Design and Analysis of Electronic Wearables for Taekwondo Sports

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Abstract

Design and Analysis of Electronic Wearables for Taekwondo Sports

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Taekwondo is a combat sport that is based on striking and involves full body contact. Initially, it a referee-exclusive sport and that led to increased controversy on referee/judges' accuracy, bias and fairness. To address these concerns, point scoring systems (PSS) were introduced in 2012 only consisting of a chest protector and in 2016 head protectors were added. Constant improvements have been made on these PSS and new impact classification algorithms and hardware were developed for a system made by 20/20 Armor. The work achieved 90% accuracy for illegal vs legal classification on the head protector and 94.4% accuracy between legal impacts to the chest protector. This work proved to be a great step forward since reliance is increasing on these PSS as they are now the "final decision" for impact detection in Taekwondo. Furthermore, our algorithms use edge computing that allow for real time application and at-home training.

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Dedication

“Dedicated to my parents”

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1. Introduction

1.1. Taekwondo

Taekwondo was officially inducted as an official Olympic Sport in 2000 in the Sydney Games. Before that, it was introduced as a featured sport in the Seoul Olympics and since then, it has gained significant popularity. The origination of the sport was in South Korea after World War II by the troops returning from Japan [1, 2]. From its origination, involvement and awareness of the sport has increased. Today there are 206 national federations that play the sport with over 80 million athletes [3]. This athlete count also includes para-athletes and the first Olympic appearance of para-taekwondo will be in the 2020 Olympics in Tokyo [3]. This has been a great achievement for the sport as countries all around the world compete in the sport, as well as the recent para-athletes, demonstrating its popularity. The World Taekwondo (WT), formally known as the World Taekwondo Federation, is the international governing body of the sport and it was formed in 1973. The World Taekwondo Federation is also responsible for promoting the sport around the world, and therefore contributed to its globalization and its introduction into the world's largest stage, the Olympics.

Moving on to taekwondo itself, it is a barehanded sport and is very similar to other self-defense sports where competitors score points by hitting their opponents [4]. It is a combat sport that is based on striking and involves full body contact. What makes this different from other martial arts, like karate and wushu, is the emphasis on high kicking [5]. There are 2 types of formats used in the competitions: Kyorugi (sparring) and Poomsae (solo pattern of taekwondo movements) [5]. However, only kyorugi is performed in the Olympics and it normally has 3 rounds of two minutes each. In-between the rounds, there is a one-minute resting period. The competitor with the highest score at the end of the rounds, wins [6]. Points can be scored by kicking the opponent or punching them. There is a certain technique required for valid hits and receiving points. Proper punching refers to a "straight punching technique using the knuckle part of a tightly clenched fist" and kicking refers to "using any part of the foot below the ankle bone". Further, there is only a certain area the opponents can hit, the trunk and the head. The trunk can be hit by the fist and the foot, however, only on the areas covered by the trunk protector and not on the spine. The head can only be kicked and anything above the bottom line of the head protector [4]. Anything outside of this would be an invalid hit and an interesting fact is that punching to the head is not allowed. The points received are then scored based on if the opponent is kicked or punched and where the hit landed. The valid points system has grown as the sport develops over time and currently includes:

- The competitors get 1 point for punching the trunk protector with a knuckle part of a tightly clenched fist
- 2 points for a kick with the foot below the ankle on the trunk protector
- 3 points for kicking the head with the foot below the ankle
- 4 points for a turning valid kick to the trunk protector
- 5 points for a turning valid kick to the head
- 1 point for a "Gam-Jeom" (deduction penalty) given to opponent [4]

As can be seen, hits to the head are worth more points and due to this athletes prefer to hit the head with a possibility of a quick win by knockout. This is why training and game strategy is usually focused on attacking the head [7]. The points are rewarded by referees and the 3 judges are located in a triangular shape. There are 4 Olympic men's weight divisions: under 58 kg, under 68 kg, under 80 kg and over 80 kg and 4 for women's weight divisions under 49 kg, under 57 kg, under 67 kg and over 67 kg [4].

1.2. Importance of Spectatorship

For any sport to be relevant, it needs a great following and martial arts has now gained that following and become an essential part of the global sport community. It not only promotes a healthy lifestyle but also provides cultural education and entertainment in the West [8]. Therefore, the sport needs consumers or spectators and should be an attraction to them. Spectatorship, in our context, refers to the viewers of the sport that attend taekwondo events contributing to its financial growth. During the early years of the sport, there were several complications surrounding spectatorship, and they all revolved around point allocation to athletes. The popularity that taekwondo received created an increase in pressure to ensure the competitors received points without favoritism or any discrimination. During this time, taekwondo was a referee-exclusive sport and that lead to increased controversy on referee/judges' accuracy, bias and fairness [1, 2, 7, 9, 8]. These concerns were significant because, initially, taekwondo could not recruit and retain spectators like the other major spectator organizations could, such as the National Football League. This was due to several factors such as a short event history, failure of event promotions and marketing and/or ineffective event operations [8]. Therefore, consumer spectatorship of the sport was at risk. This combined with the fact that ticket sales is the primary revenue stream, was a serious complication [10]. Customer retention is extremely important for taekwondo, just like many other businesses that are successful. Furthermore, another dominant issue was unintentional judgment errors by the referees [2]. Since punches and kicks can be performed in a fast sequence, sometimes referees can have a hard time observing theses sequences and assigning points to it. Therefore, quality of the tournaments, the players rights and fair judgment within a match were also at risk [2, 9]. The importance of this is significant because fair judgment is one of the most important factors that determine consumers perception of quality in taekwondo events [9].

Moving now to recent times, the concerns mentioned above are still lingering on. Granted steps were taken to eradicate these problems, such as introducing electronic point scoring systems. A study performed on customer satisfaction and event quality in 2014 (by Dr. Yong in the University of Florida) demonstrated a few key points: 1) 55% of spectators at an event had taekwondo experience with over 80% having more than 2 years of training, 2) 50.3% of spectators found out about the event through their coach, 3) Spectators believe that skill of the athlete is the most important factor of any taekwondo event and 4) Skill performance is the most important predictor of a revisit intention of the spectator [8]. Coming now to the first and second point, the majority of spectators at events have been involved in the sport and found out about it through their coaches. This means that the audience is first handedly connected to the sport and are not attending due to self-interest or support for the game (sport enthusiast). Even more, half of the attendees attended because they found out from the event from their coach. This is a major disadvantage as it indicates promotions and marketing are still not doing well. Moving on to the last two points, spectators believe that the skill of an athlete is the most important factor and a major factor in their intent to revisit. In other words, the skill of the athlete is significantly important to the spectators and hence fair judgment is required as a result. Further, if the skill performance is incorrectly measured by assigning the wrong points from referees (judgement errors), the intent to revisit the other events decreases significantly, losing spectatorship. This is why since the introduction of taekwondo in the Olympics; continual changes have been made to the sport to ensure transparency when points are rewarded to competitors and be attractive to the spectator. As a final point to solidify this argument, in 2013, taekwondo was among a group of sports to be dropped from the 2020 Olympics by the Executive Board of the International Olympics Committee (IOC) [11, 12]. The Executive Board of the IOC has several voting rounds where the primary decision is made of what sports are at risk of being dropped. Then at the official Session of the IOC, the final 25 sports are finalized. There are several voting rounds that occur between the members and then at the IOC session the final decision is made based on the Federation Reports provided by the governing body for that sport. The Federation Reports follow a universal format that basically explains how the federation plans to follow the Olympic requirements and includes sections such as: finance, popularity, athlete (for e.g. anti-doping), Olympic proposal, transparency and fairness on the field of play, and history and tradition [13]. This process occurred in 2013-2014 where several sports were considered and in the 125th Session of the IOC the final 25 sports were finalized for the 2020 Olympics. Luckily, taekwondo was not dropped, and several other changes were made in the 127th Session of the IOC. This shows, the issues of losing spectatorship always hold significant weightage and need to be addressed as they could have potentially led towards the game being dropped from the Olympics. With this in mind, we move on to how the WT promotes transparency and fairness on the field of play by using the point scoring systems that are approved by WT.

1.3. Current Approved Protectors and Hit Validation

The introduction of any technology in sports faces challenges even though its employment helps reduce judgment errors and increases spectator's enjoyment. The challenges mainly include a resistance to change by the competitors [1]. Since an introduction of new technology usually changes the competitor performance, it is not preferred. However, because of the problems mentioned in the previous section, it was apparent that a point scoring system (PSS) was mandatory for the growth of taekwondo. This was a necessary step in keeping the sport relevant by improving the quality of the sport due to its competitive nature.

This competitive nature requires fair judgment, and this is important for a positive consumers perception as well as the athlete's perception of the sport [1, 8]. All of these changes combined, in-turn increased the active global participation of the sport and gave the players greater opportunity to score points [2, 1]. A study done in 2011 aimed to examine the spectator's perceptions on the new technology (PSS) being adapted in taekwondo [9]. They concluded that the spectators had a positive view and attitude towards the PSS that reflected a long-term support for these products. This means that the spectators and participants of taekwondo, supported the use of these technologies for now and future events as well as the future improvements made to the PSS. To further demonstrate the importance of hit validation and electronic point scoring systems, a study in 2019 demonstrated an increase in performance of athletes due to their training on electronic systems and gamification [14]. In particular, they tested the performance changes by training with an electronic body protector and the effects of gamification on this change. They saw a difference in scores by athletes using the electronic point scoring systems and that it in fact does improve training techniques. They further concluded that these systems need to be used to monitor the athlete's performance over time. This requires coaches and trainers to oversee the athlete and improve their skills with the use of technology. In fact, one of the aims of our work and design is to improve on this concept using edge computing (details in the background).

As these systems were being introduced, the World Taekwondo Federation had to change regulations, codes and judgement rules to accommodate the systems for Olympic taekwondo. Scoring is now primarily done by an electronic point scoring system that is incorporated in the protectors. However, it is important to note that certain points are still awarded manually by judges such as punching techniques and additional points for turning kicks [4]. The protectors allowed to be used in taekwondo are produced by companies approved by the World Taekwondo Federation. The 2012 London Olympics, was the first time an electronic point scoring system was introduced as a decision support technology [5, 15]. Since then, in the 2016 Rio Olympics, a new version of this system, was introduced and it contained a few much-needed features and sensors incorporated in the head protector. As of 2020, there are only 2 companies that can produce electronic point scoring systems that are also used in the Olympics and they are: Daedo and KP&P [3]. World Taekwondo (WT) decides which of these systems gets used in competitions and approves and notifies well in advance so that the athletes and officials are prepared and trained properly. These systems use a combination of sensors (RFID or Magnets) that are placed in different parts of the body protectors (chest, feet and head protectors). Once a hit has been detected, it will automatically award points for that hit. Each of these systems has its advantages and disadvantages that are mentioned in the next section of this thesis.

1.4. Limitations of the Systems

The introduction of the PSS's lead to significant transparency in rewarding competitor's points and helped increase spectatorship; this was a major step in the right direction. However, as the WT put it themselves "The PSS is in constant process of technical evolution" and hence both these systems have limitations. These limitations mainly include: hit validation and high prices [4, 16]. Starting of with the first, hit validation, for our purposes, refers to the assessment of legal and illegal taekwondo techniques. This means the system counts an illegal hit as a legal one and both systems fall prey to this problem. A simple example of this is a case where a knee hit to the chest protector is considered as a legal hit (i.e. the system picks it up as a kick to the chest). The RFID or magnet is close enough to the proximity sensors when hitting with the knee and this is then picked up as a legal hit. The second part of hit validation involves the level of impact and the techniques used. Based on the official Competition Rules by WT, a legal hit needs to have a proper level of impact that is detectable by the point scoring system. The impact level has to pass a threshold, which is decided by officials as being a satisfactory hit for that weight class, and then it will be considered a scoring hit. What this lacks is, a hit that is significantly harder than the threshold, will be rewarded the same points as a hit that just passes the threshold. Furthermore, an interesting point to consider is that the hits picked up by the point scoring systems are not allowed to be reviewed by an Instant Video Replay. This means there is a significant level of reliance and trust put in the point scoring systems by the World Taekwondo rules. In addition to that, there are several hits that are still rewarded solely by the three corner judges using hand-held device. The hits are: any kick to the face (legitimate target), punches to the chest protector and technical points (turning kicks) [5, 15]. A quick point distribution of judges and technology is shown in Table 1 below.

Table 1. Point distribution

Hits	**Points**	**Assigned by**
Kick to the face	3	Corner judges
Turning kick to face	4+1 turning point	Corner judges
Kick to chest	2	PSS
Turning kick to chest	3+1 turning point	3 point by PSS, 1 turning point by judges
Punch to chest	1	Corner judges

[1] **Note.** PSS: point scoring system

These limitations tend to restrict the growth of the sport. The athletes will only perform hits that will be easily picked up by these point scoring systems avoiding effective combative techniques. In addition, several impacts are still scored by judges and they still face the judgment bias concerns mentioned earlier. For this reason, hit validation techniques are necessary in taekwondo in conjunction with superior sensors for picking up all the taekwondo hits and impacts. Therefore, it is evident that the current point scoring systems can be further improved. Moving on to the second problem, the cost of a chest protector alone is around USD 800. When this is combined with the other protectors and accessories necessary for the sport, the cost adds up and puts a burden on the coaches, taekwondo schools and the competitors. Hence creating a system that is affordable will greatly benefit the sport. Summing up, there are a total of 3 limitations with current systems: 1) hit validation between legal and illegal hits does not exist and therefore any kick to the face, punches to the chest protector, and technical points (turning kicks) are still rewarded by judges alone, 2) no relationship between impact energy and sensor response (a strong hit is still rewarded the same points as a weak but scoring hit), and 3) the cost of the systems is significant. With these limitations in mind, we move on the next section, Organization, that will explain how the rest of the thesis is organized and what the focus of this thesis is.

1.5. Organization

From the beginning, it was seen the sport adapts new technology and changes its rules, regulations and scoring methods to adapt for the new technology. Now a similar process will be taken as this 20/20 Armor system is introduced to the Olympics in 2020. We saw this in the 2012 and 2016 Olympics where new features and continuous improvement of the point scoring systems occurred in taekwondo. In 2016 we saw major changes in the way taekwondo was scored and viewed by the international audience. It was the first-time electronic head gear was used in the sport. This will further be the case in the 2020 Olympics as new technology (smart textiles) is being introduced in sports. This, combined with the constant desire for unbiased scoring by spectators, will lead to new innovations and improvements. Even more, the reliance put towards point scoring systems is unparalleled and is visible in the World Taekwondo's Rule book where a point scored by the point scoring system is the final decision. Therefore, it is evident that further work needs to be done in validating hits as the rules themselves require them to be accurate and continuously improving. The work here aims to use the 20/20 Armor's point scoring system and suggest improvement in scoring and hit validation for the chest protector (vest) and the head protector (helmet). The following sections will go over the background, literature survey and some important factors to consider when designing any device that is used by engineers. Moving on from there, chapter 3 will focus on the improvement to the head gear by making an eHelmet (electronic helmet). This section will cover some of the limitations current head gears face and how they were addressed by our work. Next, chapter 4 will then focus on the chest protector and the limitations current chest protectors face and how they are addressed by our work. Finally, chapter 5 will conclude all our results and open a conversation for the future works. The diagram below (Figure 1) shows a clear flow of how this thesis work is organized.

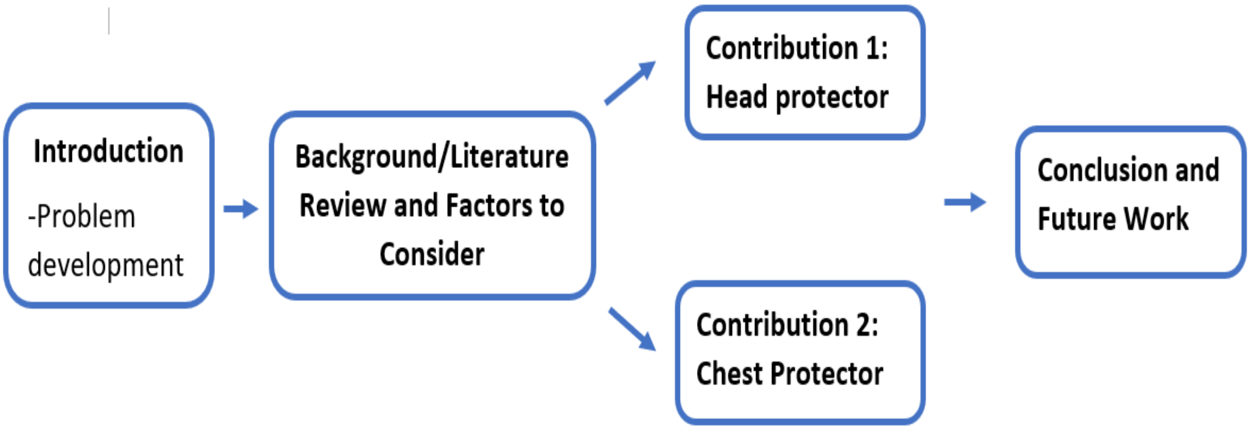

Figure 1. This figure shows the overall organization and flow of this work

2. Background/Literature Survey and Factors to Consider

2.1. General Hardware

The devices we use in our daily lives begin as separate components that are combined to function as one unit. We see many examples of this from mobile phones to expensive equipment in the health and entertainment industry. More recently, there has been an overwhelming effort to miniaturize hardware leading to smart and highly connected devices available in every industry [17]. This was in part due to the advancements the Internet went through in the early 2000s, from being used just as a communication platform, to connecting billions of people together with the introduction of wireless technologies (mobile phones). Designing a point scoring system for taekwondo requires the use of this miniature hardware that is connected wirelessly to the internet or a computing platform. Therefore, understanding the background is vital so we can determine why certain hardware is chosen over others in different applications. To get an understanding of this, we will be looking at the different industries that are currently using wearable devices for data collection and performing analysis on data retrieved. Particularly, we will be focusing on internet of things (IoT) and some of its popular applications tested by our work in the Signal Analysis Research (SAR) lab.

2.1.1. Internet of Things

As mentioned above, the internet played an important role in technology advancement and this eventually led to the development of the concept called Internet of Things. Starting off with a simple definition of Internet of Things (IoT), it is defined as a network of physical objects that are supported by sensors and embedded technology for data communication that allows for interaction with the environment [17]. What this means is, sensors, actuators and robots are connected together and can communicate with each other via the internet. This led to the next advancement in this field, wearables or wearable devices. Simply, wearable devices are devices that can be worn by an individual that can continuously monitor an individual’s activity without interruption [18, 19]. These wearables use sensors, such as tri-axial accelerometers, magnetometers, altimeter and gyroscopes, to create an intuitive virtual environment.

Due to the fast-paced development that is occurring in the IoT domain, it is important to understand some of the key terminologies and their variations that are used by engineers and the Industry. We start with the Internet of Wearable things (IoWT); simply put, this is the combined use of the IoT and wearable devices. As development continues on wearables, they start to incorporate advanced features and we start to transition into the Internet of Wearable Things [20]. It is evident that wearables significantly benefit from the IoT, and hence, we see that they have already made it into many aspects of our lives, such as in fashion, health, and entertainment [21, 20]. Some well-known examples of IoWT devices in the market are computerized watches, such as the Samsung Gear and the Apple watch. They can gather information, such as a user’s step count, pulse rate, kilometers travelled, and calories burnt [22]. One distinction to consider is that these devices are lifestyle devices; however, the Health Industry is one of the most promising industries for IoT applications. In the same way as the IoWT, when wearables are used in medical applications, it creates another term and an industry called the Internet of Medical Things (IoMT). Biomedical wearables are then the devices used in the IoMT and, thus, function through the cloud to perform complex tasks. An architectural diagram is shown in Figure 2 below. This industry is pushing towards minimizing the size of the wearable while capturing more vital signs, and finally sending reliable and secure data [18]. This architecture design is relevant to our work as combining edge computing to a wearable device that can record impacts to the head and chest is one of our goals.

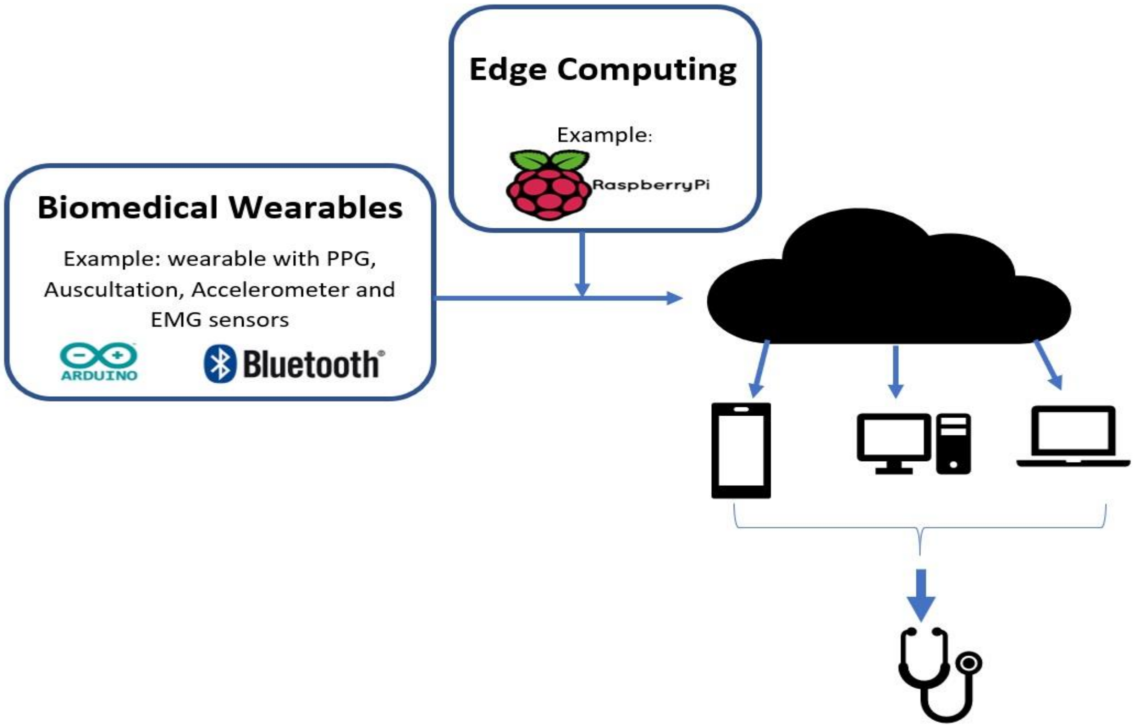

Figure 2. This figure shows the IoMT architecture [1]Logos: [23, 24]

To understand the significance of the IoT, wearables, and telemedicine, we will be looking at some crucial facts and numbers. The IoT is said to be the next trillion-dollar industry, and The Global Wearable Technology market has grown significantly since 2012. In 2012, it was 750 million and now, in 2018, it is worth 5.8 billion [4]. Furthermore, U.K.-based research projects estimated a 10-fold increase in the number of wearable devices being shipped in the last 5 years. They found that the number increased from 13 million in 2013 to 130 million in 2018 [4]. In North America alone, the wearable device market is said to reach out to 385 million users [5]. Currently, in the market, there are 429 wearable devices and they have an average price of $326 USD. Within this, there are only 87 medical devices, since the majority of wearable devices are targeted towards lifestyle and fitness [9].

2.1.2. Lifestyle/Fitness applications

Wearable devices contain sensors, either one or a combination of a few, that capture signals generated by the body. The body generates many waveforms, and they can be captured from various locations of the body. The four commonly used signals for biomedical wearable purposes are outlined in this section. These signals contain valuable information about a person and their activity. Table 1 includes their frequency ranges.

Table 2. Frequency range of common biomedical signals

Signal	**Frequency Range (Hz)**
PPG	0.5-5
EMG	50-150
Cardiac Auscultation	20-420
Gait Analysis	0-15

[1] **References**. [22, 25, 26, 27] respectively

The first signal is Photoplethysmography (PPG) technology and it has been at the center of the recent development of biomedical wearables whether it be in medical or lifestyle applications. This is primarily due to the need to measure heart rate variability effectively. Traditionally, to obtain accurate Heart Rate Variability (HRV) data, an electrocardiogram (ECG) signal is used, and HRV is measured as the variations in the peak-to-peak time interval for successive cardiac cycles. This is also known as the R-R interval. In diagnostics, HRV analysis provides significant information on the sympathetic and parasympathetic function of the Autonomic Nervous System (ANS) [14,15]. Hence, it is important to measure HRV; however, there are some limitations to acquiring the ECG signal. Firstly, it requires at least three electrodes positioned at specific anatomical positions. Secondly, ECG instruments are not suitable for daily use at home and also require trained technicians and nurses for use. Finally, the electrodes may cause irritation to the patient's skin [12]. This is why significant effort has been made to measure HRV by using PPG. Moving on, another important parameter than can be captured by PPG is the atrial blood oxygen saturation level of the patient, also known as SpO2 [16]. Oxygen saturation (SpO2) is the percent of oxygen-saturated hemoglobin when compared to the rest of the blood. Blood in the body is either oxygenated or deoxygenated, and they both have different light absorption characteristics [12,16]. This is an important physiological parameter for monitoring blood circulation and respiration. Having understood the significance and importance of PPG, the simple definition of photoplethysmogram or PPG is that it is a non-invasive optical technique to measure blood volume changes in the microvascular bed of tissue [14]. The basics of how an PPG sensor works is a light-emitting diode (LED) penetrates the skin, light travels through the tissue, and then the signal is received by the photo detector. The most common locations to detect PPG signals are the finger-tip and at the wrist. Figure 3 below, shows these 2 types of sensors.

Figure 3. This figure shows the finger-tip (iHeart) sensor on the left and the wrist (Fitbit Charge 2) sensor on the right Image source: [18].

The second signal is Electromyography (EMG) and for the past few decades, surface EMG, or just EMG, has been successfully used in medical and research applications. Surface EMG allows for the diagnosis of a wide range of motor and neural conditions [20]. EMG is a technique that measures the response of a muscle when an electrical stimulation is applied by the nerves [5]. This electrical stimulation is known as the action potential (AP), and the signal (EMG) at the skin's surface is the summation of the electrical activity of the motor unit action potential (MUAPS). There are two ways to measure EMG: one is by an invasive approach that uses a needle, and the other is a non-invasive approach that uses dry or wet electrodes on the surface of the skin [5]. Acquisition of these surface EMG signals is usually done by surface sensors that lead to the inputs of a differential amplifier. In clinical applications, an EMG is captured using dedicated medical instruments that are composed of silver-chloride (Ag/Cl) electrodes in combination with a conductive gel. The gel reduces the contact impedance with the skin, and this system is able to capture extremely high-quality signals that allow for the diagnosis of muscular and neural human systems [20]. On the other hand, wearables cannot use Ag/Cl electrodes as they are limited in terms of their form factor (i.e. size, shape) and power consumption. Accordingly, they usually employ dry electrodes. Besides that, dry electrodes also have an advantage over the Ag/Cl electrodes in long-term use while still providing comparable signals to the Ag/Cl wet electrodes [5,20]. A few factors that affect the ability to detect surface EMG signals are: skin perspiration, the distance between the active muscle fiber and the sensing site, crosstalk between adjacent muscle fibers, and signal variability that is caused by sensor impedance [20]. These factors need to be considered in clinical applications as well as wearables. Looking now at some wearable designs using EMG, we see examples, such as the Myo band, that use eight EMG channels. The Myo band detects the signal by placing the sensor securely above the muscles that generate the signals in the forearm, allowing it to detect five gestures (finger spread, fist, wave in, wave out, and double tap) [21]. However, a recent study, done in 2018, proves that only two EMG channels—one placed on the wrist flexor and other placed on the wrist extensor—are sufficient to classify four of the same five hand gestures as the Myo band [21]. Figure 4 shows the Myo band and the 2 channel EMG sensor below.

Figure 4. This figure shows the Myo band on the left and two EMG channel sensors on the right. Image source: [21,22].

