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PERFORMANCE GAINS THROUGH SENSORY SYSTEMS: A DISSERTATION

By

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A decade, 3 degrees, job, wife, and a BCS Championship. What a college experience. I will always love FSU.

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ABSTRACT

Over recent years, sensors have increasingly become used to improve the performance of humans. Popular sensors provide a cost efficient way to gather various inputs ranging from temperature to movements to sound. Today, smartphones are packed full of sensors that enable us to go about our daily lives allowing us to find the closest restaurant and get turn-by-turn directions at a glance. External Bluetooth sensors are also integrated to help aid in medical tasks such as checking glucose levels or monitoring weight. These sensors have been so ingrained in everyday living that it is hard to imagine life before their existence. In fact, a good amount of our performance and decision making process relies on the information we gather from these sensors.

Two main demographics, in particular, benefit from performance improvement sensors. The first demographic is older adults. Several sensor-based systems have been created to help older adults perform at a higher level, which increases their quality of life. Fall monitor systems are being created using various sensors such as accelerometers, video cameras, and acoustic sensors. GPS sensors are being used to create wandering tracking systems of dementia patients. Various other systems have also been constructed to assist with the day-to-day medical care of older adults. While targeted for different purposes, they all have the same goal, which is to positively increase the performance of the user.

The other demographic that sees a marked performance increase is athletes. In general, a key difference between older adults and athletes performance level. Older adults may display minimal function while athletes may display advanced function. There have been several approaches that offer ways of improving the performance for both demographics. For older adults, systems are available that allow them to live more independently and provide peace of mind to loved ones. The systems achieve this goal by using sensors to monitor the user and automatically send alerts in an emergency. These emergencies can range from falling and not being able to get up or wandering outside in extreme conditions and becoming lost. On the other hand, other systems use sensors to evaluate and train athletes at the highest level. Often times, these systems are designed with speed and information as a key goal. They aim to improve several functions such as reaction time, spatial awareness, and agility. Data from the sensors is commonly evaluated in order to fine tune the athlete's movements that may be sport specific.

While sensors provide valuable information, they can be limited in several ways. One main concern is erroneous output from excessive noise. In the case of purely vision-based systems, background objects and movements create unwanted data that must be filtered. On the other hand, systems based only on inertial sensors incur noise when mounted to body parts that frequently move, such as hands. In addition to noise, single sensor systems are limited by processing time. Most video capturing inputs and processing algorithms are capable of running at 60 frames per second or every 1000 milliseconds. However, reaction time occurs on the order of 50-100 milliseconds, which will require additional time to compute (or expensive specialized hardware).

One way of addressing this issue is by using several sensors. Fusing the inputs from several sensors provides a robust, context-rich collection of data. This data can be used in numerous applications to better the fields of medicine, sports, and computer science. One particular area that can benefit from such sensor-fused systems is the improvement of visual cognition. Visual cognition is the process of decoding information visually as it is collected by the eyes and moves into the brain's waves. These brain waves then perform object recognition and invoke memories and emotions. With assistance from these sensory systems, people can be trained to see better and faster while strengthening the neural connections in the brain.

This dissertation explores a training program aimed to improve the visual performance of athletes. The training program consists of several exercises designed to workout the visual system of the trainee. Both commercial and custom sensors are used to gather data and evaluate the progression of athlete through the program with special focus on reaction time and visual evoked potentials. Several algorithms are implemented to evaluate the data and a novel sensor fused, reaction time algorithm is proposed.

CHAPTER 1

SENSORS OVERVIEW

This section provides a brief introductory to various commercially available sensors. It then discusses several strengths and limitations using sensors individually or as part of a group. The section is then concluded by suggesting several emerging areas in which sensors provide a solution. These areas include a range of different fields of study and are intended to highlight the versatility of sensors.

1.1 Hardware

A sensor, or detector, measures a physical quantity of something and converts that information into a signal. Today, electronic sensors have become commonplace [61]. With a huge shift in interest toward mobile devices, these sensors have become increasingly inexpensive and are included all together in one device, as shown in 1.1. Perhaps more importantly, they have become more accessible, leading to widespread use and adoption.

