b-', label='data')
plt.plot(t, y, 'g-', linewidth=2, label='filtered data')
plt.xlabel('Time [sec]')
plt.grid()
plt.legend()

plt.subplots_adjust(hspace=0.35)
plt.show()

```

```

In [79]: # The data to be filtered is as follows:
cols_to_filter = ['Ax', 'Ay', 'Az',
                  'Gx', 'Gy', 'Gz',
                  'Qw', 'Qx', 'Qy', 'Qz']

# Filter the data, and plot both the original and filtered signals.
for cols in cols_to_filter:
    head_raw_temp_df[cols] = butter_lowpass_filter(head_raw_temp_df[cols],
    cutoff, fs, order)
    neck_raw_temp_df[cols] = butter_lowpass_filter(neck_raw_temp_df[cols],
    cutoff, fs, order)
    shoulder_raw_temp_df[cols] = butter_lowpass_filter(shoulder_raw_temp_
    df[cols], cutoff, fs, order)
    heart_raw_temp_df[cols] = butter_lowpass_filter(heart_raw_temp_df[co
    ls], cutoff, fs, order)
    com_raw_temp_df[cols] = butter_lowpass_filter(com_raw_temp_df[cols],
    cutoff, fs, order)

```

```

In [80]: #Save dataframe into new .csv
head_raw_temp_df.to_csv(bmfp_v4_head + 'BUTTERWORTH_FLTR_HEAD_DATA.csv')
head_butterflt_df = pd.read_csv(bmfp_v4_head + 'BUTTERWORTH_FLTR_HEAD_DATA.csv',
                                skiprows=[0], sep=',', names=colnames_HAM_IMU, header=None, engine='python')

neck_raw_temp_df.to_csv(bmfp_v4_neck + 'BUTTERWORTH_FLTR_NECK_DATA.csv')
neck_butterflt_df = pd.read_csv(bmfp_v4_neck + 'BUTTERWORTH_FLTR_NECK_DATA.csv',
                                skiprows=[0], sep=',', names=colnames_HAM_IMU, header=None, engine='python')

shoulder_raw_temp_df.to_csv(bmfp_v4_shoulder + 'BUTTERWORTH_FLTR_SHOULDER_DATA.csv')
shoulder_butterflt_df = pd.read_csv(bmfp_v4_shoulder + 'BUTTERWORTH_FLTR_SHOULDER_DATA.csv',
                                    skiprows=[0], sep=',', names=colnames_HAM_IMU_ALT, header=None, engine='python')

heart_raw_temp_df.to_csv(bmfp_v4_heart + 'BUTTERWORTH_FLTR_HEART_DATA.csv')
heart_butterflt_df = pd.read_csv(bmfp_v4_heart + 'BUTTERWORTH_FLTR_HEART_DATA.csv',
                                 skiprows=[0], sep=',', names=colnames_HAM_IMU_ALT, header=None, engine='python')

com_raw_temp_df.to_csv(bmfp_v4_com + 'BUTTERWORTH_FLTR_COM_DATA.csv')
com_butterflt_df = pd.read_csv(bmfp_v4_com + 'BUTTERWORTH_FLTR_COM_DATA.csv',
                               skiprows=[0], sep=',', names=colnames_HAM_IMU, header=None, engine='python')

#For debugging purposes - Checkpoint
#Print last dataframe to show code has completed
#com_butterflt_df

```

Calculate Data

The InvenSense MPU-9250 reports accelerometer data using a 16-bit value, or 65536 counts. To convert the raw data to "g" units and "degree-seconds", accelerometer data is divided by 2048 and gyroscope data is divided by 65.536.