The next component worth considering is auscultation of body sounds. The first act that a medical professional performs in a diagnosis is auscultation, and that alone demonstrates its importance. Auscultation refers to the act of listening to the human body and is usually done by using a Littmann stethoscope [8]. Therefore, cardiac auscultation refers to listening and interpreting heart sounds. It is a very cost-effective approach as well as being non-invasive and easy to use. Moreover, it is the most used technique by doctors for the primary screening of early cardiac illnesses [8]. Cardiovascular diseases are one of the major causes of death in the world; hence, it is important to evaluate cardiac functions using a fast, non-invasive technique [23]. The main heart sounds include S1 and S2. S1 occurs at the onset of ventricular contraction. The second heart sound, S2, corresponds to the closure of semilunar valves and finally S3 and S4 can sometimes be heard as well as other clicks and snaps. Normal heart sounds range from 20 to 420 Hz [8]. Auscultation serves as the first point of diagnosis and vital sign monitoring. This is because listening to these sounds can reveal information regarding the status of the underlying functions. For example, heart sounds often reveal abnormalities if a murmur is present and allow for the detection of disorders of the body. Furthermore, there is a strong connection between the heart and the lungs, when compared to the rest of the body's systems, which is known as the cardiopulmonary system. Therefore, when analyzing the cardiac system, it is common to consequentially analyze the lungs and breathing of the patient. This is referred to as lung auscultation, which is used to detect respiratory disorders. Lung sounds can be classified into three categories: normal, abnormal, and adventitious. Normal sounds are quiet and hardly audible; abnormal sounds refer to the lack of these normal sounds; and adventitious sounds refer to wheezing and crackles that are strong indicators of disease [8]. It has been shown by our previous work, that detection of these sounds is possible using a high-fidelity microphone. Furthermore, it is also possible to classify these signals based on normal and abnormal signals with an accurate classification algorithm. Figure 5 shows the auscultation locations for the heart and lungs.

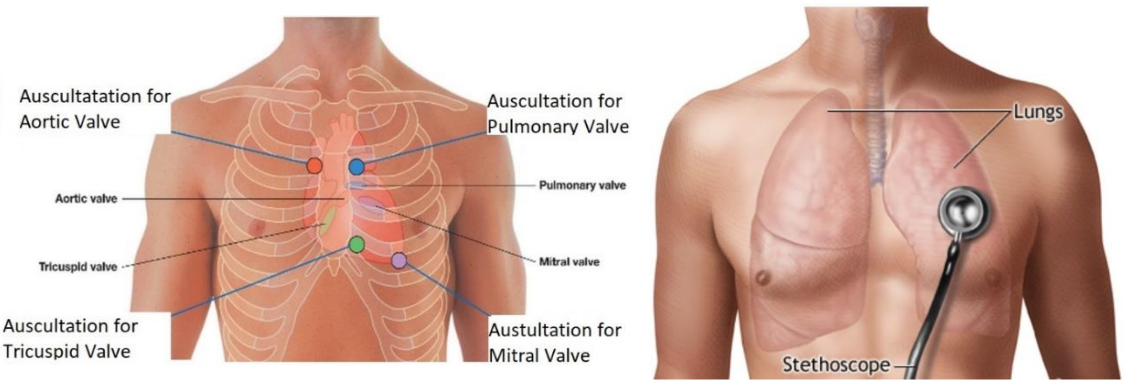

Figure 5. This figure shows heart sound auscultations and lung sound auscultation locations. Image source: [26,27].

The last component that directly relates to taekwondo measurement techniques is gait analysis. The importance of a gait analysis is evident in the fact that, each year, there are around 3.2 million deaths worldwide because of physical inactivity. As a matter of fact, physical inactivity leads to chronic disease and disability. It has also been described as a pandemic by many that has economic, social and environmental impacts [28, 29]. Physical activity refers to any movement produced by skeletal muscles that leads in the use of energy and regular physical activity is associated with health improvements in many populations. Therefore, the importance of measuring and encouraging individuals to be active is evident. Even more, the U.S Department of Health and Human Services identifies physical activity as a priority area in health promotion [29, 28]. Moreover, a clinical mobility assessment fails to mimic the real-world requirements; for example, the 10 m walk test underestimates gait velocities [28]. As a result of this, it is important to quantitatively assess mobility in real-world environments. Step counting is the most common measure of physical activity. Sensors that provide this data need to be highly accurate, lightweight, and allow for use in homes and the community. The crucial part is to mimic real-world daily activities, as it is unrealistic and an oversimplification to assume that individuals walk consistently at high speeds [28, 29]. One disadvantage of the current step detection algorithms and sensors is the decreased accuracy at slower speeds, and these slower walking speeds are the main indicators of movement disorders [28].

Detecting the physical activity of humans is possible with the placement of sensors, usually accelerometers and gyroscopes, on different parts of the body. There are different approaches to this, and the most common ones that are seen nowadays are pedometers, which are watches or sensors that are placed on the wrist for activity tracking. However, one limiting factor for these devices is accuracy. Therefore, sensor location needs to be updated, and a study done in 2014 proved that step counts can accurately be obtained from three-axis accelerometers placed on the thigh, waist, and ankles [28]. These systems performed well in low-gait-speed scenarios and outperform commercial pedometers. Due to the research done on these devices in the last decade, accelerometers are now accepted as being the most effective way of measuring physical activity levels of an individual or a whole population. With this, there are several examples of activity trackers in the market and an example is shown in Figure 6.

Figure 6. This figure shows the Moov Now device that contains nine-axis motion sensing. Image source: [29].

2.2. Sensors Used

With a strong understanding of how body signals are captured by sensors and converted into usable data, the 2 most important sensor mentioned in the previous section are accelerometer and gyroscope. These 2 sensors are important as they can capture the human movement and are proven in the industry. It is very common to find these sensors in nearly all of the pedometers or any activity recording device. Furthermore, since the aim is to capture body movement when an impact takes place these sensors are an ideal choice for our taekwondo Point Scoring System The following section dives into the background of these sensors and what exactly they capture.

2.2.1. Accelerometer

Accelerometers are lightweight, non-invasive and small devices that measure body movement in terms of acceleration on the uniaxial, biaxial or triaxial planes [29]. There are 2 types of acceleration measured by accelerometers: dynamic and static. Dynamic acceleration is one due to any force applied on a rigid body except for gravitational force. On the other hand, static acceleration is due to the force of gravity. An accelerometer converts these accelerations into an electric signal called the output. The advantage of using acceleration as a means of detecting physical activity is because acceleration is proportional to force involved as well as a direct reflective of energy expenditure [29]. Furthermore, it provides reliable information on duration of movement, intensity and frequency and these are important features commonly extracted for analysis by most algorithms to classify physical activity. The output of accelerometers is measured in terms of gravitational acceleration (G's) and it depends on its design and ranges in magnitude from -0.05 to 16Gs.

Accelerometers are generally made of 3 main components: a peizo-electric element, a mass and a housing enclosure. The proof mass (M) is suspended by compliant beams attached to a frame (enclosure). The suspension beams have a spring constant of K and a damping factor of D affecting the movement of the mass [30]. When this system is subjected to external acceleration, it displaces the support frame relative to proof mass that changes the stress in the suspension spring. This relative displacement and suspension beam stress is used to measure external acceleration. This system can then be modeled by a second-order transfer function that is a combination of Newtons second law and the general accelerometer model written below (1) and represented in the Figure 7:

$$H(s) = \frac{x(s)}{a(s)} = = \frac{1}{s^2+\frac{D}{M}s+\frac{K}{M}} \quad (1) \quad [30]$$

Where:
a is the external acceleration and x is the proof mass displacement

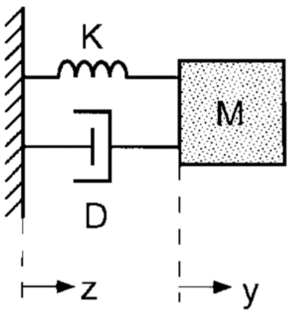

Figure 7. This figure shows the accelerometer structure. Image source: [30].

The earliest support beam design was the cantilever support however, they were not as effective as the newer integrated chip sensors due to their simplistic design. The newer sensors are smaller in size and this allows more than 1 sensor to be packaged into an enclosed allowing the ability to measure several planes (X, Y and Z). Further, they are more durable and allowed much more repeatability and this resulted in the Inertial Measurement Units we see today [29]. Within these 2 categories, are various micromachined designs for accelerometers and 2 popular examples of cantilever type are piezoresistive devices and capacitive devices. Piezo-resistive accelerometers use silicone piezoresitors in their suspension beam. As the support frame moves when an external acceleration is applied, the suspension beam expand or shorten changing their stress profile and the resistivity of the piezoresistors [7]. Capacitive accelerometers function in a similar manner. When an external acceleration is applied, the support frame moves changing the capacitance between the proof mass and fixed conductive electrode. This capacitance is measured using electronic circuitry. A popular example of an integrated chip sensor is of a piezoelectric one where a piezoelectric element has a mass that is directly over it to detect acceleration [29, 30].

2.2.2. Gyroscopes

Gyroscopes (gyro) are used to measure angular rate around a fixed axis with respect to an inertial space. Basically, this is how quickly an object turns around one of three axes: pitch, roll or yaw. The majority of gyroscopes that are micromachined, use vibrating mechanical elements that detect rotation [30, 31]. Further, most of them are based on the Sagnac effect, Coriolis effect and the angular momentum conservation. The most common types of gyroscopes are spinning mass gyros, vibrating gyros and optical gyros [31]. Spinning mass gyros have a mass spinning steadily with respect to a free movable axis. This uses the inertial property of wheels spinning at a high speed. What this property states is: the wheel will resist any change in direction and keep the direction of its spin axis [31]. This type of gyroscope is used commonly on satellite stabilization and is called the Control Moment Gyroscope (CMG). It works by the same principal and the changing angular moment of the spinning rotor (mass) creates a torque that moves the spacecraft. The main problem of this is it has a spinning mass and it can not be miniaturized effectively and this created the need for a new design of gyroscopes that developed vibrating and optical gyroscopes. Starting with vibrating gyros, they are all based on the Coriolis effect that induces a coupling between two resonant modes of a mechanical resonator [30, 31]. The Coriolis effect is named after the French Engineer G.G. de Coriolis and is best explained by Yazdi in this review article. It is the acceleration when a reference frame is rotated and is proportional to the rate of rotation. To get a better understand of it, place a person on the x-axis of the 3D-corrdinate system. The persons job is to overserve only and is observing a particle. If the whole 3D-cordinate system starts to rotate around the z-axis with angular velocity Ω, the observer sees a particle moving towards the x-axis. The acceleration of this particle is the Coriolis effect and is seen in Figure 8 below and is represented by the equation (2) below:

$v = \Omega r$ and $ta = 2\Omega v$ (2)

where:

omega (Ω) is the angular rate, v is tangential velocity, r is radius and ta is tangential acceleration or Coriolis acceleration

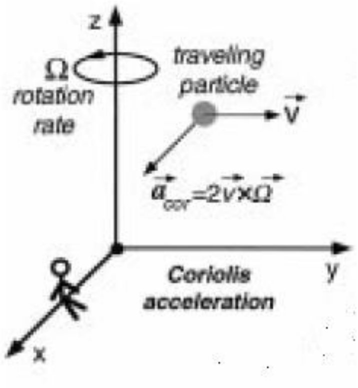

Figure 8. This figure shows the Coriolis effect. Image source: [30]

Moving now on to optical gyroscopes, optical gyros are based on the Sagnac effect. There are two possibilities of this effect, the first is, in two counter propagating waves there is a phase shift is proportional to the angular velocity. The two optical signals (waves) propagate in opposite direction within a ring interferometer rotating around an axis perpendicular to that ring [31, 30]. The phase shift between a clockwise and counter clock wise signal is described below on the left side (3). The second effect is a frequency shift, and it occurs when 2 resonant modes propagate in a opposite direction within an optical cavity that rotates around an axis perpendicular to it [31] The equation describing this is shown below on the right side (4).

$$\Phi = \frac{8\,\pi^2 R^2}{cY}\Omega \quad (3)$$

where:

Y is the optical signal wavelength, R is the ring interferometer radius, c is the speed of light in a vacuum and Ω is the rotational rate [31]

$$\Delta\nu = \frac{4a\nu q{,}0}{pc}\ \Omega \quad (4)$$

where:

a is the area enclosed by the light path, Ω is the rotational rate, vq,0 is the resonance frequency of the optical modes, p is the perimeter of the resonator, c is the speed of light in a vacuum [31]

The angular rate of these gyroscopes is measured in degrees per hour or degrees per second (°/h or °/s).

2.3. Common Kicks

As it was seen in the introduction, most of the points are rewarded for kicks with only one point rewarded for punching the chest. There are 2 types of kicks in taekwondo: thrust kicks and swing (turning) kicks. Thrust kicks are performed to hit the front in a straight movement while swing kicks use body rotation that is directed to the side of the opponent [7]. There are 5 kicks that dominate the sport and they are: jumping back kick, jumping spinning kick, roundhouse kick to the head, the outside in axe kick and the straight axe kick. The last 2 kicks are thrust kicks while the first 2 are swing kicks. Moving on, the 2 factors for an effective taekwondo kick are execution time and reaction time [7]. In taekwondo, it is important to use an effective technique to cause the most damage to the opponent and that can only be done if the sum of the time taken for kick execution and reaction is short. Therefore, the sum of reaction time and execution time demonstrates an effective kick. When kicking the chest or trunk, it is most effective to use swing kicks as they are much faster than thrust kicks. This can be seen in the biomechanics study done in 2013, where they found the roundhouse kick as being the fastest coming in at 0.773 +-0.102s or an execution time of 0.275s +-0.081s [32]. Furthermore, swing kicks are also the most effective when hitting the head. The fastest one in this case again is the roundhouse kick with an execution time of 0.460s +-0.095s or a total time of 0.740+-0.086s [7]. For the other kicks, thrust and swing, the times can be seen in table 3 above. This demonstrates that the roundhouse kick is one of the most effective kick and hence it is the most often used technique in competition and training [7, 32].

Table 3. Different kick style times to the head protector

Kick	***Total Time (s)***
Roundhouse kick	0.740+-0.086
Jump spin back kick	0.808+-0.092
Jump spin hook kick	0.809+-0.186
Front leg axe kick	0.872+-0.088
Clench axe kick	1.119+-0.122

[1] **Note.** The total time is the execution time + the reaction time [7]

Due to the popularity and effectiveness of the roundhouse kick, it will be important to look at the impact force this kick creates. This is done to understand the maximum forces that the kicks are capable of. However, measuring force directly requires the use of pressure sensors that make a force platform and is not usually an economical method. This type of equipment was used by Estevan for the mechanical analysis of the roundhouse kick [32]. However, this might be more precise, usually accelerometers are used to measure the resultant acceleration of the object. The acceleration values then need to be converted into force and this can either be done by deriving a coefficient or using energy and work done equations. The calibration of accelerometers in advance requires using a force measuring device and finding the relating coefficient between that and acceleration. This is the type of procedure used by O'Sullivan's work on measuring impact forces of turning kicks [33]. Nonetheless, it is important to consider this data and design the device for the maximum forces possible in taekwondo.

The two factors affecting the impact force are height and distance of the target [7, 32, 33]. However, research shows that target height only effects novice athletes and is not an important factor for experts. For experts, the only factor that effects impact force is target distance to the head or chest [32]. The impact force for expert athletes is 15.81N/kg +-7.12 for normal distance at 1.06 meters to the chest. However, at a short distance of 0.7 meters the impact force was higher at 19.81N/kg +-5.67 to the chest which is the highest value in all classes. Overall, the impact force on the chest is higher than the head for all target distances [32]. Finally, for novice athletes the impact force is lower than the experts at 13.93 N/kg +-5.58 for normal distance and 15.56N/kg +-5.51 for short distance. This demonstrates that the highest impact force is 19.81N/kg +-5.67 [32]. All these values are normalized based on body weight and hence it is possible to retrieve average impact forces for different weight classes. In contrast to this, the study done by O'Sullivan on the comparison of taekwondo turning kicks and the impact forces generated by those kicks demonstrated significantly higher forces. They found the maximum force to be 6400N for a turning kick to the head [33]. This difference is in part due to the data not being normalized for the body weights.

2.4. Factors to Consider

The most important step required occurs before any design has taken place, and it involved doing a survey to determine if there is a need for the product. There are several names for this stage and the most common is called market research. This is basically done to prove the idea does not already exist in the industry. Once this is proven, the design can officially begin, and this then requires a strong technical understand of the signal being measured. For example, for an ECG signal, it can be easy for experts to identify the QRS due to its distinguishable characteristics that can be used in an analysis. However, that is not the case for all biomedical signals, and a considerable number of transformations is required to extract information from the signal [22]. Therefore, it is important to consider these factors before beginning the design of the wearable since for our application (taekwondo) there are no commercially available data sets making these factors to consider crucial to this thesis.

2.4.1. *Four Design Factors*

When the design of a wearable commences, whether it is for medical purposes or non-medical purposes, there are some factors to consider. Those factors are: (1) the characteristics of the measured signal, (2) the human factors, (3) the economic costs, and, finally, (4) the environment that the device will be in [22].

Starting with the first factor, it requires an understanding of the signal generation source and the properties of the signal. For biomedical applications, signals that are captured by sensors are commonly retrieved from the skin and are responses to the electrical stimulation of the nerves and muscles. Alternatively, the properties of the signal include several aspects, such as: determining whether the signal being recorded is reliable, whether there are usable signal-processing techniques for the signal, whether the signal is stationary to allow for analysis, and whether the signal needs compressive sensing algorithms at the acquisition stage [22]. This is important, because, based on these factors, a decision on which sensor to select will be made during the design phase to allow for signal capture without any information loss. The second factor, medical risks, requires an understanding of the user of the device and the interactions they have with the device. This means considering the environment the device will be used in, what materials the device should be made of, safety requirements, and how the device will affect the patient's daily life [22]. For example, in a hot environment, the patient will be subject to more sweating than usual: will that change the obtained signal? Moreover, does the material the wearable is composed of cause any allergic reactions, pain, or discomfort? Finally, do the patients deem the device to be obstructive or overly complicated, and prefer not to use it? These factors are important, since a convenient device that is both hardware and software friendly will be used more often by the patient than one that is not. This is also referred to as the technology adoption rate, and is a considerable downfall for many devices. The third factor, economic costs, refers to designing an instrument that is affordable, is compatible with existing technologies, and is readily available. The designed device should be affordable and should not require extensive changes to their existing technologies. Furthermore, it should be available to purchase on many platforms, so patients do not have to go to specific locations to buy them. The importance of this factor arises because lifestyle or non-medical wearables can be relatively cheaper than medical wearables, since they do not go through an extensive process for approval. The last factor, the environment, refers to the environmental noise the device will face when in the real world. For example, the signal-to-noise ratio is a crucial measure of how effectively the device can capture the signal and reduce the noise.

Considering and meeting these factors does not guarantee a successful product, and they are only for lifestyle or nonmedical wearable devices and not medical devices. The FDA in the United States and the Therapeutic Products Directorate (TPD) in Canada regulates all medical devices extensively, and these devices must go through a time consuming process that comes at a significant cost to ensure that the devices are safe for consumers.

2.4.2. Important Distinction: Medical versus Non-Medical Wearable

One of the most important distinctions that will determine the hardware and software requirements of biomedical wearables is the difference between medical and non-medical biomedical wearables. The term “medical devices” is loosely defined in Canada by the Food and Drugs Act as “a wide range of health or medical instruments used in the treatment, mitigation, diagnosis, or prevention of a disease or abnormal physical condition” [34]. Some common examples are artificial heart valves, pacemakers, synthetic skin, and medical laboratory diagnostic instruments. These devices are evaluated and monitored in Canada by the Therapeutic Products Directorate (TPD) and in the United States by the Food and Drug Administration (FDA). The TPD is a national authority that determines the effectiveness and quality of diagnostic and therapeutic medical devices in Canada. There are four classes that any device for sale is classified and grouped into. The first class is the lowest potential risk class (Class 1), and an example of a device that belongs to this class is a thermometer. The last class (Class 4) is highest potential risk class, and an example of a device that belongs to this class is a pacemaker. Class 1 products do not require a license, while the rest of the classes do, and the review process becomes more onerous as you move into higher classes [34]. Two items can be issued: either a Medical Device or an Establishment License. The process is similar to that of the FDA in the U.S., and many of the rules are adopted by the FDA. Further information can be found in the Medical Devices Regulations of the Food and Drugs Act of Canada [34]. On the other hand, fitness, lifestyle, or non-medical wearables are those that do not intend to provide any diagnosis, mitigation, or treatment of a disease. This is further supported by the FDA, who states that the concept for determining if a device is medical or non-medical is based on the intended use [35]. The technologies of both medical and non-medical devices can be the same, so both devices can measure the exact same signals with the same quality; however, if a device is analyzing the data to provide treatment, it will be considered a medical device and will have to go through an extensive process for approval [35]. To put it in another way, non-medical devices are not useful in diagnosing most medical conditions but can be used to track fitness and allow for patient-centered disease prevention.

2.4.3. On Chip and Edge Computing

While the majority of IoT devices in the market use some sort of Cloud Computing, it is not the only option. Cloud Computing is currently very popular and refers to transferring data to a remote server for data analysis. However, lightweight tasks can be performed on the micro-control unit itself. This is limited by the processor on the board, how much memory is available, and if the micro-control unit has storage capabilities. Some Arduinos contain enough memory to perform lightweight tasks and computations on the chip. Therefore,

An extension of this is called Edge Computing, which performs computations at the edge of the internet [36]. As the shift towards IoT and IoMT continues, large quantities of data of exceptional quality will be generated by all of the devices surrounding us. It is estimated that around 50 billion things will be connected to the internet by 2020, and by 2019 people and machines will be producing 500 zettabytes of data while the global data center's (Internet Protocol) IP traffic will only reach 10.4 zettabytes [36]. This means that all of these things and devices will be producing data at a much higher rate than can be processed by the cloud. As a matter of fact, growth in the bandwidth of networks has come to a standstill, and the speed of data transportation has become the main bottleneck for cloud-based computing [36]. This means that most of the data produced by IoT and IoMT devices will never reach the cloud. Therefore, the simple definition of edge computing is any computation that occurs between the data-generating devices and the cloud data centers [36]. This includes processes such as data offloading, data storage, data processing, and IoT management, as shown in Figure 9. This also improves user privacy, since the data that are sent for edge computation are normally private when compared to the cloud. Finally, this improves on and allows real-time applications. The latency between data capture and some analysis being performed in edge computing is less as no data transmission is required.

2.5. Review of Point Scoring Systems

Following the Factors to Considers section, market research needs to be performed before any design has taken place. From the World Taekwondo's official website, we can see that there are two companies approved to produce point scoring systems and they are: Daedo and KPNP. As mentioned in the introduction, 2012 was the first year point scoring systems were used in the London Olympics. During that year, only the truck (chest) protector and the socks had electronic sensors. The socks or foot protector at that time had 7 sensors and in 2016 this was upgraded to include 4 more sensors in the heel, the side of the big toe, the inner ankle, and the top of the toes [5]. The electronic head protector was first introduced in 2016. Since the kicks on the head are not as hard, as the chest, the sensitivity is high. However, in 2016 the trunk protector was not changed since its introduction in 2012 [5]. The IOC has contracted Swiss Timing for their time keeping as well as several other services and one of them includes a technical evaluation of the point scoring systems for Taekwondo. They do this in their headquarters and during the WT competitions. Swiss timing has chosen Daedo's PSS to be used in all 3 Olympic Taekwondo competitions [3]. Perhaps, this demonstrates some advantages Daedo's PSS has over KP&P in terms of accuracy.

Moving on to the systems themselves, we will be using the Allocation of Hardware design to review them. Basically, this design includes 3 blocks that combine to make a product. They are: Signal Acquisition, Data Processing and Visualization of the data and are shown in Figure 9.

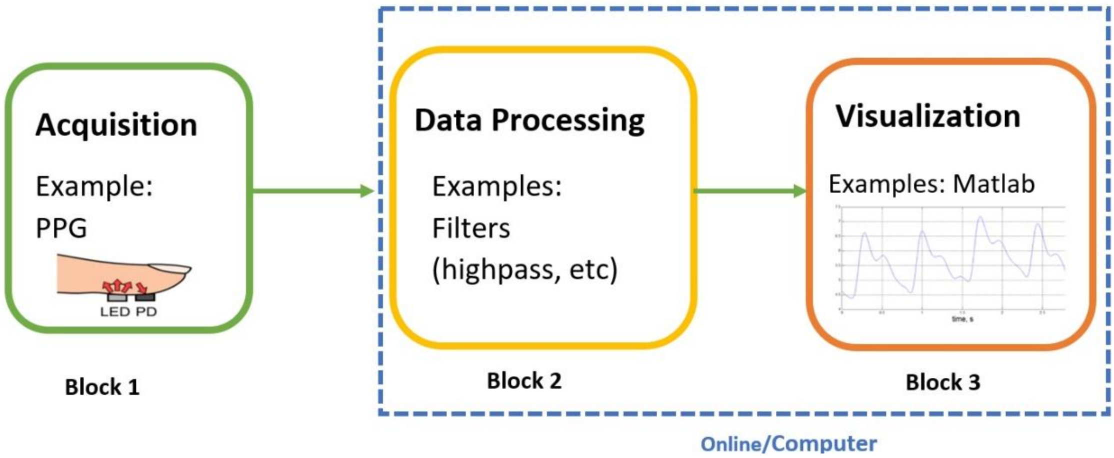

Figure 9. This figure shows the allocation of hardware. Image source: [17]

The three blocks represent different parts of a product and are usually comprised of different teams. The first block in Figure 9 and the first block, Block 1, is the Acquisition phase where raw data are captured from the source. For wearables this is usually the human body and it is done by the sensor placed on the integument of the body. Block 2 is the data processing block, where digital filters and further data conditioning such as segmentation, de-trending and feature extraction can be applied. Block 3 is the visualization of the data in a user-friendly technique. Blocks 2 and 3 are commonly performed on a personal computer with the aid of software (MATLAB) in basic prototyping applications. In IoT applications, Block 2 and Block 3 can be done on the Edge using a hardware (microcontroller example raspberry pi) on the person/device or on the cloud/server and this is due to change depending on the application. Based on this design, the two systems will be broken down into the following 3 blocks and evaluated.

Starting with Block 1 Acquisition, for Daedo PSS uses a cable impact sensor within the chest protector and does not include an impact sensor within the head gear. This means that hits to the head are not detected and manual points need to be assigned. Further, it uses magnets in the foot protector that generate a current in the proximity sensors included in the chest protector. This allows hits to only be considered when the foot is in contact with the chest so falls or any other impact is not accidentally considered a legal hit. Due to the design of the sensor, the limiting factor is the detection spots on the chest protector. This creates a non-uniform sensing area where there are certain hot and cold impact detection spots. Moving on to the next, the KP&P system uses a thin film sensor for impact detection in the chest protector and the head protector. Furthermore, because the film is uniform, it allows detection for all impacts with a linear response of impact pressure. This further allows for distinctions between the types of kicks. Finally, it includes a RFID antenna in the chest protector that communicates with RFID chips in the foot protector to determine if the foot hit the chest protector. This system is better at impact detection when compared with Daedo PSS and it can also detect hits to the head unlike the Daedo. However, it is important to note that both systems come with a hand-held scoring device for points not picked up by the PSSs. Even more, video replay is also available to use with both these systems and it can be called by the coach and allows separate referees to view, analyses and view the score.

For Block 2, Data processing, both the systems are of boolean type. What this means is, if the hit passes a certain threshold, it will register it as a legal hit. That impact threshold is used to determine what is and is not a scoring it and that hit will carry the same value regardless of how much harder the hit was over that threshold value. This means, that the current point scoring systems do not determine the true impact of the hit, rather they just pass a human satisfactory threshold of what a legal punch should be. For Block 3, both systems have software that is able to transmit the data and visualize it. These transmitters and the software have to be bought at an extra cost. This leads us to another main issue with both these point scoring systems, and that is the cost to get a complete working set requires not only one component but several. For example, to get a complete Daedo PSS costs around 3367 USD that includes 2 two chest protectors, receiver, chest protector transmitter, chargers, World Taekwondo Software and judging triggers [37]. Moving on to KP&P, their system costs 2770 USD including 2 chest protectors, receiver, referee scoring box and chargers [16].