1.1.1 Capabilities

A variety of sensors are available, each with different purposes. Accelerometers, for example, measure the total gravitation forces exerted. Global Positioning Satellite (GPS) sensors provide information on location, including a person's longitude, latitude, speed, and even altitude. Touch sensors gather users' responses and human reasoning for parts of various algorithms. Cameras gather images that provide a matrix of useful information such as color and luminescence. Gyroscopes measure orientation and angular momentum; thermometers obtain information about the temperature; radars detect objects using radio waves. Sound Navigation and Ranging (SONAR) uses sound propagation to detect objects, usually underwater. Seismometers measure the motions of the ground, including seismic waves. Magnetometers measure the strength and direction of magnetic fields. Proximity sensors provide a distance measurement. All of these sensors produce

Figure 1.1: Common sensors on smart phones

different information, and there are many techniques of analyzing this information depending on intent.

The popularity of Bluetooth has given birth to even more sensors, many of which may be highly specialized or too difficult or too expensive to be directly integrated into a standalone consumer device. However, by connecting via Bluetooth, these sensors are able to be used. These Bluetooth sensors also cover a huge area of uses and applications there are reverse parking radar sensors, OBD2 sensors to get information from vehicles, weight scales, heart rate monitors, and many more for just about anything.

1.1.2 Singular Limitations

While these sensors provide valuable information, they can be limited in several ways. First, single sensors are prone to erroneous outputs. There are numerous situations in which a sensor will produce invalid data; for example, the sensor may not work because there was problem in manufacturing. In this case, it may not arrive at its destination. The sensor could also malfunction once the system is deployed. Operating conditions or even physical environment may cause a sensor to stop working as intended. Often times, detecting and replacing a sensor once in the field can be a difficult, expensive, or even non-viable task. Another reason for erroneous output could be excessive noise. During certain conditions, such as shifts in static or magnetic fields, interference may arise with the sensors causing invalid results.

Lack of complementary information is another limitation of single sensor use. Imagine operating an automobile with only one sensor. While a speedometer or gas gauge is informative, the use of just one of these sensors is not enough to safely or effectively continue operation. Even sensors in non-complex systems may lack the contextual information needed to perform the task. There are many areas to monitor. Each of these produces different types of data that calls for specialized equipment. Sensors are also configured for various ranges. While a single sensor may work for a system under one condition, a change in conditions might lead to the data exceeding the sensor's range. The opposite is also true. A sensor may require fine grain readings, which would be lost in a large range.

1.1.3 Data Fusion

To help increase the process of information flow, a technique called data fusion can be used. Data fusion joins together input from several different areas to be analyzed. One type of data fusion, sensor fusion, applies to gathering information from sensors. For example, gyroscopes are often combined with 3D accelerometers and called inertial sensors. Together, sensors give a deep and rich insight about the activity or situation taking place. In current times, smartphones have become very popular handheld systems that are able to fuse together large amounts of information from the user.

However, gathering and analyzing data as it is received is only one aspect of sensor monitoring. This data is stored and compared over time to both itself and other instances. The areas of robotics, medicine, and sports use and combine sensors extensively for an array of purposes. By monitoring sensors over time and in many different situations, baselines can be developed. These baselines can then be used as a metric to determine when something out of the normal range has occurred. This data can also be analyzed to find trends and correlations that enable answers to more complex questions.

The ability to mine data from these sensors over time gives a rise to contextually using this information. Context enables applications to make smart decisions about what actions should occur and when they should occur. For example, an application can use time and GPS to figure out if someone is in a meeting or class and put the phone on silent. Alternatively, they could use the accelerometer to detect when the user is running and automatically play the music they like.

1.2 Examples of Sensor Fusion

1.2.1 Robotic Applications

Data fusion also has uses in networked systems. One sensor node produces information. However, it is subject to limitations previously mentioned such as malfunctions or erroneous readings. The sensors may be needed to increase the physical range of the system, in which case several sensors are deployed to gather information individually. That data is then fused to discover larger trends over an extended area. The fused data can eliminate any erroneous or outlying data by averaging out any errors that may be introduced. The result is a robust consensus network as in [47].

Cameras are combined with inertial sensors for a variety of applications. Alone, a camera captures only images but has no frame of reference when it comes to orientation. However, when combined with an inertial sensor, the camera instantly senses what direction it is pointed in relation to gravity. Together, this information is processed and has several applications. Much research has been done using this combined sensor to aid in augmented reality. By knowing the orientation of the camera, the sensor can display virtual objects on a screen in more realistic fashion [5] [27]. The uses for these visual overlays are seemingly limitless. This combined sensor can also help navigation of robotics [36]. By adding a sonar sensor, this robot is even able to navigate and report information from under water, allowing researchers to map out surfaces that are extremely difficult to access otherwise [37].