```

In [81]: #Divide columns Ax, Ay, Az by 2048
#Divide Gx, Gy, Gz by 65.536
acceleration_cols = ['Ax', 'Ay', 'Az']
gyroscope_cols = ['Gx', 'Gy', 'Gz']
count_g = 2048
degree_sec = 65.536
is_int = np.int64
if_float = np.float64

for a_cols in acceleration_cols:
    if (head_butterflt_df[a_cols].dtype == np.float64
        and neck_butterflt_df[a_cols].dtype == np.float64
        and shoulder_butterflt_df[a_cols].dtype == np.float64
        and heart_butterflt_df[a_cols].dtype == np.float64
        and com_butterflt_df[a_cols].dtype == np.float64):

        head_butterflt_df[a_cols] = head_butterflt_df[a_cols].divide(count_g)
        neck_butterflt_df[a_cols] = neck_butterflt_df[a_cols].divide(count_g)
        shoulder_butterflt_df[a_cols] = shoulder_butterflt_df[a_cols].divide(count_g)
        heart_butterflt_df[a_cols] = heart_butterflt_df[a_cols].divide(count_g)
        com_butterflt_df[a_cols] = com_butterflt_df[a_cols].divide(count_g)

for g_cols in gyroscope_cols:
    if (head_butterflt_df[g_cols].dtype == np.float64
        and neck_butterflt_df[g_cols].dtype == np.float64
        and shoulder_butterflt_df[g_cols].dtype == np.float64
        and heart_butterflt_df[g_cols].dtype == np.float64
        and com_butterflt_df[g_cols].dtype == np.float64):

        head_butterflt_df[g_cols] = head_butterflt_df[g_cols].divide(degree_sec)
        neck_butterflt_df[g_cols] = neck_butterflt_df[g_cols].divide(degree_sec)
        shoulder_butterflt_df[g_cols] = shoulder_butterflt_df[g_cols].divide(degree_sec)
        heart_butterflt_df[g_cols] = heart_butterflt_df[g_cols].divide(degree_sec)
        com_butterflt_df[g_cols] = com_butterflt_df[g_cols].divide(degree_sec)

```



```

In [82]: #Save dataframe into new .csv
head_butterflt_df.to_csv(bmfp_v4_head + 'MANIPULATED_HEAD_DATA.csv')
head_mnptd_df = pd.read_csv(bmfp_v4_head + 'MANIPULATED_HEAD_DATA.csv',
                             skiprows=[0], sep=',', names=colnames_HAM_IMU, header=N
one, engine='python')

neck_butterflt_df.to_csv(bmfp_v4_neck + 'MANIPULATED_NECK_DATA.csv')
neck_mnptd_df = pd.read_csv(bmfp_v4_neck + 'MANIPULATED_NECK_DATA.csv',
                             skiprows=[0], sep=',', names=colnames_HAM_IMU, header=N
one, engine='python')

shoulder_butterflt_df.to_csv(bmfp_v4_shoulder + 'MANIPULATED_SHOULDER_DA
TA.csv')
shoulder_mnptd_df = pd.read_csv(bmfp_v4_shoulder + 'MANIPULATED_SHOULDER
_DATA.csv',
                                skiprows=[0], sep=',', names=colnames_HAM_IMU_ALT, head
er=None, engine='python')

heart_butterflt_df.to_csv(bmfp_v4_heart + 'MANIPULATED_HEART_DATA.csv')
heart_mnptd_df = pd.read_csv(bmfp_v4_heart + 'MANIPULATED_HEART_DATA.cs
v',
                              skiprows=[0], sep=',', names=colnames_HAM_IMU_ALT, head
er=None, engine='python')

com_butterflt_df.to_csv(bmfp_v4_com + 'MANIPULATED_COM_DATA.csv')
com_mnptd_df = pd.read_csv(bmfp_v4_com + 'MANIPULATED_COM_DATA.csv',
                             skiprows=[0], sep=',', names=colnames_HAM_IMU, header=N
one, engine='python')

#For debugging purposes - Checkpoint
#Print last dataframe to show code has completed
#com_mnptd_df

```

Appendix II - Frontward Arrival Case

Appendix III - Backward Arrival Case

Appendix IV - Sideways (Left Side) Case

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