2.5.1. Review of RUPunch

Taekwondo and boxing are usually researched together as they both share several aspects. Both are combat sports that have a primary objective of striking the opponent for points. Further, they both focus on the head as the primary target and therefore several aspects of these sports are often studied together in research studies [38, 39, 40]. Therefore, it is beneficial to consider relevant work in boxing. Innovative work was done on a product called the RUPunch and this product uses an inertial measurement unit, microcontroller, a communication module and a hardware circuit. This captures motion from the user as they perform a punch. The product uses a microcontroller (Arduino) that was programmed to retrieve data from the IMU (accelerometer and gyroscopes x,y,z values) and transmit this data to be processed and classified. This work is of interest as it successfully uses data primarily from an IMU to classify different punches. Further, they were able to accurately classify illegal vs legal hits with an accuracy of 89.66% and then had 5 subclasses with different types of punches with accuracy higher than 98.46%. What this demonstrated was firstly, classification can be done solely using IMU data in combative situation, secondly, it can be done with high accuracy even with the noise and motion involved in the sport. It is important to note the placement of the IMU and the electronics as it accounts for essential differences. For their system, they electronics were placed on the hand and therefore captures the motion of the punch as it strikes the opponent. This work provided us with important insights on sensor placement and showed the possibility of accurate classification that was successful and appreciated by the industry.

3. <u>*Contribution 1: Head Protector*</u>

Most, if not all, combative sports require some form of protective head gear that is worn by athletes in a competition. Combative sport refers to any sport that requires an athlete to hit the opponent for points. These sports are played at many levels and the competition rules for head gear can change over time for those different levels. This was recently seen in boxing where athletes are now not required to wear head gear, nonetheless, Olympic taekwondo requires the use of headgear. Not only that, but headgear is the primary form of protection for the head and is proven to be effective in reducing skull fractures, major traumatic brain injuries and head impacts. It was first introduced in 1985 in taekwondo by World Taekwondo and was first used in the 1987 World Championships in Spain [40, 41]. Ever since then, it has been used in all taekwondo competitions.

There have always been significant amounts of research done on helmets and how they affect a person behavior, how effective they are and what the best design is. These types of studies are commonly done to improve athlete safety and are done in all types of sports such as American football and boxing. As for Taekwondo, there are a limited number of studies done on headgear and it all started in 2013 by a team in Korea testing WT approved head gear [41]. From there, this same group did several studies on helmet effectiveness in dissipating impacts. As their findings became popular, research on taekwondo helmets was also picked up by Andrew Mclntosh and work was done on impact performance [38]. The type headgear used is similar in both taekwondo and boxing and therefore historically studies began by combining these sports and using the findings from boxing as a basis for hypothesis and testing [38, 39, 40, 42]. This eventually transitioned into studies focusing on taekwondo and interesting results followed. Moving on to taekwondo gear, any innovation done on an existing product requires a solid understanding of how that item currently functions. Therefore, it is paramount that the current standards used to make helmets are considered and the most important of them being human factors affecting the design. To understand how a helmet is usually evaluated, we will use criteria mentioned in the Background and Factors to Consider section. There are four design factors to consider before the design of any device begins: (1) the characteristics of the measured signal, (2) the human factors, (3) the economic costs, and, finally, (4) the environment that the device will be in. The current headgears are not recording any signals and hence, only the second and third factors will be considered: human factors and the economic costs. Then we will move on to the first and last factor as they affect the electronic-helmet design and they are: the characteristics of the measured signal and the environment that the device will be in.

3.1. Standards and Considerations for Head Protector (head gear or helmet)

Starting with the first point to consider, human factors include understanding the user of the headgear and what interactions they will have with it. This includes medical risks, safety requirements and technology adoption rate. A figure of the WT approved helmet is shown below. This was also the helmet used and tested on at the SAR lab.

Figure 10. This figure shows the adidas headgear. Image source: [43]

3.1.1. Human factor 1: Medical Risks

Medical risks for taekwondo headgear are high as there are significant forces and accelerations acting on it and it is the only form of protection athletes have. The main purpose of the headgear is to reduce the impact acceleration caused by a hit (kick or punch) or from an athlete falling and hitting their head on the ground [39]. Current headgears are effective at this purpose as it is proven to drastically reduce forces that cause skull fractures and major traumatic brain injuries [44]. However, impacts to the head are not straightforward as the head contains the most complex organ of humans, the brain. Therefore, it’s not simply about stopping major skull fractures but rather considering concussions as they are a very common occurrence in combative sports. In taekwondo, with the head gears in use, concussion and head wounds are the most common head injury among athletes [38]. Head wounds are relatively easy to understand, if an impact is great enough to break or cut the persons skin, this will result in a visible wound. However, the same is not the case for concussions. Considering some facts, the concussion incidence for taekwondo is 9.4 per 1000 for male athletes and 4.6 per 1000 for female athletes, which is nearly four times that of American football [39]. What this demonstrates is that, the head gear used in taekwondo is effective in reducing major head injuries potentially leading to death, but concussions are still a topic to examine.

To understand how concussions occur, we have to assess the accelerations on the head right after the impact has occurred. The first thing needed for accelerations to occur on the head is an impact. That comes from the opponent's foot travelling at a certain velocity, v, hitting the athletes head. From Newtons laws of motion, the head will react to this impact and an acceleration will result. There are two accelerations known that cause head injuries and they are linear acceleration and rotational acceleration [39, 40]. In the real world, a hit on the head creates both linear and rotational acceleration components and if they are great enough, will result in skull deformation. However, traditionally both these accelerations were studied separately as it was believed that linear acceleration solely led to concussions [45]. Recent studies have shown that this is not the case and both linear and rotational accelerations can cause damage that was previously not well understood [45, 46, 39, 40]. Linear acceleration is caused by direct impact to the head and results in the translation of the head. This translation leads to skull deformation and pressure gradients that cause intracranial damage. The impact for this is pointed directly towards the center of mass for the head. Rotational acceleration, on the other hand, does not require a direct impact (e.g. whiplash) as it refers to the differential motion between the skull and brain and it results in shear stress. This can also be caused by an oblique hit where the impact is not pointed directly towards the center of mass for the head and this is shown in Figure 11 [47, 48]. Furthermore, studies show that diffuse (widespread) brain injuries were only present when rotational acceleration was present, while focal (specific) brain injuries were only present when linear acceleration was present [47]. What this demonstrates is that rotational acceleration and linear acceleration are important factor to consider when the head is hit in combative sports, specifically taekwondo. To relate linear acceleration to force, we can consider the Newtons laws of motion, when a person is hit on the head with a certain force this creates a reaction force as well as an acceleration on the head. The relationship is represented in the formula below and is an approximation of head movement:

$$F=ma \quad (5)$$

where:

F is the force in Newtons, m is the mass of the object in kilograms and a is the acceleration in meters per second squared

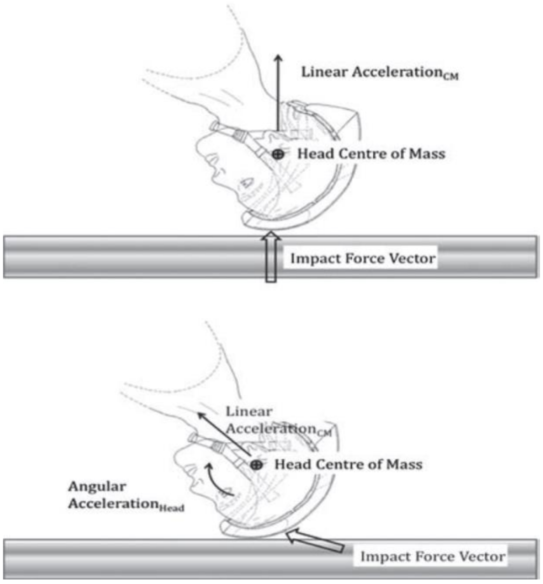

Figure 11. This figure shows angular and linear acceleration on the head. Image source: [48].

A study done in 2016 found that hits to different parts of the head produce different levels of rotational acceleration [39]. A hit to the front of the head gear usually produce the highest levels of rotational acceleration when compared to side impacts. This is an important point to consider as the impact location does in-fact have different levels of rational acceleration. Moving on to the final point why there is a significant medical risk related to headgear in Taekwondo, this, by itself, is enough to keep headgears permanently in Taekwondo. It is the scoring that WT has recently implemented in June of 2018. As mentioned in the introduction, kicks to the head are worth the most points and athletes usually train with this in mind. Further, there is a good chance of winning a game by a quick knockout and hence it is common to see big blows to the head.

3.1.2. Human Factor 2: Safety requirements

The safety requirement for a helmet are set by regulatory bodies that govern the sport, for taekwondo this is World Taekwondo. They approve all the gear that the athletes use and have a major role in their safety. However, going back to how the standards were developed, it started in 1995 by Moffitt and Lieu. In that year they tested the response of martial art kicks on headgear and this was the first work of its type specifically focusing on taekwondo. From that work the American Society for Testing and Materials International (ASTM) developed recommendations for testing protective headgear in 2004 [41]. It is called “Standard Specification for Protective Headgear Used in Combative Sports (F2397)” and includes performance requirements for sports such as karate, taekwondo and wushu [49]. There are several tests performed such as falling impact test and striking impact test and they all use a Hybrid III head and neck foam that is hit with a 500mm striker made of aluminum. The striker uses a spring and has a pivot point that impacts the head foam and an accelerometer capable of measuring 1000Gs is attached to the center of the head foam at the center of mass point [49]. Furthermore, the performance requirements state that low energy impacts (impact velocity of 5m/s) are to produce maximum impact below 50G and the high energy impacts (impact velocity of 8m/s) should produce a maximum of 150G [49]. Moving on to World Taekwondo, it is still unclear if the approved helmets use this standard for testing or if they have their own version of this. In 2013, this issue was brought up by David O’Sullivan where they tested the Safety performance of WT approved helmets [41]. Regardless, helmets are commonly assessed on their ability to attenuate impact force (energy) using drop tests [38]. Therefore, it can be assumed World Taekwondo uses similar testing methods for their certification and approvals. They currently have a total of 7 companies that are approved by the World Taekwondo and they all look similar to the Figure 10. They are soft foam head gear without a hard-slippery outer shell often seen in motorcycle helmets. A very interesting point is, none of the current head injury safety standards consider rotational acceleration but rather use only linear acceleration [41, 39, 38, 45]. The first work done on rotational acceleration and the limits that can cause injury to a person’s head was done as recently as 2018 by Gabriel P. Fife [40]. Their studies provided some limits for head injury for rotational acceleration and linear acceleration that can be used to develop safer headgear.

Based on these medical risks mentioned, it is normal for the regulatory body to define dimensional criteria of the head gears such as the thickness, maximum mass and the total area of head coverage [38]. The WT approves helmets for use in competition consequently they should have their own criteria, however it is not public knowledge. The material the headgear is made of has a significant impact on its performance and this is something the regulatory body will consider. In an ideal situation, the material should reduce the accelerations on the head to a safe level by dissipating the kinetic energy of the impact. The design needs to consider the shape of the structure and its ability to absorb elastic energy. The shape of the structure influences load transfer during impact, on the other hand, the ability to absorb elastic energy controls rebound [50]. Usually, headgears are made out of closed-cell polymer foams and there and they are usually characterized by their density, Young's modulus and yield stress [51, 50]. These foams are commonly used for impact protection and can undergo significant compressive deformation. They have excellent energy dissipation properties and are flexible that allows them to be molded in complex helmet shapes [50]. The large deformation these foams are capable of is done by cell bending, cell collapse and cell buckling [51]. To visualize this, we can use a stress-strain curve of typical closed-cell foams and an interesting point is the long plateau seen in Figure 12. There are three distinct parts to this figure: 1) the elastic region, which is defined by the Young's modulus and is usually at less than 5% strain. 2) the long plateau, this area is where the main energy absorption takes place as at this point the cells collapse and deform. This is at a constant load and stress plateaus until the third part. 3) the densification, when the opposing cell walls meet then the stress increases significantly.

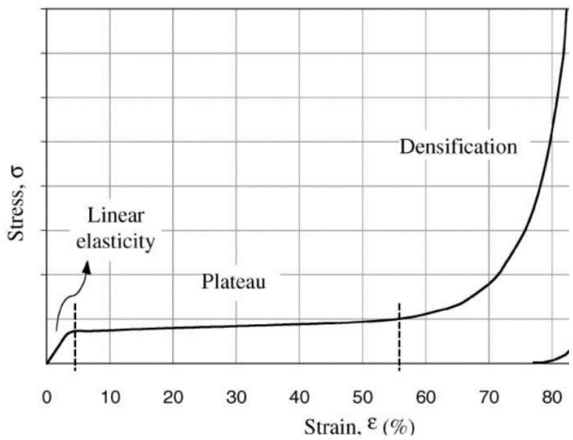

Figure 12. This figure shows the stress-strain curve for common foams. Image source: [50].

The foam used to make soft head gear, such as the one shown in Figure 10, is composed of polyethylene. It is intuitive and correct to think that as the thickness of this foam increases, the protection increases. This is because as the thickness increases, the work performed through the deformation of the foam also increases and hence the impact force is reduced by the headgear [52]. However, there are opposing views on this in the academic world. In 2016 a study done on impact attenuation of taekwondo and boxing headgear showed that that thickness does not necessarily provide better attenuative properties [39]. On the other hand, a study done by another group in 2015 on impact performance of headguard for combat sports (focusing on boxing and taekwondo), showed that the best performing head gear was the thickest and most dense [38]. The thickness of the Adidas taekwondo helmet is uniform around the protector with the ear protection extending outwards with the same thickness. What this shows is there are several factors to consider when designing head gear such as the stress-strain curve for a material, the density, the thickness and overall design. These factors are necessary in keeping the athletes safe and hence should be considered by the regulatory bodies.

3.1.3. Human Factor 3: Adoption rate

The next human factor to consider is the adoption rate. This refers to the idea if the users find the device or equipment overly complicated or obstructive. Further, is the device or equipment convenient to use in both the hardware and software side. It is common to associate this with software, for example, if an application is not intuitive to use it will not be adopted by the users in a timely manner and could lead to its demise. However, this is also important for hardware and headgears. For athletes it is important that the headgear they are using does not affect their performance and it is preferred that the head gear is thin [39]. There are several reasons why this is preferred as a thinner and lighter head protector would be less obstructive and provide better movement as there is less weight on the head. Further, it is possible that soft head gears have another disadvantage of the dig-spin. What is meant by this is, as the opponent kick the athlete, there is a possibility that the kick might dig into the soft material and cause additional spin or rotational acceleration. This is something that does not occur in hard shelled head gear as they tend to “slide” upon impact.

Moving on to the next element that has an impact on technology adoption, and it is the thermal effects of headgear. For anyone who rides a motorcycle, they are far too familiar with this point. Helmets are known to cause discomfort when worn however, this is magnified when an athlete that is exercising is added into the equation. Now another factor comes into play and that is thermal discomfort [53]. A helmet limits the heads capability to dissipate head and hence it has been documented that the heat storage occurred during activity, potentially leads to reduced physical performance. This can be due to several reason such as: impaired voluntary neuromuscular activation, reduced mental arousal and heat-induced altered brain neurochemistry [53]. This is then another element that needs to be considered as a “hot” helmet will lead to a lower adoption rate. This is because in a competitive environment, athletes are looking to get rid of all the disadvantages they have when compared to the competitor and a “hot” helmet, which limits their performance, will be discarded. Therefore, the design of the helmet needs to be that it does not impact the natural ability of the head to dissipate head.

3.2. Economic

The next factor to consider is the economic cost of the headgear itself and the development phase of the headgear. Economic costs, refers to designing an instrument that is affordable, is compatible with existing technologies, and is readily available. This means that the sensors used in the helmet design should be cost effective while still performing the required task. However, this is a rather small task when compared to prototype testing. That is where the main cost is. For example, it is cost effective to choose a device or sensor that is already proven in the industry, rather than using something that is completely new and requires complete prototype evaluation and testing. A similar concept is even seen by regulatory bodies and how they govern devices. A good example of this are medical devices that require approval by the U.S Food and Drug Administration (FDA). As mentioned in the background section, *Important Distinction: Medical versus Non-Medical Wearable*, we know there are several classes of medical devices and the high-risk class requires an approval before it can enter the market. There are 3 possible ways to get this approval: Pre-Market Approval (PMA), Pre-Marketing Notification (PMN): 510(k) application and the Humanitarian Device Exemption (HDE) [54]. The 510(k) is known to be the fast-track approach and it is more cost and time effective to go through this when compared to the full premarket approval. The 510(k) is a submission made to the FDA that demonstrates a device is substantially equivalent to an already legally marketed device. This removes the PMA requirements of clinical testing and significantly reduces the time and effort to obtain approvals for some devices. What this means for companies is, faster approval times leading to more sales. The same reasoning exists for non-medical devices as they have similar goals and a device that has been tested once in the industry, is preferred by the company as it make economic sense. There is proof that, that device works and will not lead to unexpected situations that are not related to the company's goal. This is dominant in start-up companies as they generally do not have the funding to deal with such scenarios. These elements then trickle their way into the final product cost and if a product goes through an extensive testing and prototyping stage, it will evidently cost more. This might be a downfall for that specific product as consumers are always looking for the cheapest option and competitive companies could offer that. Therefore, for taekwondo, it is extremely important that the choice of sensors for our helmet design is a buildup or development of existing sensors that are tested in the industry.

3.3. Considerations of eHelmets (electronic helmet)

eHelmet represents a helmet that passes the above medical risks and safety requirement and further improves on it with the addition of electronic sensors. Therefore, for this type of helmet there are now, for a first time, new factors that need to be considered. Going back to the to the Factors to Consider section, it was mentioned there are 4 important factors to consider: (1) the characteristics of the measured signal, (2) the human factors, (3) the economic costs, and, finally, (4) the environment that the device will be in. The additional factors that now need to be considered for an eHelmet are the first and last one so: (1) the characteristics of the measured signal and (4) the environment that the device will be in.

3.3.1. Characteristics of the measurand signal

Characteristics of the measurand signal requires an understand of the signal generation source and the properties of the signal. Commonly, signals are captured by sensors placed on the skin or object. There are 2 electronic sensors added to the helmet and they are an accelerometer and gyroscope. The basis of this decision is the literature review described in Chapter 2. Several applications and sensors were studied in an initial study to determine their relevance for our application. From this, it was apparent that for motion tracking an accelerometer and gyroscope are the most common sensors used. Inertial measurement unit or IMU contains both these sensors and usually have a third sensor that is a magnometer. The most common application of these is cell phones and is the main sensors used in orientation detection for phone. One significant advantage IMU’s have is they can measure physical quantities of a moving object regardless of external references, friction, and environment lighting [55]. What this means is that the signals recorded are directly related to the object the sensors are attached to and is an important aspect for our application. We saw that these IMUs are most effective for step counting applications and can be used in meticulous applications proving their capabilities. In a combative situation, we are attempting to capture the athlete’s motion as they are hit. This is exactly the same task that step counters do and classification of different hits is a specific extension of motion capture just as step counting is a specific extension. As a final point, accelerometers are also used by regularity bodies to test taekwondo systems and therefore are a natural choice for our purposes. The signal retrieved is reliable and will allow for analysis to be performed. Moving on, the accelerometer will be combined with a gyroscope. This is because the combination of accelerometers and gyroscopes allows for measurement of linear acceleration and angular velocity, respectively [56]. This is especially important for motion tracking in a combative environment as the hits are complex in nature and the rotational aspect of a hit could be an important aspect to classification. In addition to this, most of the hits in combat are oblique in nature and as a result have a rotational aspect. This rotation is also an important indicator for injury and therefore both an accelerometer and gyroscope are necessary for our application.

3.3.2. Environmental Device usage (noise)

The last factor that needs to be considered is the environment. What this means is the environmental noise the device will face when in the real world. Sensors usually have filters built in by the manufacturers that allow for clean signals. For example, IMUs have built in analog anti-aliasing low pass filters with cut off frequencies decided by the manufactures. They also include digital low pass/high pass filters that have cut-off frequencies dependent on the output data rate selected and this reduces noise in the signal. Furthermore, another approach to reducing noise is by sensing algorithms that can be applied after data is collected. There are some known limitations that accelerometers and gyroscopes functioning individually face. Therefore, these limitations lead to the use of sensing algorithms. The limitation for accelerometers are that it faces noise in short term data [55, 57]. This means the data can not be relied on for precision, however, long term data is said to be more reliable. As for gyroscopes, they are known to have a drift over time. This is because they calculate the rotational angle by integration and that drifts in long term data [55, 57]. Therefore, these limitations need to be addressed for higher accuracy applications and it is normally done by sensor fusion algorithms. These algorithms consider the weakness of each sensor and compensate for it with other sensors. Since, accelerometer data does not drift, it can be used in combination with gyroscope data to give a better signal. There have been several approaches to these sensor fusion algorithms but most common and widely approved are the Kalman filter and Complementary filters [55, 56, 57]. Out of these 2 sensor fusion algorithms, Kalman filtering is known to be a more robust algorithm however it is complicated and hence harder to implement when compared to complementary filters [57]. The Kalman filter is more of a prediction algorithm where it uses the previous value and a predicted error to estimate the future value. Therefore, this algorithm is continuously changing, and it requires an initial value and an error prediction [57]. On the other hand, a complementary filter uses a combination of filters. For the accelerometer, small forces acting on the accelerometer creates an error in the measurement and hence a low pass filter is used for correction. As for the gyroscope, there is a drift and a high pass filter is used for correction here [57]. From a hardware point of view, complementary filters are usually used due to their easy implementation. The use of these algorithm further increases the accuracy and precision of the data retrieved therefore reducing noise. However, dependent on the applications, these might not be necessary and for our case, it might be not be a possibility due to hardware limitations.

3.4. Overview

The section above covers important factors that go into the design of head gear in sports. There is a need to understand these factors completely before any innovation can begin on the headgear in taekwondo. The human factors that are considered for the design of a helmet are clear as well as what to consider when designing of an eHelmet. As it is mentioned in the first chapter of this thesis, *Introduction*, there are limitations to currently WT approved head gear and the point scoring systems. The purpose of this chapter is to focus on the headgear and address these limitations. Therefore, an electronic helmet is designed and tested in this chapter while still passing the basic safety requirements demonstrated by normal headgear. This means, the eHelmet not only passes current standards, but also improves on it dramatically. To reiterate the limitations and areas for improvements, they are: 1) hit validation between legal and illegal hits does not exist and therefore any kick to the face, punches to the chest protector and technical points (turning kicks) are still rewarded by judges alone, 2) a strong hit is still rewarded the same points as a weak but scoring hit, and 3) the cost of the point scoring systems is significant. Recently, we have seen a great shift in all sports towards electronic scoring systems. This is true for taekwondo as point scoring systems were introduces as recently as 2012 and the first head gear was used as recently as 2016. Therefore it is, now more than ever, important to design and implement better headgear that can detect impacts without the need of judges and classify legal vs illegal hits to the head. Further, the gear should be able to not only detect a hit but also determine if a certain hit with more force than before. An extension of this impact level detection can lead to concussion detection during the game. If an impact is over a certain level, the system can identify and warn the athlete that there is a chance of concussion based on the previous hit.

3.5. Robustness Testing for IMU: Linear Response Testing

Before any work can be done, a sensor for recording signals had to be finalized. Therefore, work began with researching what signals can be retrieved from a person as they get hit. Several signals were considered, and they are mentioned in the Background section in General Hardware. Based on that reasoning that IMUs are commonly used in motion tracking, what we are trying to capture is exactly that, the motion of the head as it is hit. Therefore, IMU's were a natural choice when compared to EMGs, PPG and sound signals studied in the Background section. Once this was decided, the first design was proposed and it included of an IMU (MPU9250), an Arduino UNO and a Bluetooth module (HC-05). These were chosen due to the ease-of-use and support for Arduino as there are significant online resources available for using MPU9250 with Arduino for different applications. Figure 13 shows the proposed design and the actual created design. The one created consisted of a power bank to supply power to the Arduino and from there to the rest of the circuit. The purpose of this design was to determine the best sensor placement that can capture usable signals that are relatively free of noise. Therefore, it was important to have a portable design that can be placed on different locations for testing. This design provided a solid initial approach for the electronics that were later used in the eHelmet. This design was eventually discarded, and the explanation is provided in the next paragraph.

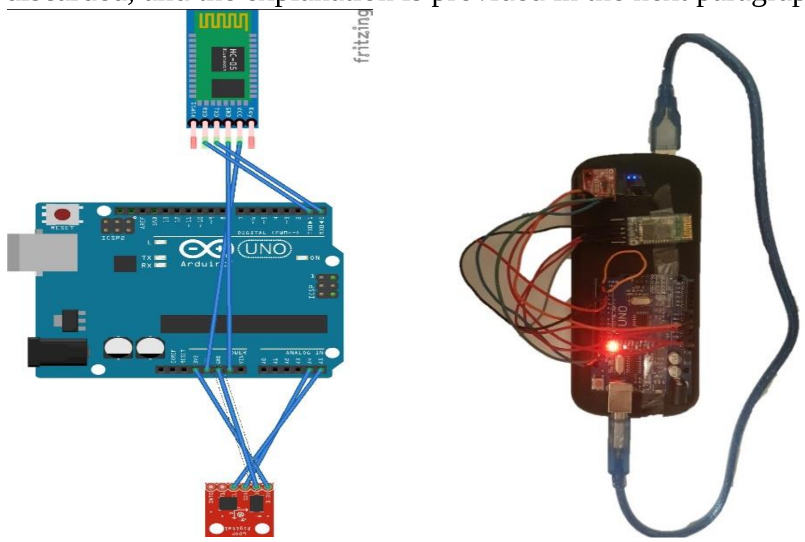

Figure 13. This figure (left) shows the Fritzing connections and the actual design (right) using a power bank to supply power to the Arduino, Bluetooth module and MPU9250

Industry projects often times are confined by external economic costs and external limitations that are not necessarily focused around research as is in the academic world. Therefore, those external limitations had to also be addressed in our design. As mentioned in section 3.2, it is cost effective to choose a device or sensor that is already proven in the industry, rather than using something that is completely new and requires complete evaluation and testing from scratch. The partnership with 20/20 Armor lead to significant improvements and insights. The most evident was access to industry leading and tested hardware that is currently being used in taekwondo clubs in Ontario with over 1200 students. This in itself is a substantial benefit and step forward for our research as we now have a system that is proven to provide accurate signals capable of classification. To elaborate on this, the initial design consisted of an IMU durable till 10,000g however the Arduino Uno, HC-05 and battery source were not tested with the forces faced in a combative environment. This process requires years of testing and development and also reduces unseen complications in the future as we now know the hardware is capable.

Linear response of a sensor is mandatory for any analysis to be done on the signals received from that sensor. Traditionally, this is done by some sort of quantified impact testing for newly designed sensors. Several linearity tests are performed by the manufacturers to determine the overall mechanical characteristics of these sensors such as IMUs. For example, the IMU used in 20/20 Armor board is LSM6DS3 that has a linear acceleration measurement range from ±4 – ±16g with a linear acceleration sensitivity of ±0.06 – ±0.488 mg/LSB (milli-G's per Least Significant Bit). For the gyroscope the angular rate sensitivity ranges from 4.375 – 70 mdps/LSB for the angular rate range of ±125– ±2000 dps. The smaller this sensitivity is the better the linear or ideal relationship is between acceleration (mechanical energy) and output (electrical signal). This sensitivity value changes very little with temperature and time and hence the linearity for this IMU is acceptable. In general, IMUs are known to have a linear response that is accepted by the industry and we see them in all sorts of applications from the technology industry (phones, tablets etc.) to the automobile industry. However, to be used in research, this linear response needs to be tested and proved. Even more, the harsh situations faced in taekwondo, required this testing to be performed in order to determine if this is the response was linear with significantly higher impacts using a drop test. A certain weight will be dropped at different heights to determine if a larger impact generates a larger electrical signal. Drop tests were chosen to isolate only the impact and not any movement from the BOB (dummy). This is because if BOB was used for impact testing, the signal captured will be the initial impact as well as the reaction of the person wearing the vest and getting hit. Therefore, it is important to have a rigid body (ground) behind the vest so it does not move, and we can capture the deviations between different impact levels. This drop test study will provide us answers to 2 questions: 1) can an accelerometer and gyroscope be used to detect impact level alone, and 2) is this relationship linear? Since the acceleration and rotational rate of a drop test is significantly lower if the vest does not move and react, this test will provide a good start for the rest of the classification algorithms. Since no similar work has been done before and no data sets available, this drop test investigation was necessary to determine linear response characteristics of the IMU in the 20/20 Armor board. Finally, data retrieved in this study was used in finalizing sampling rates for accelerometer and gyroscope as well as determining the proper linear measurement range for the IMU.

3.5.1. Materials and Methods

The drop test required us to create an in-house apparatus (called SARput apparatus) that was precise in dropping a mass from a desired height. The apparatus is required to be stable and allow repeated drops of a mass. The mass was chosen to be a 4kg shot put (also referred to as SARput) as it is a sphere allowing the same surface area to impact the vest every time. The mass chosen was similar to the study performed by Taiska and an explanation is mentioned in [58]. Off the shelf items were used and modified to create the drop test apparatus such as: Rockwell RK9033, 316 Stainless steel quick release shackle, Champro cast iron shot put and a 2 x 4x 8 stud. The Rockwell stand is designed as a work support and therefore provided excellent support and stability required for this drop test. The 90 degrees tilt and levelling indicator allowed for ideal height selection ranging from 43 inches to 83 inches. To prove precision, the 4kg SARput was dropped 15 times on an indicated dot seen in Figure 14 on the right. The SARput repeatedly landed on the exact same location indenting the foam as also seen in Figure 14. Further, the SARput was covered with a thin 100% cotton cloth to allow it to be hooked to the quick release. This drop test apparatus (SARput apparatus) allowed us to drop a weight from different heights with excellent accuracy.

The setting of the accelerometer and gyroscope in the IMU were kept to their default settings set by 20/20 Armor team and the total specifications are seen in the table 4. The default settings for the accelerometer are ±4g and for the gyroscope ±250dps that is the lowest possible setting. The sampling rate (output data rate) was set to 1.66kHz which was also the default setting. At these setting the IMU has the lowest sensitivity allowing for the smallest possible error of 0.06mg/LSB and 4.375 mdps/LSB (Table 4 below). Once an impact is detected on the IMU passing a certain threshold, the microcontroller saves all the data inside the fifo buffer (explained in detail in the next section). This means 682 samples for each of the 3 accelerometer axes and 3 gyroscope axes. Figure 15 shows the IMU that contains the accelerometer and gyroscope. Further, it demonstrates the direction the acceleration is captured, the direction the rotational rate is captured and the pin connections of the IMU. Moving on the methods, the pseudo-code explains the steps taken from receiving data in the computer to the final analysis performed in the next few steps:

1) Drop-test data was collected and saved as a .json file
2) Data was then sorted and analyzed on a computer
   a. All 682 samples were considered, and data was truncated to 400-682*n* where *n* is the samples
3) The energies were calculated for different heights
4) The total acceleration was calculated using the formula: $Atotal = \sqrt{ax^2 + ay^2 + az^2}$ where *ax, ay* and *az* represent the individual axis
5) The total rotational rate was calculated using the formula: $Gtotal = \sqrt{gx^2 + gy^2 + gz^2}$ where *gx, gy* and *gz* represent the individual axis
6) The mean for each signal was calculated for the total acceleration and rotational rate using the formula: $\mu = \frac{1}{N}\sum_{i=1}^{N} Ai$ where *A* is a vector made of *N* observations

7) The grand-mean was also calculated by taking the mean of the means of individual signals: $\mu 1 = \frac{1}{N} \sum_{i=1}^{N} \mu i$
8) Linear model (degree 1) was applied to the grand-means using the formula: $f(x)=mx+b$ where m is the slope and b is the intercept

Figure 14. This figure shows the SARput - drop-test apparatus (left) and the drop location (right). The vest is tied into place using anchor points.

Table 4. Specifications for LSM6DS3

Acceleration range (g)	±2 – ±16
Angular rate range (dps)	±125 – ±2000
Output data rate (kHz)	12.5 – 6.66
Power consumption	425 µA – 1.25 mA
Buffer size (kbyte)	8
Temperature range (°C)	-40 – +85
Dimensions (mm)	2.5 x 3 x 0.83
Linear Acceleration Sensitivity	±0.06 – ±0.488 mg/LSB
Linear Angular rate Sensitivity	4.375 – 70 mdps/LSB

[1] **References**. [58] [59]

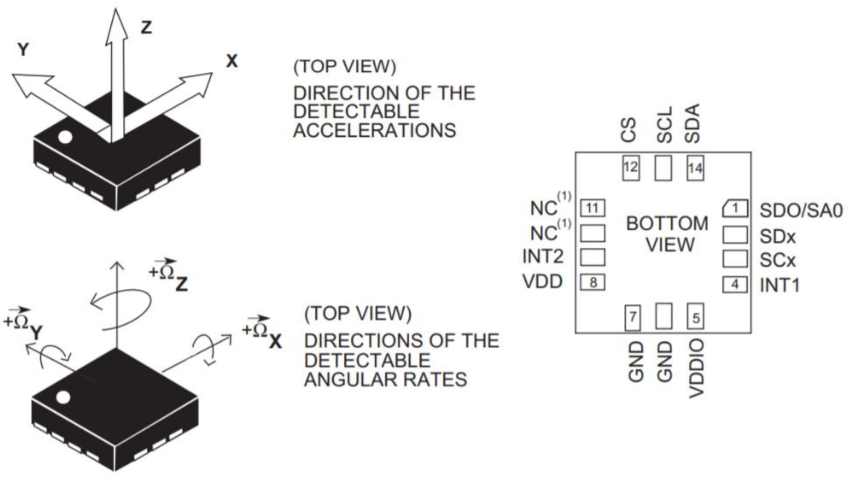

Figure 15. This figure shows the IMU (LSM6DS3) as well as the pin connections. [1] **References**. [58, 59]

3.5.2. Drop-Test Data Set

For the drop test 4 different heights were chosen (0.67m, 1.13m, 1.5m, 1.75m) resulting in 4 potential energy levels (29.5 J, 44.35J, 59.3J, 68.7J). This was calculated by using the formula *PE=mgh* where m is the mass, g is the acceleration due to gravity and h is the height in meters. The 4 kg SARput was dropped from these 4 chosen heights in a localized location on the vest. The vest was divided in 4 sections: 1 is top, 2 is bottom, 3 is left and 4 is right. The location where the SARput was dropped was kept to only location 1 which is the top. This is because since the vest is placed on the ground, there will not be significant acceleration forces as the movement of the vest is limited. Therefore, to capture those small signal deviations or vibrations between the different heights, it was necessary to drop the mass as close to the IMU. As a result, only the top 1 location was used and the shot put was dropped inside this location. Video 1 in the appendix demonstrates how the mass was dropped on the vest. In total 25 signals were captured each at the first 3 different heights and 26 signals at the last height of 1.75m. This resulted in a total of 101 drop test signals where we captured 3-axis accelerometer data and 3-axis gyroscope data for linear response testing.

3.5.3. Results

Considering the purpose of this study, it was evident that the signals retrieved needed to be quantified to determine if there is a linear relationship. The pseudo-code above shows the formulas used, and they were mean and grand-mean of the individual signals. Therefore, the mean for each individual observation was calculated and is shown in Figure 16 for the accelerometer signals and for the gyroscope signals are seen in Figure 17. A linear trend was visualized and for better analysis the grand means were calculated for both acceleration and rotational rate. Grand mean for accelerometer was 1.12, 1.33, 1.88, 1.65g's and for the gyroscope 54.35, 65.96, 105.05, 113.81 dps for drop energies 29.5,44.5,59.3,69.8J, respectively. Once the grand means were calculated for the total 101 drop-test signals there was a visible increase in amplitude for both accelerometer and gyroscope. To better visualize this, a linear model of degree 1 was estimated using the equation: $f(x) = mx + b$ where *m is 0.2947 and b is 1.499* for the acceleration data. This curve is also shown in the Figure 18 below in red. Further, the same approach was taken for the rotational data and the linear model that was estimated using the equation: $f(x) = mx+b$ where *m is 28.33 and b is 84.8* seen in Figure 19 and both these models had 95% confidence bounds. In addition to these results, the Figures 20-21 show the saturation points for the accelerometer and the gyroscope. The circled areas demonstrate the saturation point in this example signal number 2 from the drop height of 1.75m. It is clearly visible that the signal is being clipped at the maximum measuring setting set (4g and 250dps) and data is being lost.

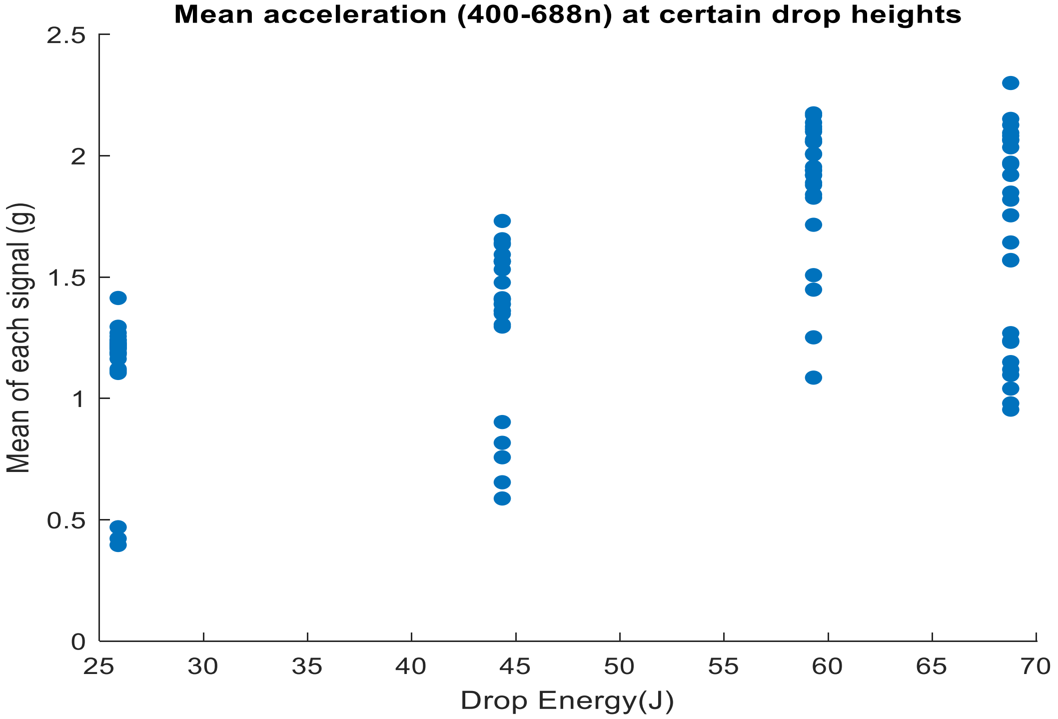

Figure 16. This figure shows the mean acceleration at four different energies.

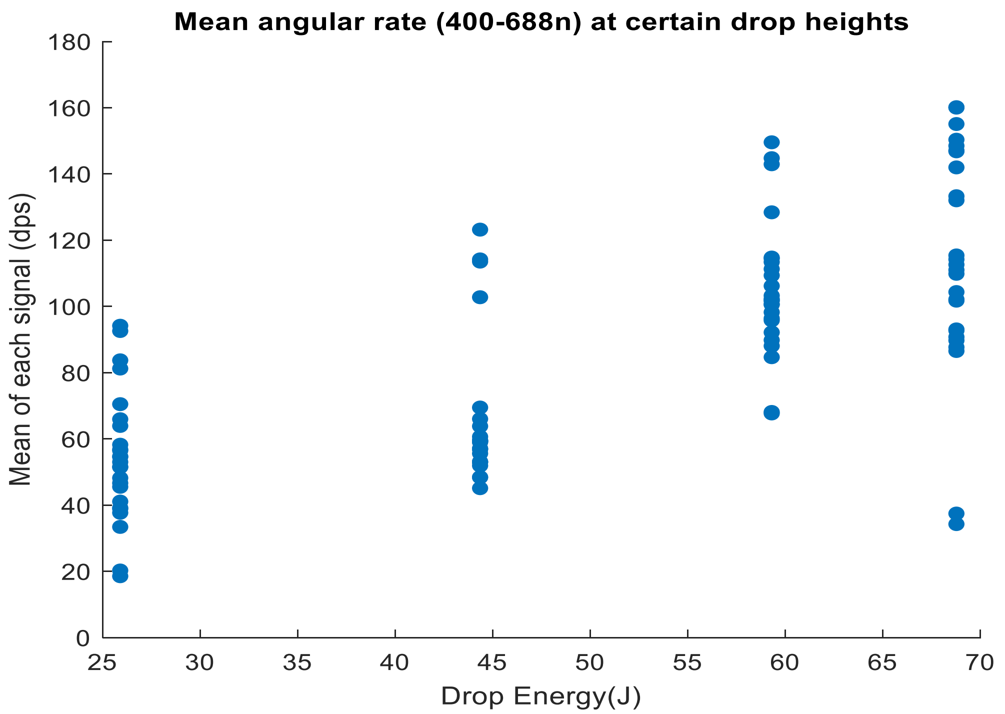

Figure 17. This figure shows the mean rotational rate at four different energies

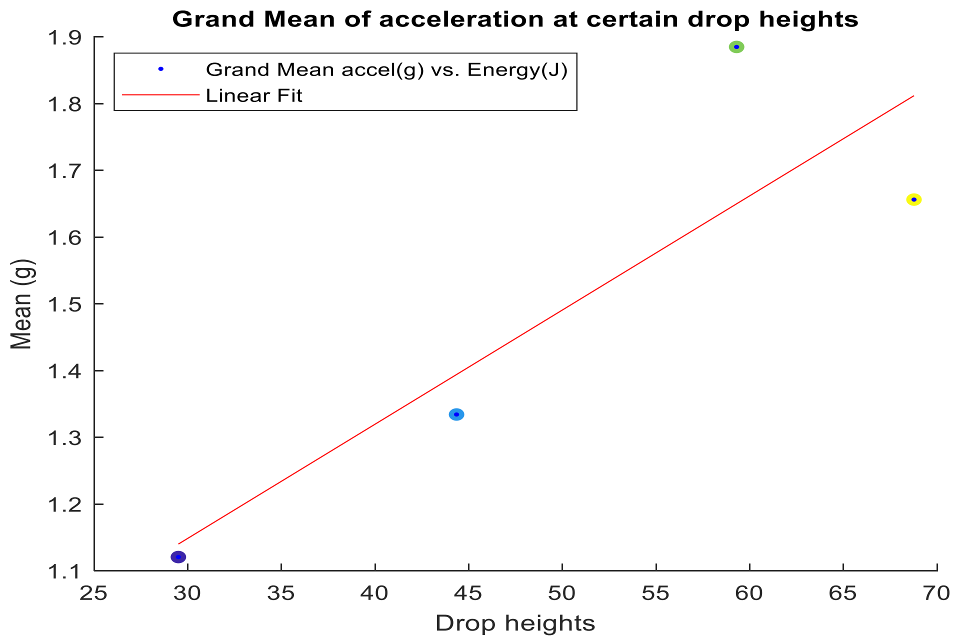

Figure 18. This figure shows the grand-mean and the linear curve for acceleration

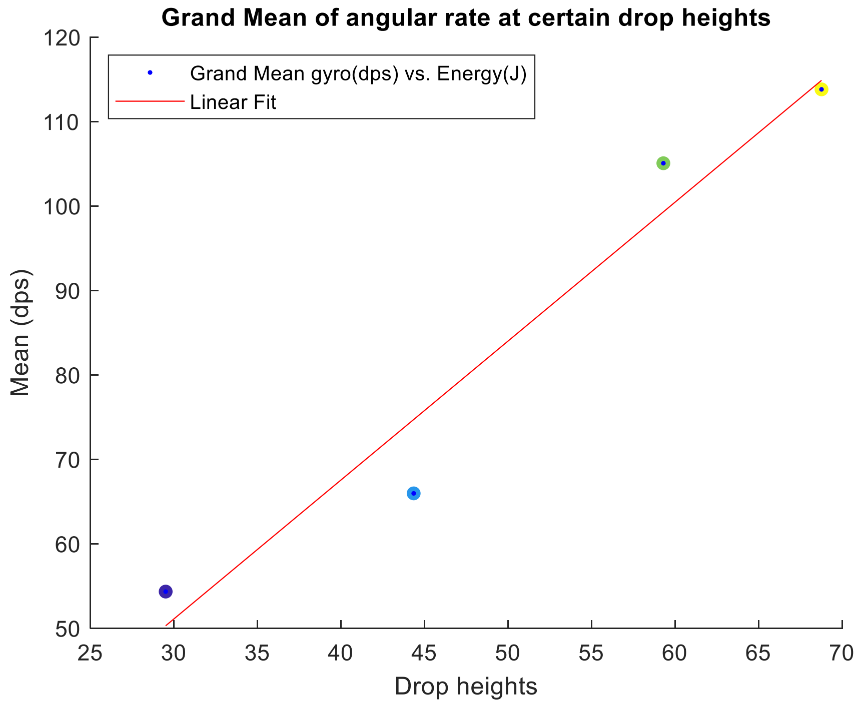

Figure 19. This figure shows the grand-mean and linear curve for rotational rate

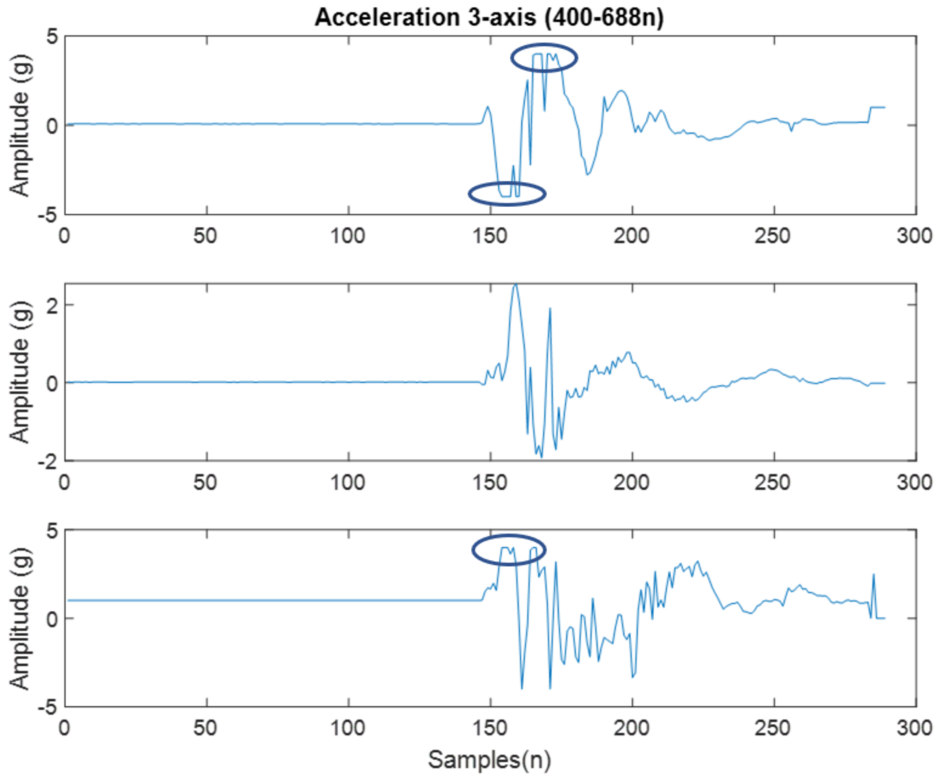

Figure 20. This figure shows the 3-axis and saturation points for acceleration at 1.75m

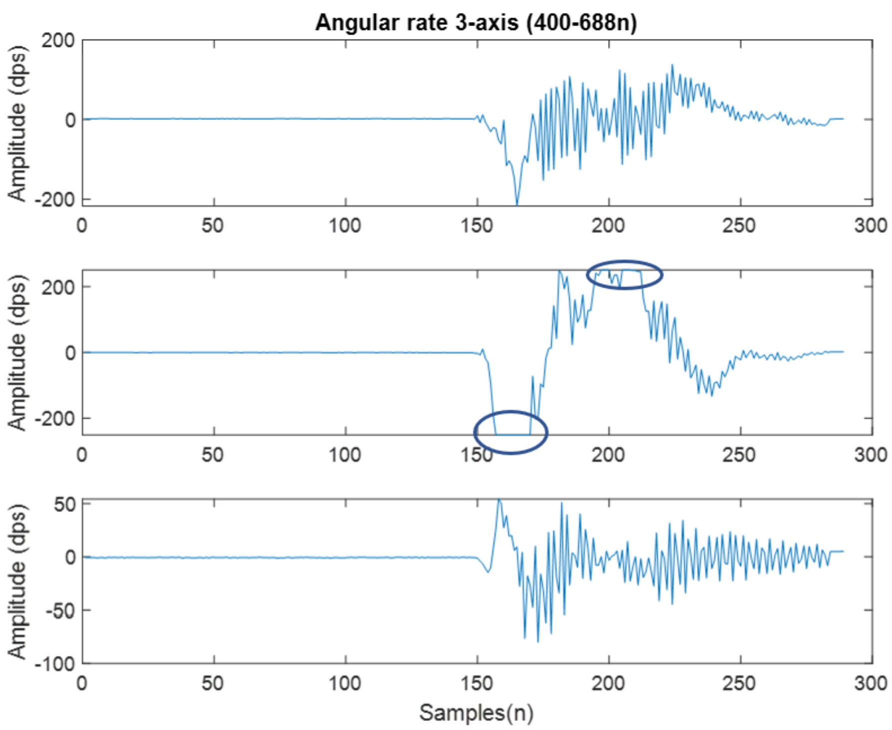

Figure 21. This figure shows the 3-axis and saturation points for rotational rate from 1.75m

3.5.4. Discussion and Conclusion

The purpose of this initial study was to determine two things: 1) can an accelerometer and gyroscope be used to detect impact level alone, and 2) is this relationship linear? We were able to see both that the accelerometer and gyroscope can detect differences in a linear fashion. Figures 16 and 17 show the mean for accelerometer and gyroscope, respectively. There is some variation in the values, however this is expected in an experimental setting which is why the grand means were found. There were a few key things that were observed: 1) a saturation point was seen in the accelerometer after dropping from a height of 1.51m and above, 2) the gyroscope had a better linear response in our study when compared to the accelerometer and 3) finally there is definitely a linear relationship seen as the drop energy increases. Starting with the first finding, a saturation point was seen when the 4kg shot put was dropped from 1.75m. The signals here for the accelerometer especially were being clipped thus being out of measuring capability. The same was observed in the gyroscope however to a much less extent. This saturation can be seen in the Figures 20-21 by the circled areas and this has an effect on the overall mean values of each of the 101 individual signals as well as the grand-mean values. This again was seen since the lower drop heights of 1.12m and 1.33m were basically linear for both the accelerometer and gyroscope. Furthermore, the second question, is this relationship linear, is also answered in this study. Considering the lower drop heights, the signals have a linear gain with the increased impact level. This proves that there definitely is a linear relationship however, due to the signals saturating for the accelerometer and gyroscope, we lost some data in the higher drop heights. The results in this study proved to be vital as they provided us with insights on the data collection process as well as demonstrating the effects of data saturations. On the other hand, this saturation can even be used as a feature in machine learning if a relationship can be determined between data saturation and impact level. Therefore, it can also be considered as a point of interest in the following work.

3.6. Preliminary study 1: Sensor Placement

Before work can begin with on classification and addressing the 3 concerns mentioned above, the next task worth investigating is sensor placement on the eHelmet (electronic helmet). As mentioned in the Background: Review of RUPunch section, the location of the electronics and therefore the IMU is a key element that needs to be considered. Not only is this important for durability purposes, but it significantly changes the signal captured by the IMU. Generally, there are two possibilities for the placement of electronics, one can be on the what is hitting the opponents (hand) and one can be what is getting hit (head). Therefore, the signals captured will be different with a slightly different focus. For the first, the initial signal before the impact will be a major component in classification and for the latter, the signal after impact will be a major component used in classification. This is because for the electronics placed on the hand, the technique used for a specific punch will be concentrated on before the impact and will vary depending on what punch was performed. As for the latter, if the electronics are placed on the head, the signal after the impact has taken place is vital as the reaction of the head or body will be captured in that location. Moving on, there were complexities and limitations placed on the design due to the nature of taekwondo as being a combative sport. Firstly, the chosen location needs to be out of the impact zone as hits directly to the electronics will be destructive. Secondly, the design needs to be cost effective as multiple sensors can be costly.

With this in mind, the purpose of this preliminary study is to qualitatively and quantitatively determine the ideal location of sensor placement when compared to on the hands/feet or on the head. With an understanding of why this preliminary study is relevant, we move on to the materials and methods used to perform this study. This section is especially relevant since a new data logging and analyzing approach was taken and created from scratch. This required an in-depth understanding of all the components used and therefore the next sections cover all details on the hardware and software.

3.6.1. Materials

There are two distinct locations being tested in this preliminary study and they are the 1) IMU placed on the glove and 2) IMU placed on the head using an Adidas taekwondo helmet. For both these studies the same 20/20 Armor board was used and securely fastened to both the helmet and the glove. Finally, Matlab was used for visualization and analysis. The 20/20 Armor board is designed specifically for this specific application and hence includes all the materials we need for our research. Therefore, we will be beginning this section with an overview of the all the components used in this study and the settings they were set to give an overall picture of how they function together to provide the signals seen in the results.

The most important component for this research is the 20/20 Armor board and it consists: of a microcontroller (STM32L475RGT6), always on 3D accelerometer and 3D gyroscope (LSM6DS3), Radio Frequency Transceiver (SPSGRF-915) and four 1.2v batteries to power it. The hardware schematics of these components are shown in Figure 22 and 23 below as well as their connections to the microcontroller.

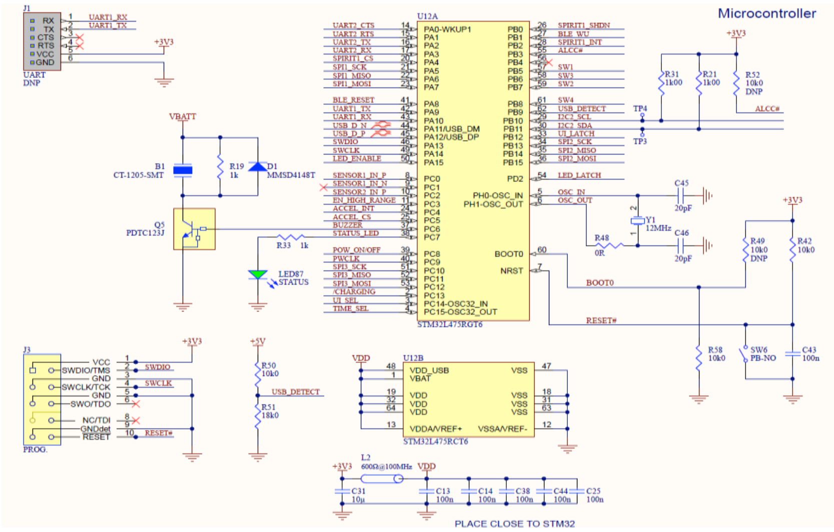

Figure 22. This figure shows the microcontroller and its hardware connections

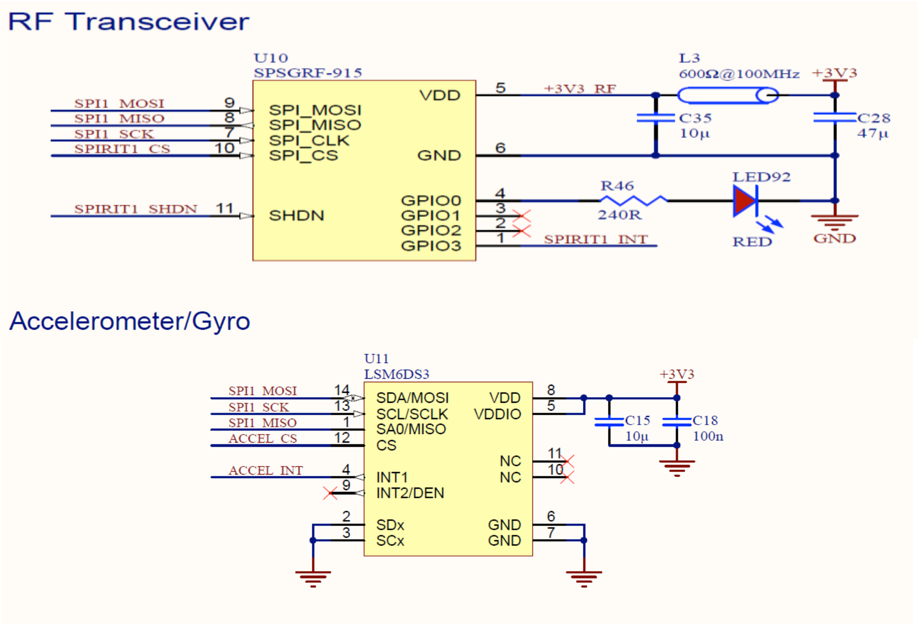

Figure 23. This figure shows the connections for the accelerometer and RF transceiver to the microcontroller

The materials used for the hitting component of this research paper was Century Fitness BOB Body Opponent Bag – Body and Base – XL ($700) [60] . BOB was used for the entirety of this research is it is made for this martial arts and combative sports. It has a life-like upper torso that is made of high-strength plastisol and filled with urethane foam. This replicates the human body and therefore serves as a great striking surface for body and head shots in training. Even more, this item is normally used in taekwondo centers for training and the 20/20 Armor team has been using it for research with validated results. With this, a helmet was created and the 20/20 Armor board was securely attached to it. Finally, an Iron Body Fitness glove was used and then the 20/20 Armor board was attached to it. Figure 24 below shows how the board was attached to the glove and the helmet.

Figure 24. This figure shows the eHelmet with 20/20 board and IBF glove with 20/20 Board

3.6.2. Methods

With the materials in mind, we move on to the methods used for programming the IMU as well as the methods for the analysis. We will begin with a data flow diagram that covers all the steps taken for the data to be retrieved in the computer. Next, the pseudo-code will cover the steps taken after the data was received in the computer. From there, we will provide explanations on how and why certain settings were chosen and what exactly was changed and adjusted from the original 20/20 Armor configurations.

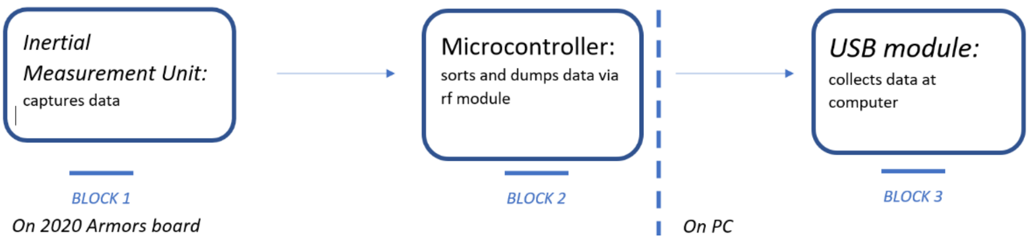

Figure 25. This figure shows the data flow diagram from IMU to the computer

Beginning with the data flow diagram, it is shown in Figure 25 and we first look into Block one of this diagram. In block 1 data is captured by the IMU and was subsequently the setting were adjusted from its original. The specifications and limits of the IMU are listed in table 4 in the previous section and were initially set to 1.66 kHz sampling rate (or output data rate) at 4g and 250dps by 20/20's team. The engineering team at 20/20 Armor, deemed these settings as sufficient as they provided clean signals that were usable in testing. However, our initial data capture and testing showed these can be further improved and were consequently changed to 8g and 500dps (double). The output data rate was reduced significantly to 208 Hz from 1.66 kHz after testing determined no data was lost as the signal was being significantly oversampled. In fact, the 20/20 team were certain 1.66 kHz was too high for our application but needed further testing to prove what was optimal and we found 208 Hz provided a clean and usable data. Next, we move on to block 2 which is the microcontroller, the microcontroller reads data from the IMU and sends it using the rf module. Block 3 is where data is received by the computer. Data is transferred from the 20/20 Armor board using a low power radio frequency transceiver and into a USB dongle (SP1ML915) that is connected to the computer. This module functions in sub gigahertz. The microcontroller was programed to "dump" all the data it receives from the IMU using this radio frequency module to the USB dongle. What this means is, as soon as the 20/20 board is turned on and the IMU is calibrated, it starts to record and dump all the data non-stop to the USB dongle.

Next, we look at the pseudo-code that covers all the steps taken after data is received in the computer in the following steps:

1) Data was collected and saved as a .jasn file
2) Data was then sorted and analyzed on a computer
    a. All 682 samples of the accelerometer and gyroscope were used
3) The total acceleration was calculated using the formula: $Atotal = \sqrt{ax^2 + ay^2 + az^2}$ where *ax, ay* and *az* represent the individual axis
4) The total rotational rate was calculated using the formula: $Gtotal = \sqrt{gx^2 + gy^2 + gz^2}$ where *gx, gy* and *gz* represent the individual axis
5) The variance of the total signals were calculated using the formula: $v = \frac{1}{N-1} \sum_{i=1}^{N} |Ai - \mu|$ where μ is the mean, *A* is the vector of *N* observations
6) The Hjorth Parameter was then calculated for total acceleration and total rotational rate including Activity, Mobility and Complexity using the formulas:
    i. *Activity*: *var(y(t))* where var is the variance using Eq 1 above

ii. *Mobility*: $\sqrt{\frac{var(\frac{dy(t)}{dt})}{var(y(t))}}$

iii. *Complexity*: $\frac{Mobility\ (\frac{dy(t)}{dt})}{Mobility\ (y(t))}$

Having understood the pseudo-code, we will move on to the in-depth details of the IMU and the explanations of why certain adjustments were made. Starting with the IMU, there are several steps taken before the raw data is received by Matlab. The accelerometer sampling chain is a cascade of 4 blocks shown in Figure 26 (a) and a similar cascade for the gyroscope as shown in Figure 26 (b) below. Basically, what these figures show is the steps taken for the analog raw data to be digitalized and filtered. The accelerometer data goes through an analog anti-aliasing low pass filter that is only active in high-performance mode. For our purpose, the accelerometer was configured in normal mode and hence this block is deactivated in normal mode. The next block is the ADC, then a digital signal is passed through a digital low-pass filter whose cut off frequency is determined by the output data rate of the accelerometer and was set to 742 Hz and a total bandwidth of 740 Hz. Moving on to the gyroscope, it was also set to normal mode and the analog signal was passed through an analog anit-ailiasing low-pass filter, then to the ADC and then a digital low pass filter whose cutoff frequency was 60.2 Hz. The digital highpass filter is deactivated in normal mode and was therefore not configured. The reason why normal mode was selected over high-performance mode was the current consumption by both the accelerometer and gyroscope. For normal mode it was 900 μA vs 1.25 mA when in high-performance mode. Finally, the last item that was considered were the samples to be discarded due to the turn on-time. For the gyroscope it was 2 samples and none for the accelerometer. Once the IMU is turned on, it automatically downloads the calibration coefficients from the internal registers, and this takes around 20 milliseconds. The data is then stored inside a first-in first-out (FIFO) buffer. This is an 8kbyte buffer that can store up to 4096 samples of 16 bits each and can be configured in 1 of 5 possibilities, Bypass, FIFO Continuous, Continuous to FIFO and Bypass to Continuous. FIFO mode was selected as it stopped collecting data until it was read by the microcontroller to avoid overwriting data. Further, communication speed of the IMU between the microcontroller is not very important in this mode as there is no risk of overwriting the data however it should be equal to or lower than the output data rates of both the accelerometer and gyroscope [58, 59].

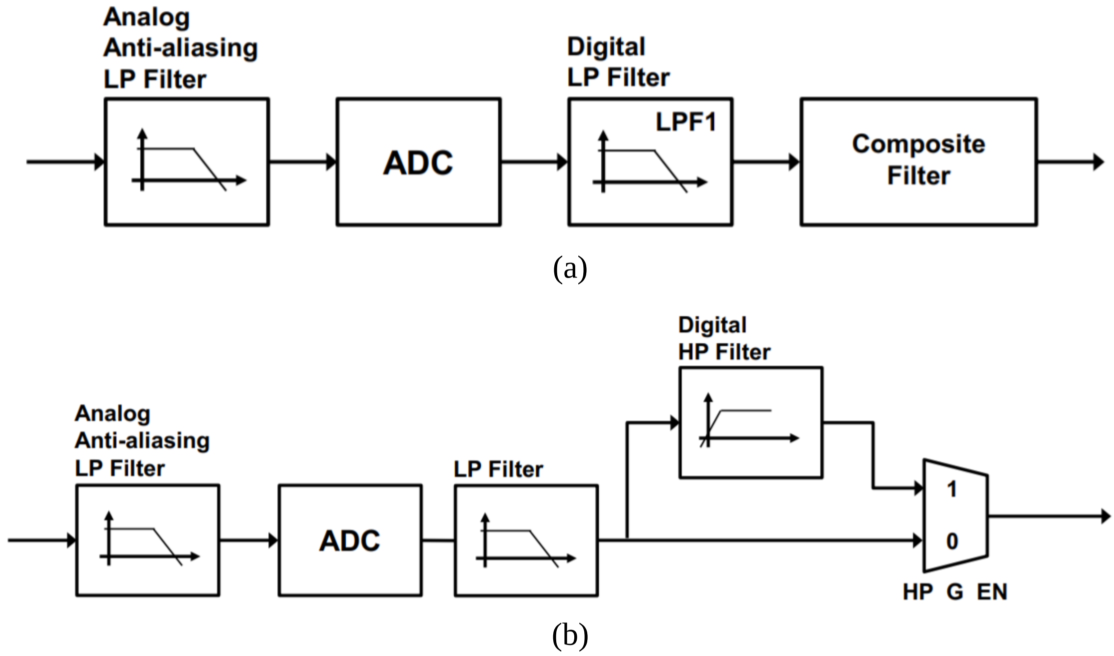

Figure 26. This figure shows accelerometer sampling (a) chain and gyroscope sampling chain (b)

The next part involves the algorithms that was designed to capture real-time data from the IMU, sort it and then analyze it. This means there were a total of 3 algorithms written and we will begin by the first one, the real-time recording algorithm. Since this was the first-time data from taekwondo headgear will be recorded, it was valuable to visualize this data in real time as it is being collected. This allowed us to make effective and efficient adjustments. During the development of this algorithm, the main task was to determine no data is lost while it is received. This was done by 1) determining the total expected delay in receiving data and 2) determining the total characters sent by the 20/20 Armor board. The total expected delay is the time taken for the buffer to fill and the data to be read from the buffer by the microcontroller. Firstly, the output data from the accelerometer and gyroscope is expressed as a two’s complement number that is 16-bit number. This data is then stored into the FIFO buffer at an equal or slower rate than the output data rates for both the accelerometer and gyroscope and hence it was chosen to be 208 Hz. What this means is, 6 samples (Gyroscope x,y,z and Accelerometer x,y,z) will be sent to the FIFO butter at one time. Therefore, the expected time for it to fill 4096 samples is 3.28 seconds. This included with the time taken to send the data via rf (explained next) the total delay has to be 5.96s. This is the only expected delay and was checked, and confirmed to be that, once the algorithm was complete and data was streaming. Moving on, the next verification step was to determine how many characters are sent by the microcontroller. Before the data is received by the USB module, it is separated and labeled. Thus for the accelerometer the x,y,z axis are labeled XXX, YYY, ZZZ, respectively. As for the gyroscope, the data is labeled AAA, BBB, CCC for the x,y,z axis, respectively. With this, there is a new line character (/r) as well as a comma that separates the hexadecimal 16-bit values shown in Figure 27. The microcontroller is set to send 80 bytes of data every 10ms however that 80 bytes buffer is not full when it sends. The microcontroller only sends a total of sixteen 16-bit hexadecimal values so a better way to calculate how many bytes are sent is by calculating the total number of packets it sends. There are a total of 682 samples for each axis (4096/6) and if we send 16 values at a time, that is a total of 43 packets of data. Now, there is a XXX and new line character /r that accounts for 1 additional packet and then the following /r adding one more to the packets making a total of 45 packets per axis. This means, the microcontroller sends 45 packets of 80 bytes making a total of 3600 bytes and 21600 bytes for all 6 axis.


```
XXX
00ad,00af,00a9,00a8,00a7,00a4,00ab,00ba,00ad,00b0,00bc,00aa,00a7,009d,00a2,00a9,00ac,00ae,00a8,00a9,00b6,00b9,00af,009b,00a2,00ad,00a5,00a4,00a6,00a7,009f,00aa,00a3,00a4,00af,00b0,00a0,00a7
,00a4,00a1,00b2,00aa,00ab,00ad,009b,00ad,00ad,00a2,00af,00a9,00a2,00af,00ad,00a6,00aa,00a0,00a3,00b5,00b1,00a4,00a6,00aa,00b5,00ac,00ac,00b1,00a4,00a3,00ad,00a3,00b3,00ad,00b1,00a0,00a1,00a
a,00b8,009f,009e,00af,00a0,00b2,00ab,00a1,00a7,00ab,00a3,00a8,00ac,00aa,00a4,00af,00a3,009f,00a4,00a6,00a5,00b4,00aa,00a3,00a7,00a2,00b3,00ab,00a3,00ae,00aa,009f,009b,00a8,00ab,00a9,00ac,00
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,ffc2,ffba,ffcb,ffcd,ffc5,ffcc,ffc4,ffc9,ffc9,ffcd,ffc6,ffc1,ffc1,ffc1,ffbc,ffc0,ffc2,ffc4,ffbb,ffc5,ffc0,ffc6,ffc8,ffc4,ffc8,ffc7,ffc3,ffc8,ffc0,ffc8,ffcc,ffc6,ffc3,ffcd,ffc7,ffbb,ffc0,ffc
7,ffc4,ffcd,ffbe,ffc6,ffc3,ffc0,ffc4,ffc6,ffbe,ffc2,ffce,ffcb,ffd0,ffcc,ffc0,ffbd,ffbf,ffc7,ffc8,ffc2,ffbd,ffc4,ffbf,ffba,ffba,ffbd,ffbf,ffc0,ffcb,ffc1,ffbc,ffca,ffca,ffc7,ffc3,ffc5,ffc0,ff
ba,ffbf,ffc1,ffbb,ffcb,ffc8,ffcc,ffca,ffcd,ffca,ffc8,ffc9,ffbd,ffbd,ffb7,ffbe,ffbf,ffb6,ffc4,ffb8,ffc5,ffcd,ffc1,ffcd,ffd2,ffc7,ffc1,ffbf,ffca,ffd2,ffcd,ffba,ffc7,ffc1,ffb7,ffc3,ffbe,ffc1,f
ZZZ
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,007e,007a,007b,0082,0087,008c,0082,0089,0075,0083,0085,007b,0078,0081,007d,0085,007f,0088,007f,007f,007e,0081,007f,0086,0080,0083,0080,007c,007d,007a,0083,0087,0082,0085,0080,0077,007b,008
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8e,008d,0076,0079,007a,007a,0086,0089,0090,007d,0084,0073,0082,007f,0086,0085,0084,0083,0086,008b,008c,0088,008d,008f,0082,0080,0078,007e,0090,0089,008e,0086,0089,008b,0080,0083,0085,007b,0
BBB
ff26,ff22,ff1c,ff1c,ff1a,ff22,ff1f,ff2f,ff24,ff15,ff2a,ff2d,ff1d,ff25,ff27,ff22,ff22,ff19,ff22,ff27,ff22,ff21,ff1e,ff1e,ff26,ff1f,ff18,ff20,ff21,ff1d,ff20,ff20,ff23,ff1e,ff2e,ff23,ff1a,ff21
,ff2b,ff27,ff25,ff22,ff1f,ff22,ff23,ff23,ff28,ff16,ff2b,ff2d,ff19,ff23,ff1a,ff1c,ff19,ff1f,ff28,ff29,ff28,ff25,ff20,ff22,ff2b,ff2a,ff20,ff2b,ff2a,ff25,ff24,ff29,ff1e,ff25,ff27,ff26,ff20,ff1
6,ff23,ff25,ff25,ff29,ff27,ff20,ff27,ff2e,ff24,ff24,ff27,ff28,ff22,ff20,ff29,ff2c,ff1b,ff24,ff22,ff2a,ff1d,ff22,ff1c,ff23,ff24,ff1e,ff18,ff2b,ff2c,ff24,ff25,ff25,ff25,ff23,ff2c,ff20,ff29,ff
29,ff1c,ff25,ff1c,ff28,ff27,ff24,ff1b,ff21,ff1f,ff22,ff24,ff21,ff22,ff2a,ff25,ff1f,ff27,ff29,ff26,ff29,ff2a,ff26,ff1f,ff1b,ff19,ff28,ff2a,ff1c,ff23,ff1e,ff20,ff20,ff28,ff2b,ff27,ff1a,ff25,f
CCC
feff,fef2,fef9,fef7,fefe,fef7,fefd,fef9,feff,fef7,fefb,fefc,fefe,fef8,fefc,feff,ff00,fef9,ff03,fef8,fef7,fefc,fef8,feff,fef9,fef9,fefa,fef9,fef7,fef8,fefa,ff01,feff,fefa,fef9,fefc,fef9,fef4
,fef8,fef3,fefe,fef8,fef6,fef8,fefd,ff03,fef8,fef4,fef8,fefe,ff03,fef9,fefd,fef5,feef,fefa,fef8,fef6,fefc,fef6,fef5,fefa,ff03,fef5,fef7,fef8,fefb,fefe,fef9,ff02,ff02,fef8,fefb,fefc,feff,fef
0,fef8,fefb,fef8,fefa,fefb,fef8,fef8,ff03,fefe,fef9,fef9,fefb,fef9,fefa,fefd,fefc,ff00,fefd,fefd,fef9,ff00,ff03,fefd,fefd,ff00,fef9,fefc,fefe,feff,fef8,fef4,fef7,fefd,fefd,fefc,fefc,fefc,ff
fd,fefa,ff07,fef4,fefd,ff05,fefd,fef6,fef8,feff,fefb,fefc,fefe,fefc,ff04,fefe,fefa,fefb,ff03,fefe,fefb,ff01,ff00,ff06,feff,fef8,fef5,fefe,fefd,ff02,ff00,fef5,ff01,ff00,fefa,fefc,fefa,fefc,f
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Figure 27. This figure shows the raw data using tera term for visualization.

This value of 21600 is important for our calculations as it determines the minimum buffer size Matlab will need to read in order to get the proper data. The serial function works by creating a software input buffer during the read operation that stores the total number of bytes being sent. Once this was set to 21600 and the baud rate was synchronized, the data started to flow without any losses. This was proven and checked by running a read operation loop 10 times and it successfully reads every time starting from XXX. It is important to note that if there was any data that the buffer missed while the read operation was taking place, it would show up in the next read operation disarranging the order of subsequent read operations. This demonstrates no data was lost and the buffer size chosen was correct and is shown in Figure 28.

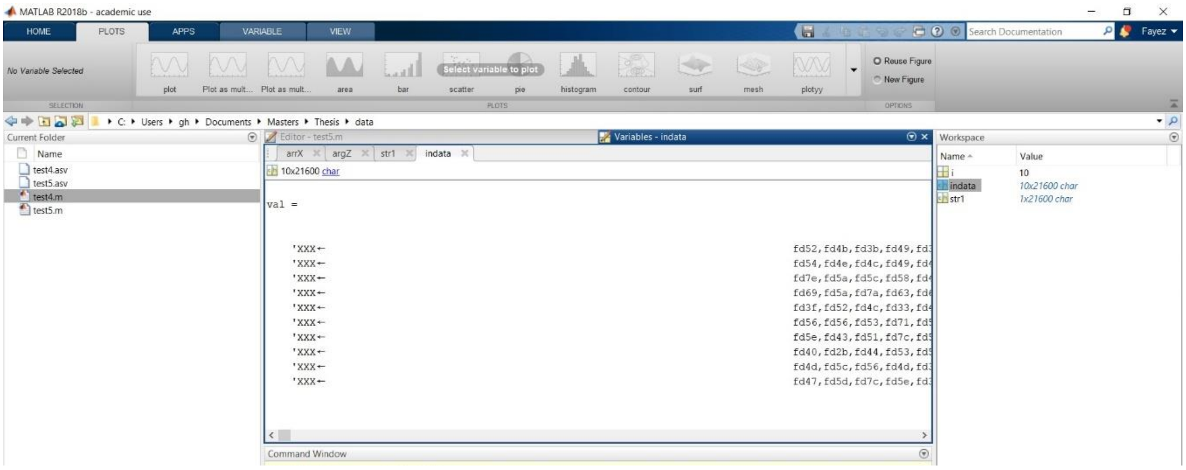

Figure 28. This figure shows the data successfully received in Matlab for 10 read cycles.

A window of 2728 samples (682 x 4) was created to visualize 4 cycles of each axis and data was then converted from hexadecimal to decimal and then 2728 samples were plot in a window. Once a hit was detected by passing a certain threshold, all 2728 samples for all 6 axes were saved in a .mat file. Not only were just the 6 axes saved, but any other computations, notes and files were also saved for future reference. Once data was collected and received, it had to be sorted and because of this a sorting algorithm was written. The total signals were saved in a folder (for example 75 signals) that were then sorted through and saved in one variable for each axis, called AX for the accelerometer, which is 75 signals x 682 samples each, and GX for gyroscope and so on. After this, finally is the analyzing algorithm which will be explained further in the results. With proof that data was being received without any data losses whatsoever, work began on collecting data and the next section will go over the data sets collected.

3.6.3. BOB Data Set 1

This section can be considered as the most important section as without data, no research or work can be performed. To our knowledge, as of September 2019, there are no public data sets available that include taekwondo specific kicks or hits. This is primarily by due to the fact that taekwondo is a specialized and specific application of accelerometers and gyroscopes with limited research. On the other hand, data sets regarding accelerometer and gyroscope for other applications were found on the UCI Machine Learning Repository. The repository includes data from a wide variety of research and studies including wearable accelerometers/gyroscopes, similar to our application. Furthermore, the repository currently has 399 data sets but nothing relating to taekwondo. Therefore, we had to create our own data sets. This data set is in created in conjunction with the 20/20 Armor team. There were two distant locations where the 20/20 board will be attached to in this preliminary study. The first is the IMU located on the IBF glove, as shown in Figure 24 right, and the second is the IMU located on the Adidas helmet, as shown in Figure 24 left. During both locations, BOB was used and the same jab punch was performed 10 times to the head. It is important to note the purpose of this study is to only determine which location results in usable signals therefore the hit performed for both sensor locations needs to be kept constant. This is why the jab was chosen and the technique used to perform the jab was kept constant as well. This allowed us to rule out any differences in the hits performed. Finally, the hitting location constant for both sensor locations. Videos of how these hits were performed can be seen in the Appendix section. In total 10 signals for the sensor placed on the glove were recorded and 11 signals for the sensor placed on the head were recorded. All settings were kept the same in both sensor locations. Video 2 in the Appendix 1 shows the technique used to punch BOB while the IMU was on the glove and Video 3 for when the IMU was placed on the helmet.

3.6.4. Results

The results are based off a few key aspects and the most important one is qualitatively using experts in the field. This is because since there are no publicly available data sets, we have no basis to compare our signals to and therefore expert opinion is the key factor for evaluation. Figure 29 shows two example signals number 3 and number 13 (x-axis only). Signal number 3 is retrieved from the IMU placed on the hand while the jab was performed. The next signal, number 13 is retrieved from the IMU placed on the head. The circled area were of interest and an explanation is provided in the discussion.

Quantitative analysis was performed in the analyzing algorithm by the Hjorth Parameters as they are good statistical properties used in the time domain and are also called normalized slope descriptors. Activity provides us with the variance (mean power) that is a measure of the squared standard deviation of the amplitude. The next statistical parameter is mobility and that is the root mean square (rms) of the slopes of the signal that is then divided by the root mean square of the amplitude. This can also be called mean frequency and finally the last parameter is complexity and that is the rms of the rate of change of slope with reference to an ideal curve shape. This is possible since we know that the complexity of an ideal sine wave must be 1 and this results in an estimate of the bandwidth of the signal [61]. With the background in mind, the results are then shown in the table below.

Table 5. Hjorth parameters

Helmet		**Glove**	
Accelerometer		**Accelerometer**	
Mean Activity	2.4456	Mean Activity	0.9354
Mobility	0.0940	Mobility	0.2565
Complexity	8.7101	Complexity	4.8710
Gyroscope		**Gyroscope**	
Mean Activity	11149	Mean Activity	1185
Mobility	0.0013	Mobility	0.0029
Complexity	18.5463	Complexity	21.5926

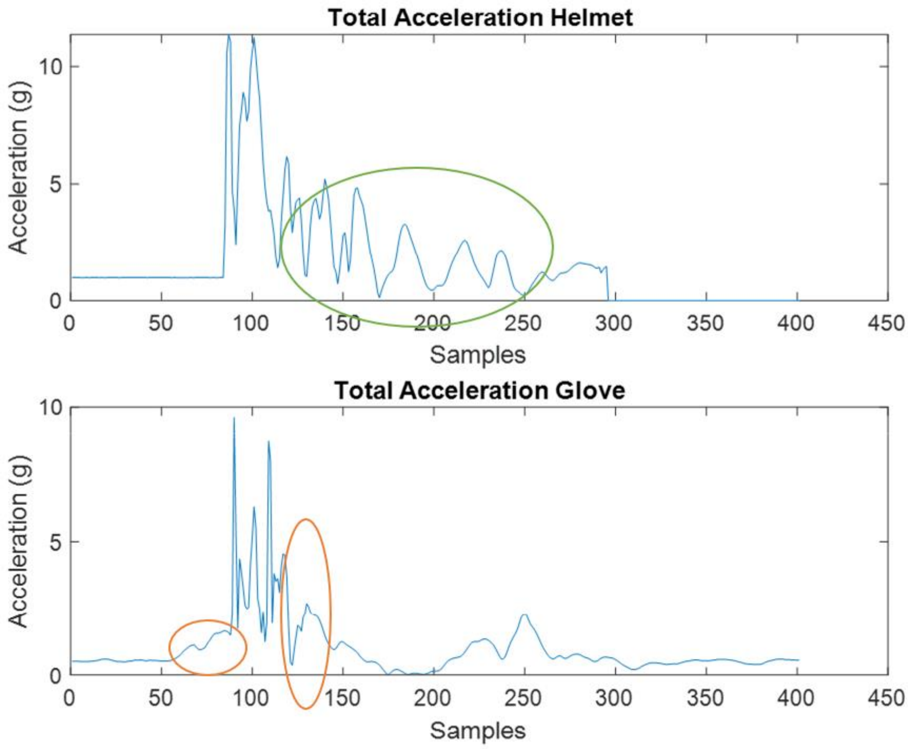

Figure 29. This figure shows the total acceleration of the helmet vs the glove. Green circled area represents the cyclic motion of BOB as it oscillates after the punch while the Orange circled areas represent the hand motion captured in the punches.

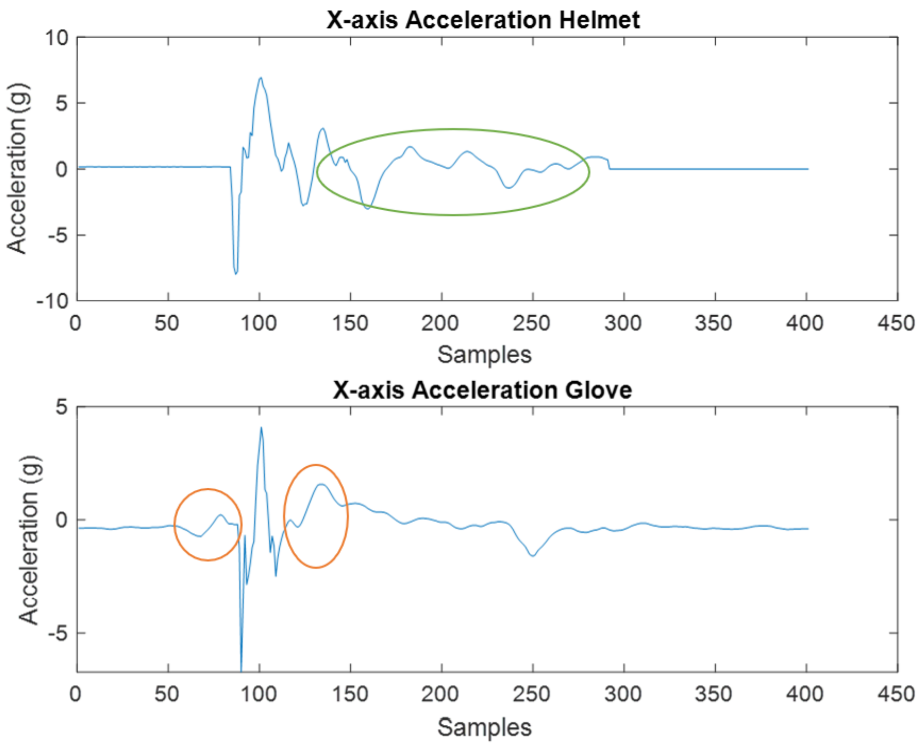

Figure 30. This figure shows the acceleration of the helmet vs the glove only for the x-axis. Green circled area represents the cyclic motion of BOB as it oscillates after the punch while the Orange circled areas represent the hand motion captured in the punches.

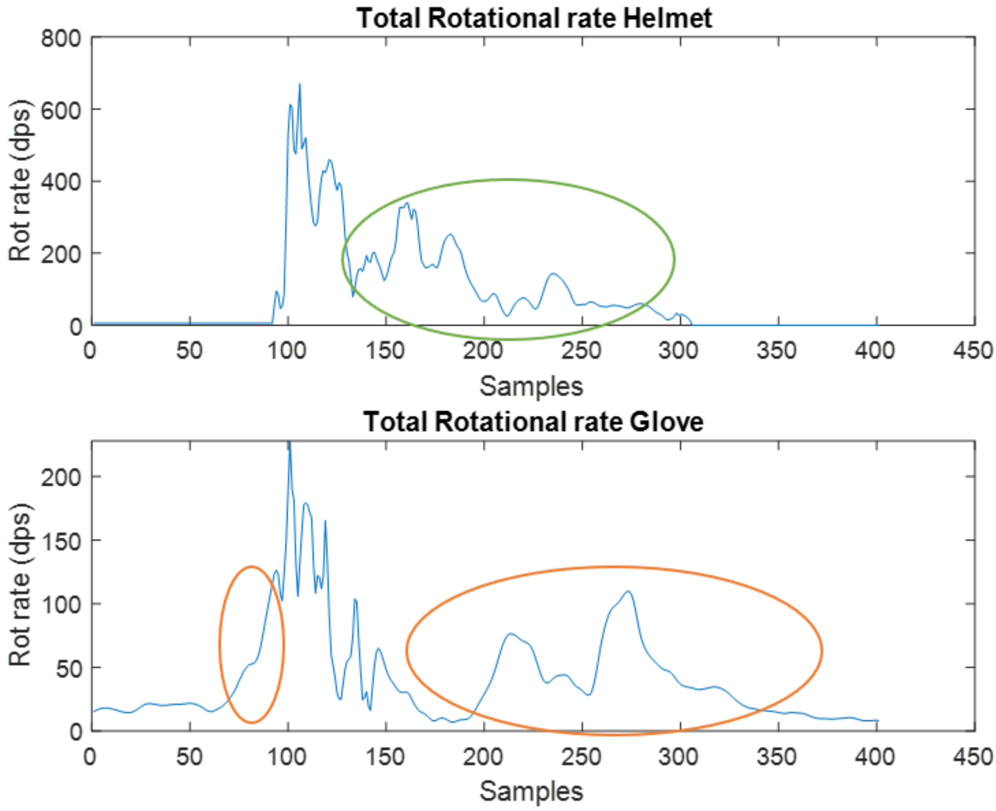

Figure 31. This figure shows the rotational rate of the helmet vs the glove only for the x-axis. Green circled area represents the cyclic motion of BOB as it oscillates after the punch while the Orange circled areas represent the hand motion captured in the punches

3.6.5. Discussion and Conclusion

From the two main locations that were tested using this system, it was concluded the best location will be on the back of the head. Qualitatively using industry experts, we were able to visually determine that the movement from the athlete's hands and feet alone will be a significant obstruction to the classification algorithm as separating what movement was part of the hit versus what was not part of the hit will be a tough task. Even in our limited movement performed during the jab punch, these unwanted movements are being seen. This is shown in the Figures 29-31 highlighted by the orange circled areas in the results section. Furthermore, the motion of the hands and feet is significantly higher in combative sports as the athlete is using them for movement, defense and to strike the opponent. This will negatively impact our classification approaches. Even more, there will be more noise from the electronics impacting the opponent as they block a hit, and this could again be picked up as a valid hit. Therefore, the choice of placing the sensors on the back of the head will further reduce the chance of false positive readings. Not only that, but from a durability point of view, it does not make sense to have the sensors placed on the hands and feet's as there will be considerably more wear and tear on any electronics placed inside the hand and feet protectors. Accordingly, the movement of the head is far less and is a much more stable location for the placement of electronics and the IMU. Next, this location will reduce the number of sensors as only 1 IMU will be used if it is located on the head as compared to 4 if placed on all hands and all feet. This reduces cost as the sensor placed in the head protector is 0.25 of the cost of 4 sensors placed in the hands and feet protector. This initial pre-study, allowed us to determine a few key points that were used in the second design of the eHelmet that follows in the next section. To solidify this point, RUPunch performed similar work with the sensors placed on the hands of boxing gloves and their results were 89.6% accurate using machine learning techniques. Our goal is to at least match this classification, or ideally have better accuracy while placing the sensors on a better and stable location such as the head. This will allow for cleaner signals required the use of less features and no machine learning techniques. Quantitatively when we look at the results, we can determine that the mean activity (variance) is higher for the IMU placed on the head placement versus the IMU placed on the hand. This is in fact due to the oscillations seen by BOB after an impact has occurred visualized by the green circle. In real-world fights, the athlete will definitely have a reaction however, it won't be as excessive as BOB, which will work in favor of our algorithm. The most important conclusion from this study are the orange circled areas. What they represent is the movement of the hand right before and right after a kick as taken place. This is significant motion that is detected and will be a cause of possible errors. From a signal analysis perspective, this motion artifact will be detrimental to any form of analysis as detecting an actual impact versus irregular movement will be nearly impossible. Qualitatively consulting industry experts in signal analysis (SAR lab) we were able to conclude that the IMU placed on the head will be ideal. As a final point to solidify this, the placement of the IMU in the head protector also allows for the opportunity to estimate concussion as the rotational movement of the head is being captured. We know from the introduction of this chapter, that rotational rate plays just as big of a factor in concussions as linear acceleration does. Therefore, our finalized design will allow for this estimation using the gyroscope sensor.

3.7. Classification of Impacts using Second eHelmet Design

Once the sensor placement was finalized, work on the main contribution began that was around hit validation. As the introduction mentions, the first complexity that exists in taekwondo is hit validation between legal vs illegal hits. There are concerns of bias and improper scoring or accidental scoring that are the foundation of why electronic point scoring systems were introduced in taekwondo in the first place. These and many other problems mentioned in the introduction lead to years of work by companies that created these current point scoring systems. Even the current systems face limitations especially for the head. All hits to the head are still scored by judges and that means the judges are still deciding what is legal versus legal. This is a big limitation to the scoring of taekwondo as hits to the head are worth the most points. Therefore, the proposed research aims at fixing these issues by creating a classification algorithm using only an accelerometer and gyroscope.

As mentioned previously, there are no data sets available and hence the major task for our research involved data collection. For this it was paramount to have industry expert's opinion and the 20/20 Armor team provided that for us. The same real-time data collection algorithm and sorting algorithm will be used in this study as the one mentioned above. This means, the data collection process is the same with the same settings, however the analysis will be different. The first task was to determine what types of hits will be measured and will have the most impact on hit validation. The first class that shows up is illegal hits versus legal hits. In taekwondo it is only legal to kick an opponent's head and that means any other type of hit to the head is illegal and this includes punches. Therefore, this is the first and very important class that needs to be considered and the next section will cover this in detail.

With this classification algorithm, there was one main limitation set by research objectives of SAR lab and 20/20 Armor team. It was that the algorithm should be “lightweight” meaning complex machine learning approaches and cloud computing cannot be used. For 20/20 Armor, all the computing is done on the board due to the real-time fast nature of the sport. The board is required to score hits instantly as the match is in progress. Therefore, all the computations and analysis take place on the 20/20 board located on the vest. For this reason, a fast and light-weight approach needs to be taken. Therefore, the purpose is to accurately classify the punches verses kicks proving that hit validation is possible using a light-weight machine learning algorithm.

3.7.1. First eHelmet design

The first eHelmet design consisted of 7 total that included of 3-axis accelerometer, 3-axis gyroscope and the smart foam signal (details on smart foam covered in next chapter). The placement of the IMU relative to the board is not important however, the axis-orientation is important and is shown in Figure 32. The benefit of this design over just using the IMU is that it will allow for impact detection on the sides. The foam cannot be placed on the front of the face or the chin area and therefore for impacts in those areas, the IMU will be the main source of classification. However, for impacts on the side of the head will have an additional signal that can be used as a validation method and can be combined with the IMU data for better classification results. We set out to design this and using the raw materials provided by 20/20 Armor team, made a helmet shown in Figure 32. The raw materials included of the electrode, the nano-composite foam (NCF) and the wiring. All these materials were tested to be in working condition before any work was done on the helmet and are shown in the Video 4 in the appendix.

Figure 32. This figure shows the eHelmet made of the smart foam material as well as the x-y-z axis relative to the board. Note, red: y-axis, blue: x-axis, black: z-axis (out of page)

Great care and steps were taken to follow the exact process used by 20/20 for the vest design as this sensor is state-of-the-art and there are no instructions available for its usage or design. Therefore, we worked closely with the 20/20 Engineering team and the manufacturers of the NCF foam to make sure no mistakes were made. The individual parts were glued together, and duct tape was used to secure the board in place. However, this design faced several complications that required use to move forward with only the 6 signals retrieved by the IMU. This is because of two main reasons: 1) during the construction, the bending of the foam to form the shape of a helmet causes the metallic layer in-between the foam layers as well as the foam to deform to a point that no signal is received in the board and 2) the bending also causes the metallic layer (electrode) to develop wrinkles in between 2 foam layers reducing or completely limiting the signal conduction. The reasoning behind this is as the smart foam was bent, the strain surpassed the densification stage of the foam and as a result permanently deformed the metal component of the nano-composite foam material (further information in chapter 4). Once the helmet was made and tested on BOB, no signals were retrieved. A confirmation step was performed to prove that the materials had in fact deformed and were not usable. The helmet was completely separating and molded back to its horizontal shape however, even after this, no signal was received.

Next, to avoid the deformation, 2 smaller pieces were cut and left as flat as possible. Those 2 pieces were then securely fastened to the helmet. Both the sensors were connected in a y-formation to the 20/20 board. This is because the board is limited by only 1 input for the smart foam sensor however, having 2 separate smart foam pieces joined to one will still work. Once this was connected, it did work, however the signals had no amplitude. Extreme impacts (much higher than 69J) were either barely noticeable or, most of the times, not detected. The results were reported back to the 20/20 Armor and it was decided that only the IMU will be used for the helmet classification. Again, for the helmet classification, the majority of the impacts will be hit on the face, the area not covered by the helmet, and thus having little effect on our overall work.

3.7.2. BOB Data Set 2

The data set consists of 2 main classes: illegal (punches) and legal (kicks) both of which are to the head. These classes were determined by a several consultation sessions with 2 Olympic taekwondo athletes who are instructors of the Master level. They are successful and experienced coaches and were able to provide detailed insights as well as concurring with our background research in common kicks performed in taekwondo. Based on this, 2 vital classes were identified, Illegal (jab) vs Legal (roundhouse kick) as the starting point. All punches and kicks were recorded in-house on BOB and training was provided by the 20/20 Armor Master level trainers. The data set includes 50 kicks and 50 punches to the head and is divided as follows: 10 punches to the forehead, 15 punches to the right side of the head, 15 punches to the left side of the head and 10 punches straight to the face. This is basically on BOBs nose to keep it constant in all our kicks and punches. This division is further seen in the Figure 33. Finally, for the kicks, the divisions on BOB were kept the same but there were 25 roundhouse kicks to the right of the fact and 25 back kicks (turning kick) to the front of the face. An effort was made to diversify the data sets by performing the jab and kicks to different parts of the face and hence we see the divided jab and kick numbers. This is done to increase variability in signals and provide a more realistic data set. The explanation of why roundhouse and back kicks were specifically chosen is explained in the Background section. To quickly repeat them, these kicks are the most commonly used and therefore it is valuable to start with these and include them in our first data set. The training was performed by the 20/20 Armor team and the kicks and punches were performed in-house on BOB. Videos of how the punch was performed are shown in Video 3 and how the kicks were performed are shown in Video 8.

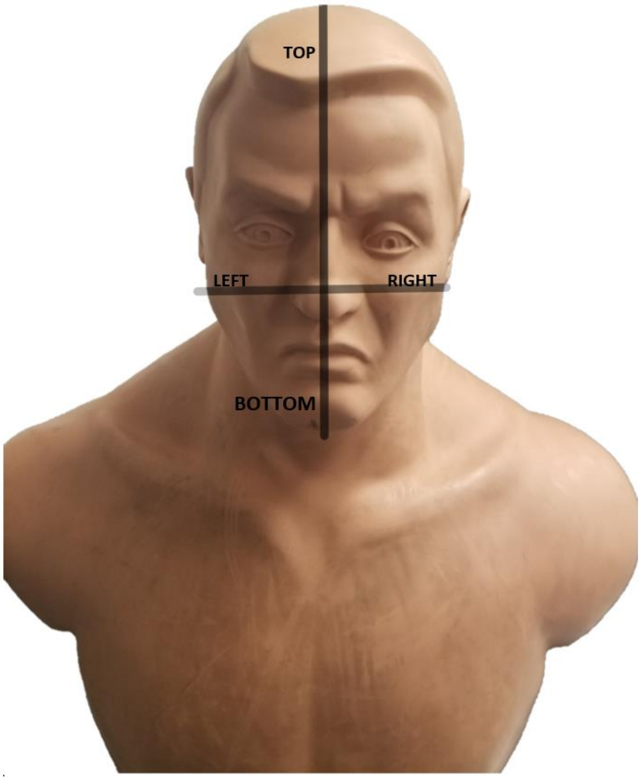

Figure 33. This figure shows our BOB and the target areas on the head

Table 6. Data set division

Punches	
Forehead	10
Right of head	15
Left of head	15
Face	10
Kicks	
Roundhouse kick	25
Back Kick (turning)	25

3.7.3. Hit-Validation methods and Classification

Hit validation and classification began by working on the first class. This includes classification between legal and illegal hits. To repeat, the only legal hit to the head are kicks and hence that was one class. For the illegal class, it was anything besides a kick to the head. Therefore, a punch was chosen as the illegal hit for the first class and this was decided with industry experts. As mentioned above the Hit-validation methods need to be lightweight, and therefore a "thresholding" and decision tree approach was taken. The kick signals were visually inspected and some basic information was extracted such as spectrogram plots. Highly selected features were extracted from the signals such as mean, total peaks, minimum value, maximum value and energy concentration. Based on these values, the signal was classified, and the results are shown in the next section. The biggest advantage of choosing simple features is it is possible to implement them on the 20/20 Armor board as it only has 1MB of flash memory and only a certain amount of that is available for classification. The algorithm flow is written below and goes over all the steps performed in the classification algorithm:

1) The total acceleration and total angular rate was calculated using the same formulas as sections 3.6
2) The entire length (682 samples) were used for accelerometer and gyroscope
3) Features were extracted for each signal such as: total number of zero crossings for gyroscope z-axis, largest zero crossing interval for gyroscope z-axis, mean value for acceleration for 1-200*n*, 150-300*n* and 400-600n where *n* represents samples, minimum and maximum values for rotational rate and the energy concentrations for both rotational rate and acceleration
    a. Energy Concentration was found using: $E = 10log_{10} \sum_{-\infty}^{\infty} |x(n)^{1/2}|^2$ where *x(n)* is the discrete time signal
    b. Minimum and maximum values were found using comparative functions for each of these vectors
    c. Zero crossing were found using the function: $z(i) = \frac{1}{2N} \sum_{n=0}^{N-1} |sgn[xi(n)] - sgn[xi(n-1)]|$where x(n) = 0,1,…..N-1 and $sgn[xi(n)] = \{1, xi(n) \geq 0 \; and -1, xi(n) \leq 0$ [101].
4) Based on these features, the signals were classified in to 2 categories: legal and illegal

3.7.4. Classification Results

The algorithm classified with an overall accuracy of 90% only misclassifying 10 signals. The confusion matrix is shown in table 7 and the sensitivity and specificity are calculated to be 90% each. An important point to note was, even with the 8g and 500dps settings of the

IMU, there was still saturation points. Regardless of this saturation, the classification algorithm still performs highly as there is still a great amount of information available in the IMU signals. Since only one or two axes were usually reaching the saturation point, this still captured enough data on that punch or kick to still classify with accuracy. These saturation points are seen in Figures 35 and 36. The features that were extracted included of the following: Mean of the total acceleration curve for 150-300N, mean of the acceleration curve for the total acceleration curve 400-650N, total number of minimum values for the gyroscope z axis, energy concentration for the total acceleration, and finally, energy concentration for the total gyroscope as well as individual axis.

Table 7. Confusion Matrix for class 1 and class 2

	Class 1 (legal)	Class 2 (illegal)
Class 1	45	5
Class 2	5	45
	90%	90%

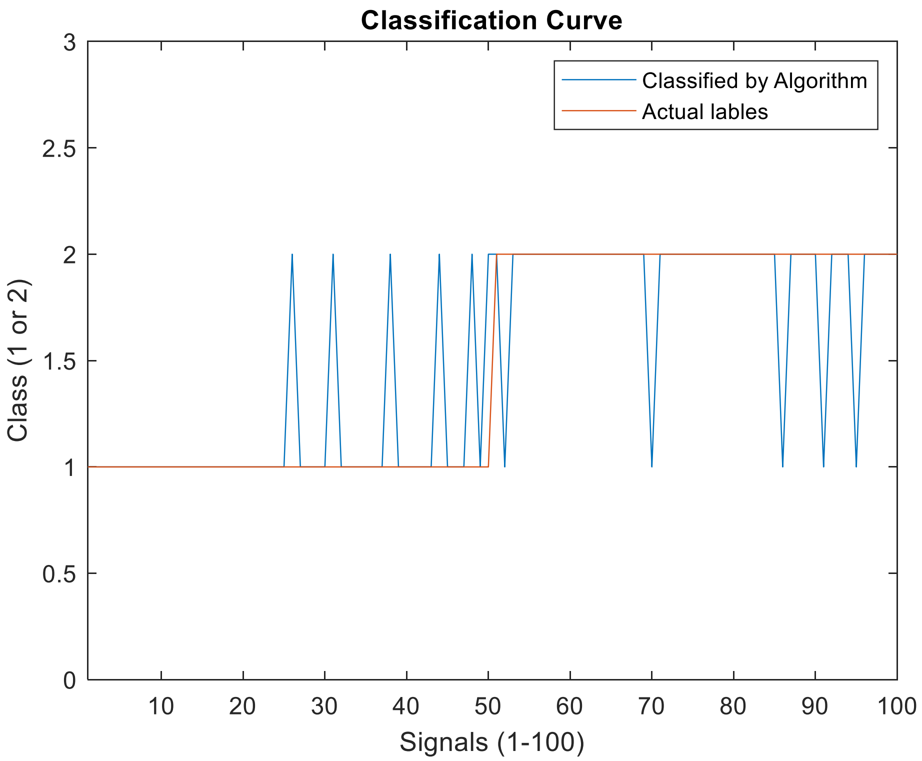

Figure 34. This figure shows the results of the classification curve for the 2 classes

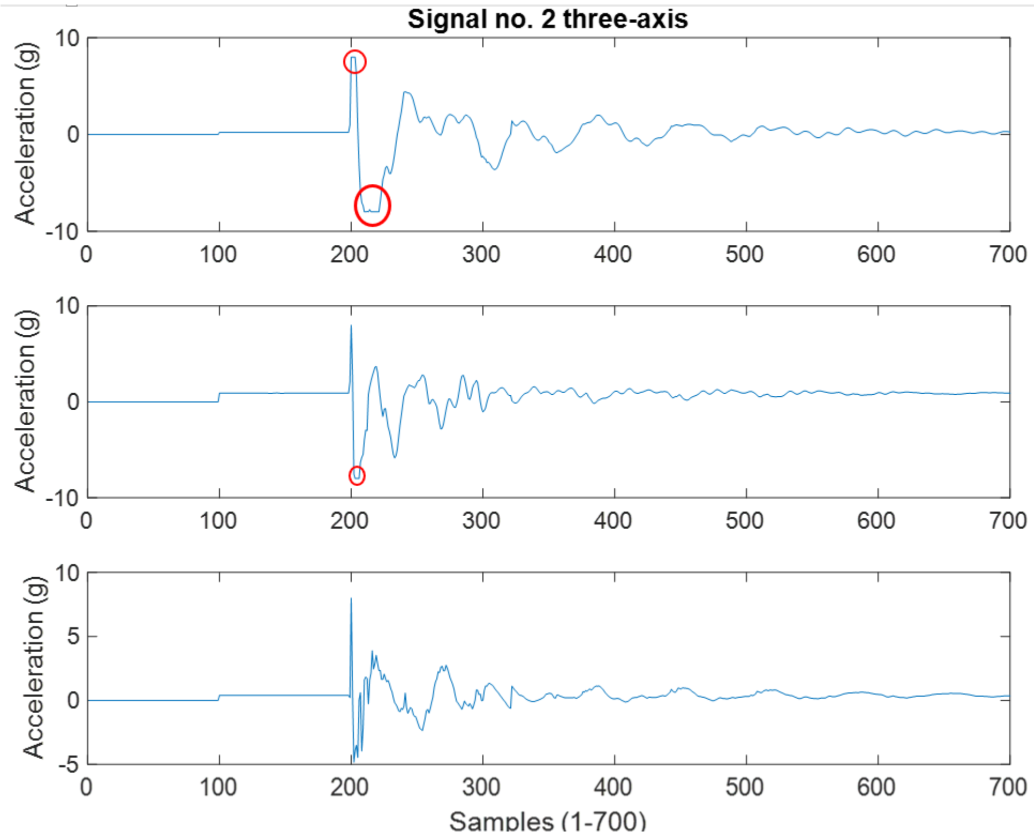

Figure 35. This figure shows the saturation point of 8g for the accelerometer on all 3-axis (X,Y,Z) circled in red

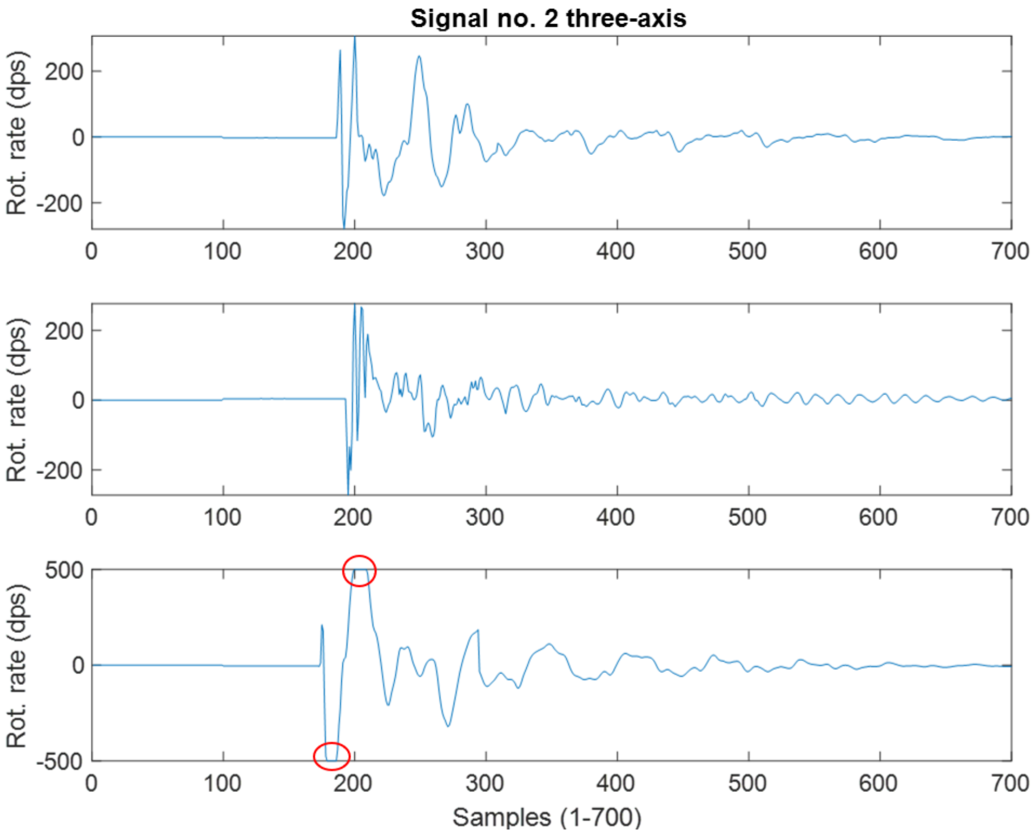

Figure 36. This figure shows the saturation point of 500dp for the gyroscope on all 3-axis (X,Y,Z) circled in red

3.7.5. Discussion and Conclusion of Classification Investigation

The point of this investigation 3.7. was hit validation between legal and illegal hits. The importance of this arises when we see the scoring scheme of taekwondo and see that the highest points are rewarded for kicks to the head. To recap, 5 points for a turning kick to the head as well as 3 points for a normal kick to the head. This is a significant portion of points that are rewarded from kicks and this is why this study is relevant. The results prove that using our classification method performs well with 90% accuracy by using the accelerometer and gyroscope data alone. No complex machine learning was used in our classification algorithm which was a sizeable benefit. This allows our algorithm to be uploaded on the hardware allowing for 1) edge computing and 2) real-time classification. Edge computing refers to performing tasks on the microcontroller itself to avoid the need of sending data to the cloud or remote servers for analysis. This has several benefits as it reduces data that needs to be sent as well as processed. Furthermore, this algorithm works by using statistics-based features that require simple computations allowing real-time classification once it is converted into C and uploaded on to the microcontroller. This has already been done by 20/20 Armor using algorithms developed by the SAR lab. In taekwondo, some impacts are known to reach 150g or more and hence having an IMU that can capture those levels is not necessary for classification. Even at 8g we were able to capture enough information about the type of hit to classify. Increasing this range from 8g to 16g will capture more data, but then that definitely decreases the sensitivity of the IMU and could lead to more errors. In addition to all this, a significant advantage of classification of legal versus illegal kicks to the head is tele-coaching using the IoT concept. IoT refers to Internet of Things and the ability to classify kicks right on the best will allow at-home coaching where students can perfect their hit techniques to determine what a valid kick is performed by Olympic level athletes. The inclusion of linearity testing as well as hit validation in our work allows this to be possible. Not only with the students know the kick impact level required for a valid hit, as well as the proper technique. The linearity testing then improves the current approach of point scoring systems that pass a certain “Threshold” required for a hit to be valid. We know have proof that higher impacts have a higher response.

The next important consideration is using both the accelerometer and gyroscope is mandatory in the helmet design. Firstly, there is no smart foam signal to determine impact level and therefore gyroscope data is relied on. Next, since the head is supported by the neck, a pivot joint, it faces significant rotational forces in impacts when compared to the vest or data retrieved from the waist. Therefore, the inclusion of the gyroscope is mandatory for classification. Moving on to one final fundamental topic, the orientation of the IMU. For our work, the orientation of the IMU was not found to be an essential as long as the placement of the IMU on the helmet was kept constant. This will definitely be the case in the production version of this prototype 1 design made in this thesis and the SAR lab.

3.8. Conclusion for Chapter 3

Overall, this chapter set out to accomplish 3 main problems and to reiterate they were, firstly, the strong hits are still rewarded the same points as weak but scoring hit. This was attempted to be solved using the first linearity testing. It was proven that till a certain saturation point (max limit) of the IMU there is a linear relation that can be used to detect the impact level. This only uses the IMU and not the NCF sensor which is designed for this exact purpose and hence in the next chapter, this problem will be addressed and validated using the vest data. Second, the next point that was tackled was the cost of the point scoring system and it was covered in the sensor placement study. The goal of that study was to choose ideal location while taking into consideration the cost, durability and sensor quality. The actual cost of the helmet when the IMU is being used is roughly 11 USD. Therefore, including that with the materials to make the helmet will be very economical compared to the current point scoring system that cost roughly 2800-3400 USD each [16, 37]. Finally, the third task, or main problem, was the hit validation between legal and illegal hits does not exist for any hit to the face. Therefore, we attempted to classify legal kicks and illegal punches in 2 separate classes proving this is possible with the use of an IMU. The setting for the IMU were *8g*, *250dps* and *208Hz* sampling rate and this proved to be more than sufficient in classification. This improved on and validated the current standard IMU setting used by 20/20 Armor by using SARput and real-world data from BOB.

With the main goals covered, it is important that our design also covers the human factors mentioned in section 3.1. To reiterate, the human factors were, medical risks and safety requirements and adoption rate. Our design covers all these parameters as we will be using the same material as currently approved helmets (polyethylene). Therefore, all the performance requirements that are necessary for the helmet will be the similar, if not the same. Moving on to the adoption rate, since our design requires no additional systems to be bought, besides the helmet itself, the adoption rate will be very high. We use edge computing to classify kicks in real-time and therefore it is an “all in one” package.

4. *Contribution 2: Smart foam (Nano-composite foam sensor)*

The fast pace at which technology is advancing requires the sports industry to adopt the latest technology and improve spectatorship and customer retention. We know from the introduction of this work that this is a significant factor that is known to be the downfall of sports. Concerns such as referee fairness, judges bias and referee accuracy in taekwondo were worrying factors that nearly cost the sport its placement in the Olympics in 2013 having only been introduced in 2000. This encouraged World Taekwondo to make several changes to the points breakdown and the introduction of point scoring systems that are now relied on as being the “final decision” of points scoring. The latest point breakdown occurred in 2018 and the current point scoring systems were introduced in 2016. All this means that there are further improvements and changes necessary in point scoring systems since they were recently introduced in taekwondo. With level of innovation occurring in the textile industry that are now creating smart-clothes, smart-foams and smart-undergarments, created a whole new industry of textiles. The innovation arises when these smart textiles are introduced in sports gear to quantify performance or detect injury. Therefore, innovative work has been done in this area by 20/20 Armor using a smart foam explained in the next section.

4.1. Background: Smart foam

The smart-textile sensor is a different concept than what was regularly done by placing sensors on top of items. For examples, automobiles used IMUs for detection of several purposes and now IMU are used in almost most electronics. The next step of this was sensors embedded inside the material rather than on-top of the materials and smart foam/textiles were introduced. This smart foam material, or nano-composite foam (NCF) sensor, relies on the triboelectric response to a compression and relaxation upon impact. The foam is composed of nickel nanoparticles and nickel coated carbon fiber that is added to the liquid components of polyurethane foam [62]. The generated charge then needs to be transmitted to the microcontroller for acquisition after an impact, and this is done by a conductive electrode. The response of this NCF sensor depends on several factors such as impact area, impact duration, strain rate, total strain, however, the most important one is that it is dependent upon impact force and initial velocity. Both these factors significantly affect strain rate and therefore the higher strain will result in a larger NCF charge generation [62]. The inventors of this foam determined a linear correlation of the foam as long as it is in the plateau region and does not reach the densification region. As we know from Chapter 3, the densification region is when the cell walls of the foam meet, and the stress increases significantly whereas the strain does not. The NCF sensors were actually designed to limit the strain to only 50% so that the response is linear. Moving on to the next major benefit of using this NCF foam, it can replace the current used traditional foam padding as it provides equivalent energy absorption. This is a significant benefit as the NCF sensor is multifunctional and can provide impact data that works directly with the IoT idea referenced in the previous chapter.

4.2. Standards and Considerations for Chest Protectors (Vest)

Due to the fact that point scoring systems have been recently introduced in taekwondo, there is limited amount of research done in this area. We see a small number of studies that use electronic body protectors and taekwondo, and most of them are focused on the effects of point scoring systems rather than the testing aspects such as this study [14]. The most relevant study so far aimed at testing the reliability and linearity of an electronic body protector is done by Tasika [63]. Before this study, no research work was done on testing the linearity of these devices and as a result not a lot of information is available on these new point scoring systems. This was also a limitation faced by this exact study as well and they pointed this out. They found that currently available commercial electronic body protectors in 2013 were not linear and therefore did “not have the accuracy, reliability and linearity for the unit of measurement used (J: joules) for accessing a standardized hit” [63]. It is important to note this study was performed 6 years ago and the electronic body protectors have definitely improved since then as a result of this work. However, no recent research work, besides Tasika work, was found by us at the time of this research. Moving on to testing methods for chest protectors, there are standards developed by the UK called British Standards and they are called “Protective equipment for martial arts- Part3: Additional requirements and test methods for trunk protectors”. As they also mention, these standards were developed as the UK committee felt there was a lack of necessary detail to testing this equipment. The main test they perform is the drop test where the vest is placed on a flat support (anvil) and a free fall striker is used. They have a performance requirement that a minimum of 3 locations be testing and impact energy should be at least 12J [64]. Using this standard, in-house robustness testing equipment (SARPut apparatus) was created, and the vest was then tested for linearity. However, it is still unclear if these standards or similar are used by World Taekwondo for testing or approval of their electronic body protectors.

4.3. Overview

With a good understanding of this sensors significant benefits over traditional padding used in taekwondo, we will move on to a description of how this chapter is laid out. The work in this chapter will begin using a similar approach as Chapter 3, with the drop test demonstrating linear response testing and then the classification algorithm. This chapter will attempt at solving the main limitations of current point scoring systems used in taekwondo and to repeat, they are: hit validation between legal impacts does not exit and a strong hit is still rewarded the same points as a weak but scoring hit. Therefore, section 4.3 is the robustness testing, 4.4 is the classification algorithm and finally 4.5 is a quick conclusion to the whole chapter covering all the tasks performed.

4.4. Robustness Testing (Drop-Test)

As mentioned in previously, the most important factor before any data can be retrieved from a sensor is to determine linearity of the sensor. Usually, manufacturers perform substantial testing, and this was done for the NCF sensor as well. Regardless, robustness testing or drop tests are very important for this new and innovative sensor as this sensor has not been tested in the impact energies experienced in taekwondo. Furthermore, the impact energies seen in the manufacturers testing was only till 15J and therefore it was paramount that this be done. Moving on to the next goal of this robustness testing, and it was to determine a relationship between the LED score provided by the vest upon impact and impact energy. This will allow for a quantified relationship that will further increase the factors the NCF response is dependent upon particularly in taekwondo and using the NCF sensor designed by

20/20 Armor. Therefore, this is then basically a validation study. Next, we will move on the materials and methods of how this robustness testing was performed.

4.4.1. Materials and Methods

The SARput apparatus was used in this chapter as in the previous section and the same heights were used. During the drop test for accelerometer and gyroscope, we also recorded the NCF sensor data. An important note was, the 4 kg shot-put (SARput) was dropped from these 4 chosen heights in a localized location on the vest. The vest was divided in 4 sections: 1 is top, 2 is bottom, 3 is left and 4 is right. The location where the shot put was dropped was kept to only location 1 which is the top. However, further equidistant divisions were made from the board as seen in Figure 39. The 4 inner-divisions were only kept to section 1 (top) and were also kept at an equal distant from the NCF sensor input on the board shown inside the white compartment. What this allowed was, to get very similar signals inside a certain localized area allowing us to keep that aspect as a constant and only height being the independent variable while the impact signal was the dependent variable. Videos of the drop-test being performed are shown in the appendix by following the videos 5-7.

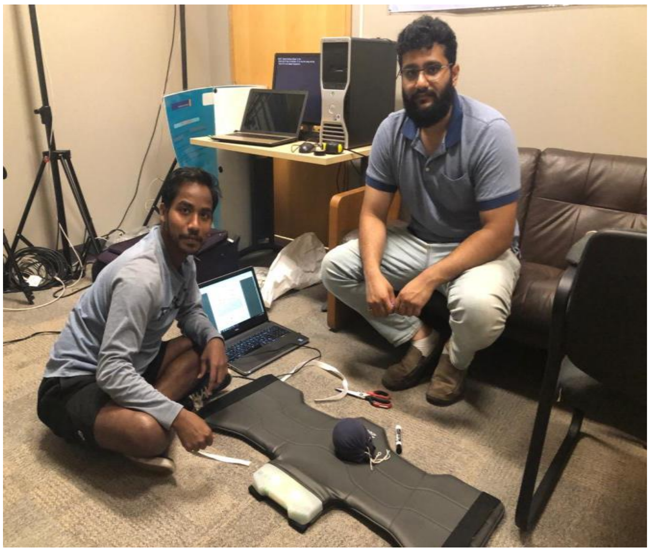

Figure 37. This figure shows the drop test being performed in the SAR lab using the SARput apparatus.

The only relevant technical specification for the NCF sensor is that the sampling rate of the NCF sensor is set to 48 kHz and a total of 3000 samples are saved based on when the impact is detected. A schematic is shown of the NCF Sensor input in Figure 38 and since the NCF sensor was being used in conjunction with the IMU, all the data was kept to the default settings set by 20/20 Armor engineering team. The IMU is to 4gs and 250dps and is being sampled at 1.66kHz. These setting were not adjusted as these values have been tested for over 1000s of signals by the 20/20 team for the vest specifically. Further, they provide good sensitivity for the short duration of the impact needed for classification. Before the pseudo-code is explained, it is vital that we go over the details on how an impact is detected and scored by the 20/20 Armor vest. The first step in the source-code used by the 20/20 board, is to find a peak and then determine if a peak is valid. For a valid peak, the width of the peak is considered and the height. If it is above a certain tested value, that peak is then considered a hit. Once a hit is detected, the board calculates the area of the peak and then a score is given to that impact based on the area and weight class setting used. The score is not calculated on the 3000 samples saved but on only 1350 samples: peak +1000 and peak -350. This score is then represented on the 24 LED bar on the 20/20 board giving an instant quantified estimation of how a certain impact. All this is done in real-time as the kicks are performed. It is vital that this exact same process is followed for our analysis so that the exact same score can be determined by our algorithm. It is important to note this is only done to calculate the LED score and not for any classification purposes (next section). A confirmation step was taken that our algorithm resulted in the exact same score by manually counting the LEDs that turned on and comparing them with our algorithms values.

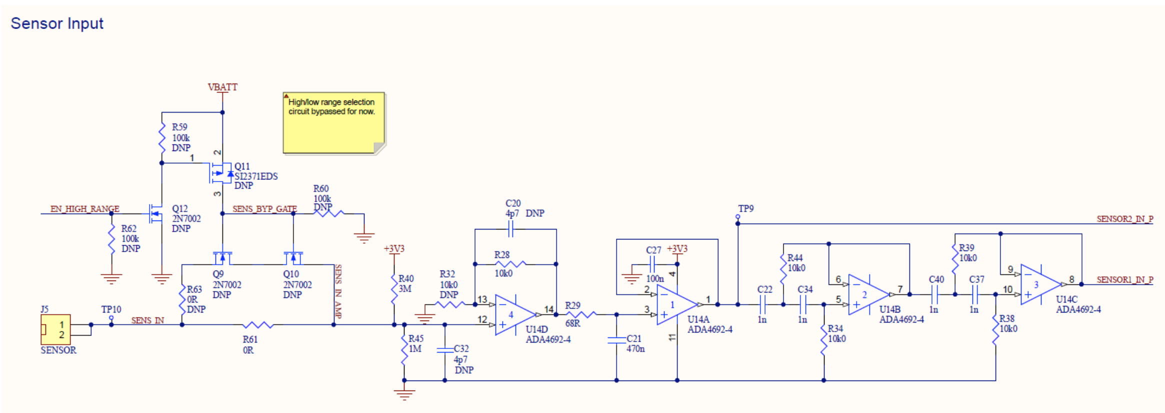

Figure 38. This figure shows the schematic of the NCF sensor input to the 20/20 board.

The pseudo-code is shown below:

1) Drop-test data was collected and saved as a .jasn file

2) Data was then sorted and analyzed on a computer
    a. The entire signals (682 samples) were used for accelerometer and gyroscope
3) The energies were calculated for different heights
4) The impact was detected using the recreated 20/20 Armor tried-and-tested code
    a. 3000 samples of the NCF sensor were saved however only 1350 samples used in calculations: peak value +1000 *samples* and peak value -350 samples
5) The area of the impact was calculated
6) The final LED score was calculated
7) Linear model (degree 1) was applied to the LED score using the formula: $f(x)=mx+b$ where m is the slope and b is the intercept
8) The Pearson Correlation coefficients were calculated for the normalized matrix of 101 signals x 1350 samples using the formula: $\rho(A) = \frac{1}{N-1}\sum_{i=1}^{N}\frac{A-\mu}{\sigma}$ where $\mu \textit{ is the mean of } A, \sigma \textit{ is the standard deviation of } A$

4.4.2. Robustness Test Data-Set

For this experiment, 25 signals were captured each at the inner-division locations 1,2,3 and at different heights of 0.66m, 1.13m and 1.51m respectively. At the last location (4) 26 signals were recorded at a height of 1.75m. These inner-divisions in the top 1 section are shown in Figure 39. This resulted in a total of 101 drop test signals where we captured the NCF sensor data for linear response testing. The LEDs were manually counted for 50 drops from heights 1.13m and 1.51m as a confirmation step that our algorithm was scoring each impact the same as the 20/20 source code is. With the drop locations and heights in mind, we will move on to the results.

Table 8. Data set division

Drop Heights	*Signals*	*Inner division*
0.66m	25	1
1.13m	25	2
1.51m	25	3
1.75m	26	4

Figure 39. This figure shows the 4 inner equidistant divisions within the top 1 section.

4.4.3. Results

The results showed that there is a linear relationship firstly in the NCF sensor signals that was retrieved. Secondly, as a result of the first, there is further a linear relationship by the calculated LED score and the impact energy. The Figures 40-42 show the NCF response at -different impact energies. As it can been seen, as the impact energy reduced, so did the amplitude of the vest and of the signal received. This shows a linear relationship is evident and it was found to be using the formula: $f(x) = mx+b$ where m is 0.4447 and b is 1.546 with 95% confidence bounds. Once this was complete, the correlation coefficients were calculated to determine the linear dependence of the signals at each of the different drop energies and the results are shown in the table below. It is important to note length of the signal the correlation coefficients were calculated for as it was not the complete 3000 sample raw signal. Rather, it was the portion of the signal the microcontroller uses (1350 samples) for its LED and area calculations.

Table 9. Data set division

Drop Energies	29J	45J	59J	69J
Correlation Coefficient	0.7957	0.8113	0.7595	0.4285

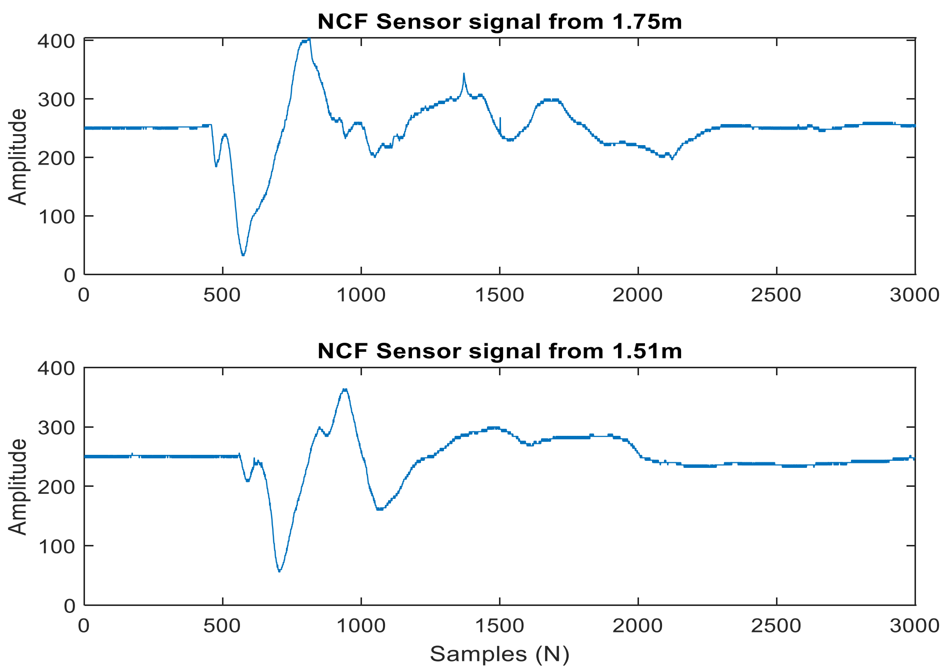

Figure 40. This figure shows the NCF Sensor response at 2 different heights

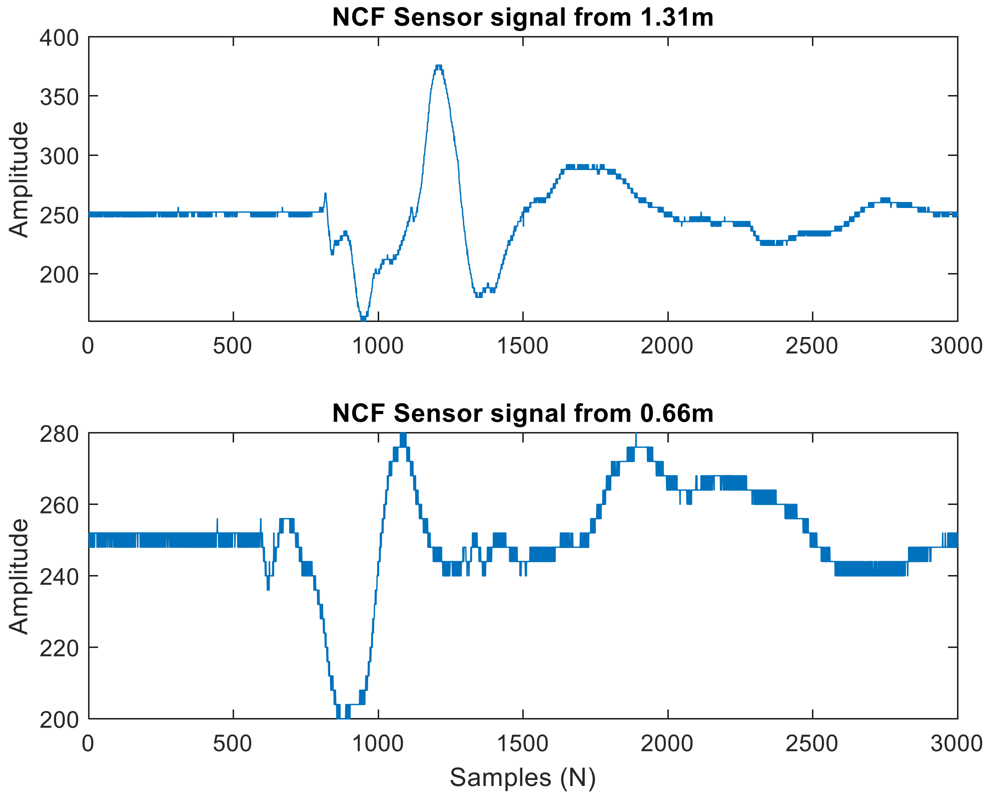

Figure 41. This figure shows the NCF Sensor response at 2 different heights

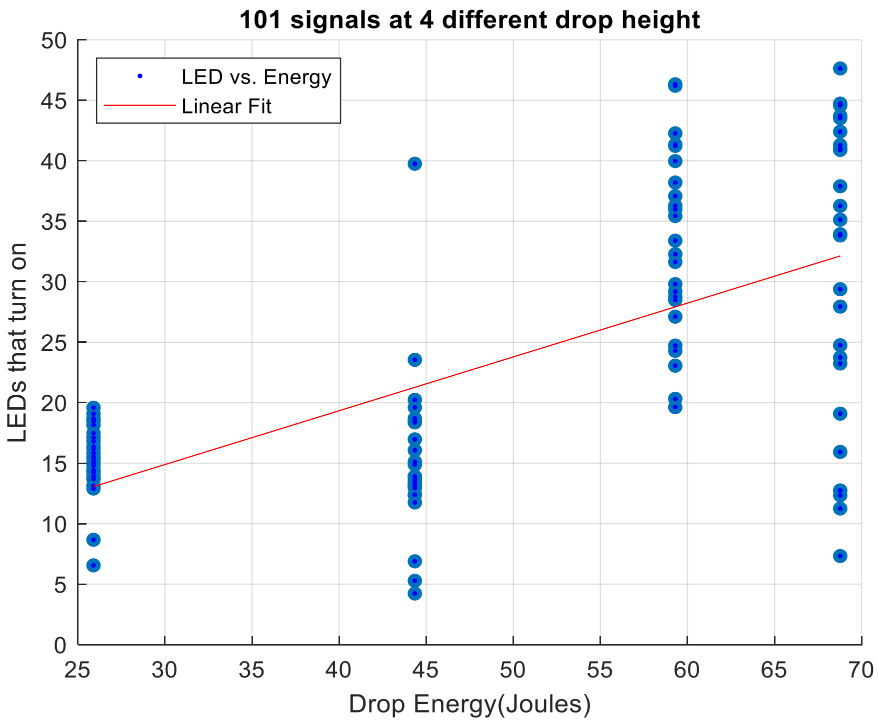

Figure 42. This figure shows the estimated linear relationship

4.4.4. Discussion and Conclusion

The first task that was completed was to determine if there was a linear relationship between the LED score calculated by the 20/20 Armor board and impact energies. Since the LED score is an arithmetic calculation based on the signal area, it can be concluded that there is definitely a linear relationship between the different impact energies and the NCF response at significantly higher energies than those tested by the manufacturer of 15J. Therefore, 2 things can be concluded from the first part of the work and they are that there is a relationship between the LED score and impact energy and the NCF sensor response and impact energy. This allows us to quantitatively determine a relationship between energy and the LED score provided, and this will be a first in the taekwondo industry as of October 2019. We have definitely determined that by using the NCF sensor, we can now start to quantify different kicks by assigning a value to them in joules.

Next, we get into the to the reasoning for why the signals are varied at the 69J energy level. There was a high spread and a saturation point visually noticed in the NCF response as the energies increased to high amounts such as 69J when compared to the low energy of 26J. The saturation point here does not necessarily refer to the entire signal (3000 samples) being saturated or reaching a clipping point (max level) but rather the LED score being saturated for the 1350 samples. One potential reason to this is because the 4kg shot put has a small surface area impacting the vest, it is believed the vest is compressing until the foam reaches the densification stage and the NCF sensors response is outside of the linear range. The spread of data in the 69J is much higher and this is definitely because of the densification stage. To test this hypothesis, we increased the drop energies to 75J and 79J and repeated the drop tests. At 75J most of the signals that were picked up were erratic and many were not recognized as an impact as the morphology of the signal varied significantly from what is seen in the results section. Furthermore, at 86J (or at 2.2m), not one impact was registered, and the Video 7 proves this. To repeat, one definite reason for this was that the 4kg SARputs small surface area combined with the high energies reached the densification region of the NCF sensor creating erratic and highly varied signals. Thus, those signals were not registered as an impact. Furthermore, one more reason this occurred was because the foam over time lost its sensitivity due to the repeated drops (over 250 drops and impact testing performed).

With the spread that was visible, the Pearson correlation coefficients were calculated to determine the similarity of the signals at different drop heights and determine this relationship. The correlation coefficient was calculated on 1350 samples, and they were the exact samples the microcontroller uses to calculate the area of the impact and provide a hit with a score. It was a requirement as well as a necessary step to replicate the exact code used by the microcontroller and perform analysis on those signals' durations (1350 samples). This is done to be consistent and our analysis is now directly related to the 20/20 Armor system. At 69J the correlation coefficient was 0.42 while at 59J it was 0.75 and this drop proved that the signals became varied and erratic in nature as the drop energies increased to the densification region of the foam. At this region, the foam loses its linearity and the response is no longer linear. This is further supported by the manufacturers of the NCF sensor as they also mention that the response is not linear in the densification region in their article [62]. The foam is designed so that it does not reach the densification region however, due to the unnatural stress of the small surface area of the shot put repeatedly compressing the vest, it eventually reaches the densification region and saturation points. We are certain this will not affect the results in the real world as first, the impact location of the kick and punches will not be as precise, hitting the same location for over 200 times and, secondly real-world impacts will definitely have a larger surface area than the shot put. We see that only at 69J does the correlation coefficient decrease significantly again supporting our hypothesis that the foam has reached densification region at large impact energy. The final point the correlation coefficients help us determine is that the signals are similarity of the signals at different impact energies. We see that the signals are nearly 80% correlated at energies up until 69J and this allows us to conclude they are similar relative to the type of impact that is detected on the vest. This means, that we can say with high confidence, that the same hit, hit at the same location, will produce the same response as long as the impact does not reach densification region.

4.5. Classification of impacts on the Nano-Composite Foam Sensor

Once the linear response was proven and a relationship found between the LED score and the impact energy, work began on the second main contribution that was classification and hit validation. As chapter 3 mentions, the complexity that exists in taekwondo is hit validation between legal vs illegal hits. For the helmet, there are much more complications as no scoring is done by the point scoring system yet, however vests are still currently being used in taekwondo. There is a huge reliance on them and to our research indicates, neither the KP&P or Daedos system is capable of this as of October 2019. The reliance is evident in the world taekwondo rules, where it mentions that if a hit is scored by the chest protector, it will be considered as the final score. Due to this reliance, it is clear hit classification will be a huge step forward for taekwondo. Preliminary research into the 20/20 Armor vest, determined that based on where the vest was impacted, the vest will deform in a different manner. This is a normal response due to the shape of the vest however, this resulted in slight variations in amplitude as well as morphology of the signals received. This provided us with another possible investigation of localized classification. This means, determining if the impact was hit at the top of the vest or the bottom of the vest. Therefore, there are 2 main goals of this section: 1) determining impact location when comparing top of the vest versus the bottom of the vest and 2) classifying legal impacts to the vest for hit validation.

4.5.1. BOB Data-Set 3 for Classification

Similar to the previous chapter, the data set included of impacts performed on Bob by trained Olympic athletes and trainees of those Olympic athletes and Master Level trainer. We began by recording kicks performed on the bottom of the vest and the top of the vest. 31 signals were recorded on each location resulting in a total of 62 signals kicks performed by the Master level trainers themselves seen in Figure 43. Next, 64 signals were recorded by performing jabs to the vest as the class 2 portion and this was done by a trainee. The roundhouse kick was performed for Class 1 and the jab was performed for Class 2. The roundhouse kick and the jab were chosen due to their popularity and rate of use in taekwondo. Furthermore, the 20/20 Armors team was consulted and these two were finalized as being the most important in building a solid foundation. This data set is divided and used in the two investigations. For the first, determining impact locations (top vs bottom). Kicks to the top and the bottom were considered as it was important to isolate only one independent variable of impact location. Therefore, the only dependent variable is the measured impact signal. For the second, classifying legal versus illegal hits. The 64 kicks captured for the first investigation were combined with 62 punches performed on top and bottom. This made a total of 126 hits that were used to classify between 4 different localized classes of: (class 1) kicks at the bottom of the vest, (class 2) punches to the bottom of the best, (class 3) kicks to the top of the vest and finally (class 4) punches to the top of the vest. To reiterate, four classes were chosen as the NCF response on different parts of the vest. This variance is a result of as the vest deforming differently at each location due to the shape of the vest. Video 9 shows how the punches were performed on the vest and Figure 43 shows how the kicks were performed.

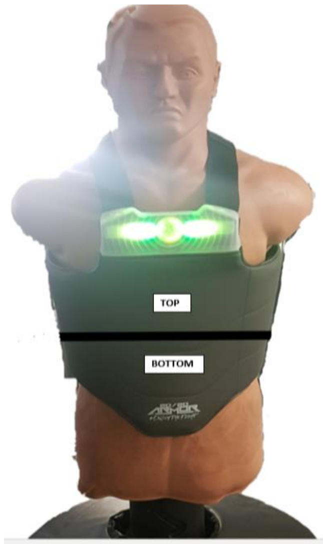

Figure 43. This figure shows the data collection process by the Master level trainer (left) and the vest division for kicking (right)

4.5.2. *Materials and Methods*

As seen in the figure in the previous section, the complete 20/20 Armor vest was used to collect the 126 impact signals. The vest was placed on BOB and since the NCF sensor data was being sent with the IMU data, all the default setting that were used as in the previous section. Therefore, the IMU was set to 4gs and 250dps at 1.66kHz. With this in mind, we will move on to the methods used for the classification by going over the pseudo-code for each investigation.

4.5.2.1. *Localized Classification (Top versus Bottom)*

The pseudo-code for the first investigation for differentiating top versus bottom hits is as follows:

1. Drop-test data was collected and saved as a .jasn file
2. Data was then stored and analyzed on a computer
    a. The entire signal (682 samples) was used for the accelerometer and gyroscope data
    b. 3000 samples of the NCF sensor data was saved and used
3. The total acceleration was calculated for the IMU data using the formula below: $Atotal = \sqrt{ax^2 + ay^2 + az^2}$ where ax, ay and az represent the individual axis
4. The total rotational rate was calculated using the formula: $Gtotal = \sqrt{gx^2 + gy^2 + gz^2}$ where gx, gy and gz represent the individual axis
5. Features were extracted such as: total number of peaks for the gyroscope data, total number of peaks for the accelerometer data, energy concentration of the NCF sensor data
6. Signals were classified in to 2 classes: Top impact and Bottom impact
7. The Pearson Correlation coefficients were calculated for a random normalized signal with compared to signals from the top and bottom the vest using the formula: $\rho(A) = \frac{1}{N-1} \sum_{i=1}^{N} \frac{A-\mu}{\sigma}$ *where* μ *is the mean of* A, σ *is the standard deviation of* A to determine linear dependence of each class

4.5.2.2. *Impact Classification (Hit-Validation)*

The pseudo-code for the second investigation for classifying top legal hits versus illegal hits is as follows:

1. Drop-test data was collected and saved as a .jasn file
2. Data was then stored and analyzed on a computer
    a. The entire signal (682 samples) was used for the accelerometer and gyroscope data
    b. 3000 samples of the NCF sensor data was saved and used

3. The total acceleration was calculated for the IMU data using the formula below: $\mathrm{Atotal} = \sqrt{\mathrm{ax}^2 + \mathrm{ay}^2 + \mathrm{az}^2}$ where ax, ay and az represent the individual axis
4. The total rotational rate was calculated using the formula: $Gtotal = \sqrt{gx^2 + gy^2 + gz^2}$ where gx, gy and gz represent the individual axis
5. Features were extracted such as: total number of peaks for the gyroscope data, total number of peaks for the accelerometer data, energy concentration of the NCF sensor data
6. Signals were classified in to 4 classes: Bottom kick vs. Bottom punch and Top kick vs. Top punch

4.5.3. Results

4.5.3.1. Investigation 1: Localized Classification

The results for the top versus bottom of the vest showed it is possible to classify based on area specificity with high accuracy. The classification curve (Figure 44) shows only 4 misclassifications and with a sensitivity of 90.3% and specificity of 96.7%. A total of only 4 kicks were misclassified. As mentioned in the pseudo-code, only 3 main features were used for optimized classification and they were: total peaks for the gyroscope z-axis, the total number of peaks in the max gyroscope z-axis and finally the energy concentration for the NCF sensor data. These features were selectively chosen and optimized to provide a total accuracy of 93.5% allowing us to differentiate impacts on those 2 locations. The subplot below shows the difference between the signals when the same kick was performed with similar magnitude by the master level trainer. An amplitude difference is apparent even after the amplitude for the hits on top of the vest is reduced by a factor of 0.75 already. This is seen in Figure 45. Next, the correlation coefficient (Table 11) was calculated to prove that signals from the top are linearly related to each other and are different from signals from the bottom of the chest protector. This was done by taking 1 random signal from the top of the vest and comparing it with 31 signals from the top and calculating the correlation coefficients for that. Next, the same signal was then compared with 31 signals from the bottom of the vest and the correlation coefficients were calculated.

Table 10. Confusion Matrix for both classes

	Class 1 (Top)	Class 2 (Bottom)
Class 1	28	1
Class 2	3	30
	90.3%	96.7%

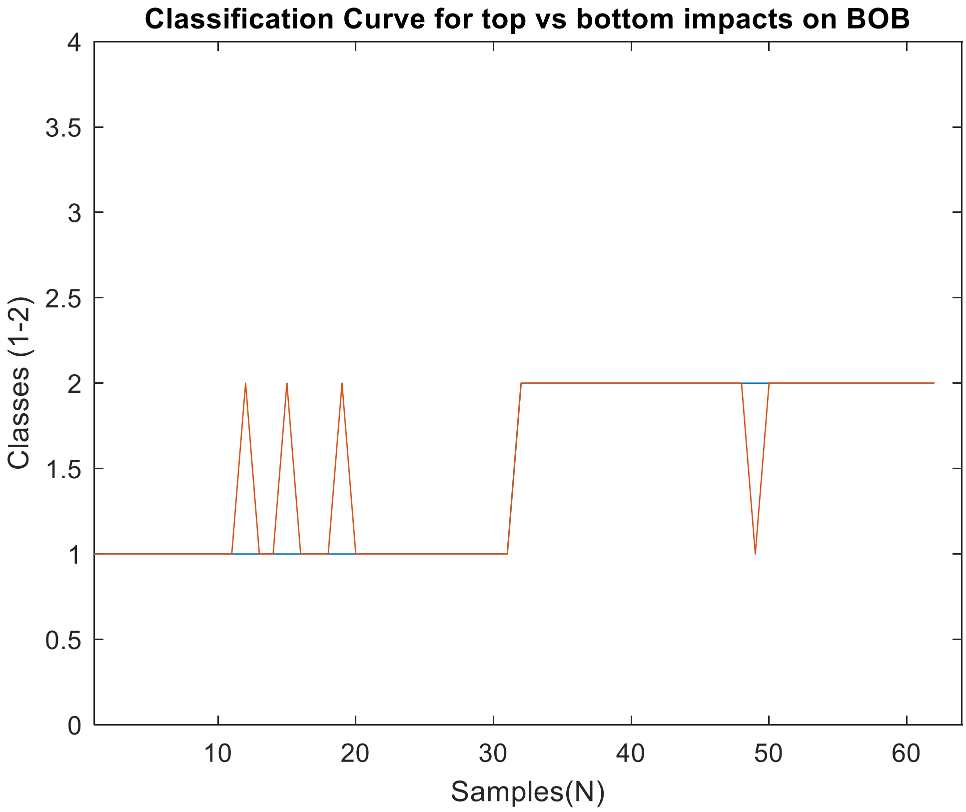

Figure 44. This figure shows the classification cure for the first vest investigation (top vs. bottom)

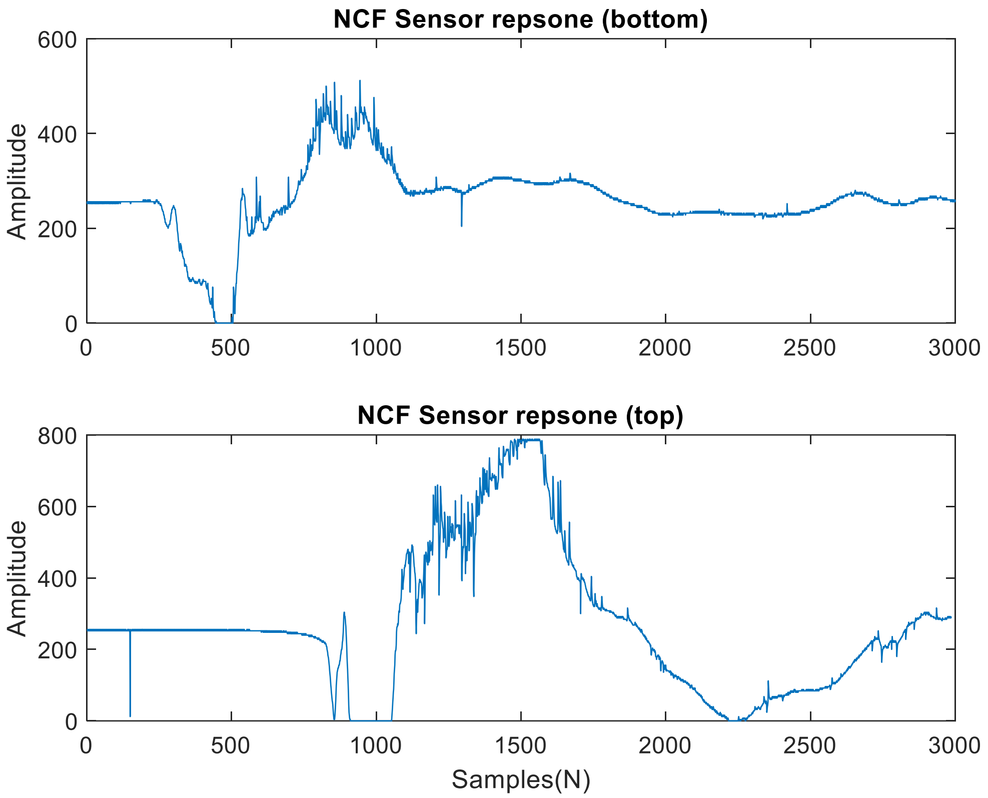

Figure 45. This figure shows the amplitude difference as well as signal deviations between the same kick at top vs bottom

Table 11. Correlation Coefficient

Correlation Coefficient of signal 1 from top of vest to 31 other signals from the top	0.5075
Correlation Coefficient of signal 1 from top of vest to 31 other signals from the bottom	0.2572

4.5.3.2. *Investigation 2: Impact Classification*

The classification of the kicks was performed on 2 localized locations since we know from investigation 1 that there is a difference in the signals received from the bottom vs the top. The main one being the amplitude difference. Therefore, it was vital that localized classification be performed resulting in 4 different classes. The sensitivity for bottom kicks vs punches was 100% and 87.5%, respectively, resulting in a total misclassification of 4 impacts out of a total 61. Further, the top kicks vs punches, the sensitivity and specificity are 100% and 90.3% respectively with only 3 total misclassifications for 61 signals. As mentioned in the pseudo-code for investigation 2, the main features that were used for optimized classification were: the mean of the NCF response from 1:1500N and from 2000-3000N, the total number of peaks in the max gyroscope z-axis and finally the energy concentration for the total rotational rate as well as individual gyroscope axis. This resulted in allowing us to classify between legal hits with high accuracy.

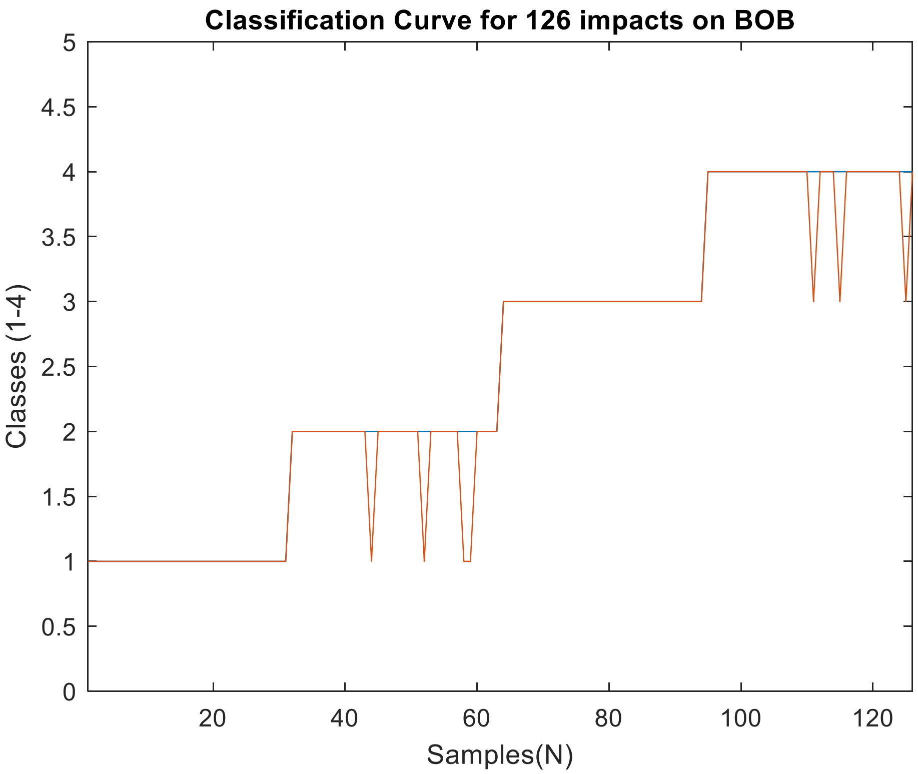

Figure 46. This figure shows the classification curve for the second investigation (bottom kicks vs bottom punches and top kicks vs top punches)

Table 12a. Confusion Matrix (Class1 vs Class2)

	Class 1 (bottom kick)	Class 2 (bottom punch)
Class 1	30	4
Class 2	0	27
	100%	87.5%

Table 12b. Confusion Matrix (Class 3 vs Class 4)

	Class 3 (top kick)	Class 4 (top punch)
Class 3	30	3
Class 4	0	28
	100%	90.3%

4.5.4. Discussion and Conclusion

The main purpose of this section was to create an algorithm for hit validation that allows for separation of legal hits to the chest protector (vest). In taekwondo, a punch and a kick can be performed on the vest and therefore a high number of points are scored by the vest. Furthermore, these points are considered to be final points and cannot be refuted. What this does is, increase the importance of classifying different types of impacts. For taekwondo, a legal punch is anything hit with a tightly closed fist to the chest protector. Therefore, the jab was chosen as it fits these rules and will provide us with a standard technique for hitting the vest. For the kick, the roundhouse kick was selected as that is the most popular and highly used kick in taekwondo due to its fast reaction time. This kick and punch were then performed on the top and bottom of the chest protector divided as seen as seen in Figure 43. The 2 main requirement for our work and classification algorithm were that 1) it had to be eventually uploaded on the vest and therefore size of the algorithm was limited to under 800 kilobytes and 2) be able to classify in real-time. As a result of these, machine learning was not an option and other options were considered.

The first task performed, investigation 1, was the classification of the same impact (kick) on the top and bottom of the chest protector. This was possible and allows us to accurately separate the impacts and localize them to a certain region of the vest. One reason that there are difference in signals is more because of the shape of the NCF sensor vest rather than the characteristics of the foam. This is because the whole vest is made of the NCF sensor, and as the vest gets impacted, only a certain part of it deforms. This is in part due to the irregular shape of the vest and it creates a varied response more than anything. The irregularities seem to work in our favor as it allows for localized classifications of signals that are indeed used to detect which part of the vest the impact has hit. To validate our results and classification, we calculated the correlation coefficients of a random kick signal from the top of the vest (signal number 1) with: all the other kick signals in the top of the vest and all the kick signals from the bottom of the vest. The results are shown in table 8. What this allows us to confirm is, impacts from different areas are in fact linearly correlated to each other. We took 1 signal and compared it with all the other kicks to the top of the vest and got a mean correlation coefficient of 0.51 and when we compare that same signal to the bottom of the vest, we get a mean correlation coefficient of 0.25. It was observed that the correlation coefficients of 0.51 is in fact lower than those seen in the drop test study in section 4.3.3. This was actually expected as there is now a human performing those impacts (kicks/punches) and there is inconsistency in the impact location, strength and duration. This means, those variations in impact will reduce the correlation coefficient values. In conclusion, we were able to determine that there is a positive linear dependence of the signals based on where the impact took place on the vest (top or bottom). In is because the variation in the deformation of the vest causes a varied signal between the 2 classes (top and bottom) that can be detected with high accuracy for localized classification.

The final task that was performed, investigation 2, was the actual hit validation and the impacts were then classified into 2 classes for each of the 2 locations (top/bottom) resulting in 4 classes. This was the main contribution done is this chapter. We are now able to classify different impacts with high accuracy irrelevant of where it is hit on the vest with 94.4 % accuracy. This shows that this NCF sensor can definitely be used for highly accurate classification of hits in real-time. The different impacts result in a different NCF response as well as the different signals in the IMU. These differences as then quantified by our algorithm and the punch vs kick is placed into separate classes for top and bottom making a total of 4 classes. The NCF response is a critical component as it allows us to get a quantified amplitude of the impact that was correlated in section 4.3 with impact energies. One final part worth mentioning is, the complexity of the algorithms developed in this chapter translates to a computing requirement of <10 kilobytes and once converted and uploaded on the 20/20 Armor system, will perform efficiently.

4.6. Conclusion for Chapter 4

Overall, this chapter set out to accomplish 3 main problems faced by the chest protector. To reiterate they were, firstly, the strong hits are still rewarded the same points as weak but scoring hit. This was attempted to be solved using the first linearity testing. This was proven for the NCF sensor in particular by the linear relation that was seen until the foam reached the densification region. This linear relation for LED scoring can then be used to estimate with what energy an impact was detected. The second goal for this study or the main problem was the hit validation between legal and illegal. Therefore, we attempted to classify legal kicks and illegal impacts (4 classes) and successfully separated them into 4 classes proving this is possible with the use of an IMU and the NCF sensor.

5. Conclusion

5.1. Head and Chest Protectors

This thesis work began with understanding the 3 main limitations (section 1.4.) to the current point scoring systems used in taekwondo. These limitations were developed in conjunction with our industry partner 20/20 Armor and were separated based on which part of the body they affected: head and chest.

Head Protector: The first point of interest was the headgear and the urgency for innovation in headgear was high. We know that currently all impacts to the head are still scored by the judges and in fact no points are rewarded by the point scoring systems alone, as seen in the official rule book of taekwondo. We know the reason behind introducing the point scoring system in taekwondo, in the first place, for the chest protector was to remove judgement bias and errors. This is still not the case for head impacts. Therefore, it was urgent that a system be designed using innovative sensors and technology. We know from our chapter 2 that the best sensors to capture human body motion is an IMU. IMUs are currently being used widely in all industries for this exact reason. Therefore, an IMU that included of an accelerometer and gyroscope was chosen since we in fact are attempting to capture that exact body motion. From our chapter 3, we can see that the initial design also included of the nano-composite foam sensor as an additional sensor with the IMU. The reasoning behind including this was, since the head gear will be made of a foam sensor, it would be optimal to use the nano-composite foam for the eHelmet rather than the traditional foam. However, some limitations were observed such as: 1) Bending the foam deforming the internal metallic layer and 2) after creating small surface area nano-composite foam sensors, the signal amplitude was significantly low, to a point

98% of hits were not detected. Both these issues required significant adjustments to the 20/20 Armor board and design which was not a possibility for our work. Therefore, the nano-composite foam sensor was removed from the helmet design. It is important to note this step did not impact our classification algorithm as any impact to the face will still not be picked up by the nano-composite foam sensor as that area is not covered by the foam. With just the IMU sensor finalized we performed a robustness test that proved the IMU was capable of detecting high impacts with accuracy. Then the impact classification algorithm classifies with a 90% accuracy between an illegal hit and a legal hit for 100 impact signals to the head.

Chest protector: Next, we move on to the chest protector, and for that all 7 signals were utilized. First a robustness test was performed to determine the sensors linearity and that proved to be high leading to the classification algorithm that classified with an accuracy of 93.7% for a total of 126 impacts to the chest. During this work, it was noted that based on which area of the chest protector a hit landed, the response of the NCF sensor varied. This provided us with the opportunity to include localized classification that separates the signals from the top of the vest to the bottom of the vest. This was done with 93.5% accuracy for a total of 64 signals and allows us to detect the location where the impact landed providing us additional information of how the athletes performed. This information is valuable to the trainer as well as judges and the athletes themselves. This chapter lead significant work that can be vital for at-home training. The next section will cover this in more detail.

5.2. Relation to Edge Computing

As we know from the introduction, edge computing removed some of the work being done on external servers or the cloud by performing tasks locally on the microcontroller or the source itself. There are several advantages to this and the biggest one being user privacy and security. What this means is, since the data does not need to be exported to an external server or cloud, the data is secured temporarily on local device, some analysis is performed, and then the data is discarded. All the work in this thesis, revolves around this idea and therefore the algorithms were designed accordingly. There are a few important concepts that need to be considered here such as algorithm complexity (O(N)) and battery performance before and after the algorithms are uploaded. Starting with the first, the algorithm complexity is a of linear time (O(N)). This means as the length of the samples (N) increases, so will the time taken to perform the analysis and classification. However, it also means that this algorithm is “lightweight” allowing it to be uploaded onto the microcontroller and perform real-time analysis. Since all the calculations performed are purely arithmetic, it is very fast to perform the analysis for all the algorithms in chapter 3 and 4. Moving on to the next factor, the battery performance. The 20/20 board uses a battery pack that is of 700 mAh capacity which last 6 hours of use. There is a 116 mAh current draw and the operating voltage for the board is 4.8V. This is supplied by four 1.2V Nickel Medal Hydride (NiMH) batteries. The performance after similar algorithms were uploaded on the 20/20 Armor had no noticeable decrease in battery performance. This means these algorithms are perfectly usable once they are uploaded on the board and can be ready to use instantly.

The greatest benefit of our design and algorithm is the is of the at-home training using edge computing. What is meant by this is, once they are uploaded on the board, they can classify different impacts by themselves without the need for a trainer. Furthermore, for the chest protector, they can even locally determine what area of the vest the impact was detected on and can provide information to the athlete, judge and trainers remotely. For example, using our algorithms uploaded on the vest, can lead to accuracy and precision practice by athletes. A new game mode can be made that scores athletes more points based on where they hit on the vest. More points can be allotted if the athletes repeatedly hits the same type of hit at the same location. Therefore, there are 2 types of points that can now be scored, 1) what type of impact is performed (chest protector and head protector) and 2) where the impact took place (chest protector only for now).

5.3. Future Work

Since this is an industry project, work is done at a much faster rate than traditional academic projects. Most of the suggestions and conclusions that came from this thesis are already being worked on by the SAR lab and 20/20 Armor engineering team. Firstly, all the limitations faced by the head protector (deformation of the foam) have been reported to 20/20 Armor and a new design of the head gear is in the works. This design will feature the headgear foam formulated of the NCF sensor rather than shaping it after removing the deformation aspect. It will be created by using a mold and molding the helmet using the liquid raw materials required for the nano-composite foam sensor. This will remove the need to manually reshape it from a flat piece eliminating the deformation and wrinkles. The other possibility is to use smaller sensors as seen in [60] and redesign the board significantly for the reduced signal amplitude for the helmet. What we saw was, the current 20/20 Armor board is not adequate for the NCF sensor response if the smaller sensors are used and hence a complete redesign of that part will be necessary to increase the gain of the NCF response. Doing this will include an extra signal from the helmet that can be used for analysis for further improved classification and impact localization. This will be a very simple modification as our chapter 4 proves better results are possible with the NCF sensor in combination with the IMU. Therefore, the next generation of the chest protector and head protector are already in progress where several changes are being made. One additional feature that is being added is of Bluetooth functionality for visualization of data right after on all smart phones. This again supports our at-home IoT training idea as those impacts and LED scores will be saved on an server and can be viewed by trainers and athletes at a later time. Again, this will use edge computing for all the calculations and only the final results will be saved. Moving on, the next benefit to the point scoring system is that it will include everything out of the box. This means, it will not require additional referee scoring boxes, no transmitters, no TVs, no staff members to operate the World Taekwondo systems and finally no computers or software. What this means is, there are no hidden costs of additional system and one cost of 599 CAD (450 USD) will result in highly functional point scoring system.

In general, increasing the data set size to include more variations of impacts, will results in a better overall system. Great effort was taken to produce real-world type signals using BOB and master level trainers and athletes for data collection. However, increasing the variation of kicks will definitely help. So far, we were able to capture a total of 448 signals that were divided amount the 3 main contribution chapters. The division is as follows: 101 IMU signals for the robustness testing, 20 IMU signals for sensor placement, 100 signals for hit validation on the helmet (illegal vs legal), 101 NCF sensor signals for robustness testing and finally 126 signals for hit validation on the vest (punch vs kick) making a total of 448 signals. Increasing these to include a variety of impacts will be beneficial. Finally, using our IMU we get informational data of rational forces faced on the head at the time of impact. This can be connected to concussions and would allow a us to pin-point impacts that can potentially lead to concussions. For this, data about concussion causing impacts, specifically in Taekwondo, is necessary and the connection can be made easily.

Appendix 1: Impact Demonstration

Video 1

Link: https://drive.google.com/open?id=11IcIM_eeDWBjQfC4zgEh_eXXGY9cpM1Z

Description: This video shows the drop test and how the 4kg shotput was dropped on the vest

Video 2

Link: https://drive.google.com/open?id=10zc-Yc4MelgDC6MAA7064_f77oVqLAlV

Description: This video shows the IMU placed on the glove and the punches performed

Video 3

Link: https://drive.google.com/open?id=114ExY00vL93tugCVcTkJHqyRnhTqAXQm

Description: This video shows the IMU placed on the helmet and the punches performed

Video 4

Link: https://drive.google.com/open?id=11_yg2eGeJQ6ATLzfmpdRWs7u17CpkP6R

Description: This video shows testing of raw materials of the NCF sensor before forming the helmet. Several impacts were performed, and 3 consecutive hits detected with appropriated response

Video 5

Link: https://drive.google.com/open?id=11IhZlnLuUmbP3M1WLIylcD6pi86vuXHR

Description: This video shows drop testing being performed at 59 inches

Video 6

Link: https://drive.google.com/open?id=11S2aqM2AXrU4vBvr2W6hSEjL8HuUHxpR

Description: This video shows the drop testing being performed at 69 inches

Video 7

Link: https://drive.google.com/open?id=11UYw6B__wCXE5Gd_n7_R8Ht0TlFLrWKS

Description: This video shows the drop testing being performed at 90 inches

Video 8

Link: https://drive.google.com/open?id=119dzZlTUIDKfsdaQLJA47da3e_b5tTiO

Description: This video shows the kicks being performed on the helmet

Video 9

Link: https://drive.google.com/open?id=117-cQFUjriLHTTZlkuXqHrHVJ3ga7CHS

Description: This video shows the punches being performed on the vest. The same technique was used for hits to the top of the vest and the bottom of the vest

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