Operation and maintenance of vehicles would be increasingly difficult or even impossible without sensor fusion. There are sensors to test the fuel level, tire pressure, engine temperature, battery life, and more. This information is even used to document the life of the automobile. Every car has an odometer documenting how many miles the car has driven. While driving the vehicle, a GPS unit can be used to obtain directions. Using a typical GPS may suffice in the two-dimensional plane of automobiles but not in the three-dimensional plane of an aircraft. Aircrafts fuse data from additional sensors, such as an altimeter. The number of sensors spikes even more when dealing with space crafts. The Curiosity Rover is a prime example of a sensor fused system which is located on the surface of Mars right now [35].

1.2.2 Medical Applications

Accelerometers do a very good job at tracking how humans move. Due to the highly rhythmic motion of running, accelerometers have a large amount of application in physical fitness. By monitoring this rhythm, the user's pace is kept and workout statistics, like calories burned, number of steps, or time elapsed, are provided. However, the context of this data could be further enhanced. When using additional sensors to perform data fusion, the application becomes more immersive. For example, the accelerometer data is combined with GPS data gathered from the run. Additional statistics can be provided, such as distance covered and route taken. Together, this data provides a great record to determine physical gain or loss. There are systems that fuse this data together with Bluetooth sensors, such as a Bluetooth heart rate monitor. This not only gives the user more information, but also accurate information, which allows for more creative applications than solely progress tracking. One system cross-references the heart rate with the tempo of a song. If the user is slacking and needs to pick up the pace, a faster song is chosen. On the other hand, if the user is over exerting themselves the system will pick a slower paced song. Similar systems are seen when extended to rehabilitation monitoring.

Many application sensors exist in the field of preventive medicine. Walking produces similar, yet mild, signals as running does. The rhythmic sine waves are an easy mark which represent a walking signature for that person. However, each person has a different signature. Over time, a person's walking signal will change due to age. By long term monitoring of this signature, detected differences can lead to diagnosing early stages of dementia. However, this method is crude and unable to fully detect dementia alone [25]. Therefore, it is used as an initial signal to begin the fusion processes with additional sensors, such as brain scans and balance tests.

Sensors are also used as an early alert in unpreventable situations such as falling [43]. By placing an accelerometer on key body parts, one can monitor whether that person has experienced a fall. Since falls may require immediate medical attention, it is important to respond quickly after they occur. It is also important to reduce the number of false positives, or the report of a fall when one did not really occur. Accelerometer readings alone can lead to false positives; however, sensor fusion helps reduce the number. The accelerometer can be combined with other sensors, such as a camera. Once a fall is detected, a wireless signal is sent to enable a camera. An image-processing algorithm provides a frame of reference and performs further analysis to reduce the number of false positives. Heat mapping is another popular technique using fused camera data to track the most common area people walk in order to determine if a fall has occurred [53].

Besides detecting falls, sensor data can also provide early alerts to the caregivers of older adults experiencing wandering due to dementia. Location data is used for this; however, this data alone will not lead to a reliable metric for wandering detection. Instead, location data is fused with additional information such as the time of day, weather, and distance from home. A learning network is constructed and these parameters are collected. The result is a probabilistic value that is used to determine the likelihood of wandering. When that value is high, the caregivers are automatically alerted to address the situation [58].

Sensor fusion has also given rise to applications that help fight fires. Firefighters operate several sensors that gather critically important information in saving lives. There are several sensors to monitor the health of the fighter and temperature of various areas. Fusing of this data provides additional information that is used to provide environmental context. Siren is a system created at Carnegie Mellon University that aggregates all of this data and presents it to the firefighter [31]. By enabling the emergency workers to communicate information quickly, life-saving decisions are made more efficiently and accurately.

1.2.3 Sports Applications

Sensor fused applications can be extended from the medical field and into sports. Due to the highly competitive nature of organized sports, there are many ways in which sensors are applicable. By gathering information from play field or equipment, techniques can be evaluated and improved upon. Much like monitoring for physical fitness, sports monitoring determines when the athlete is fatigued or injured. Accelerometers can be placed in a baseball along with grip sensors. Data is collected during practice sessions and baselines for the athletes are constructed. During the game, this data is referenced to determine if the athlete is performing at an expected level from which strategic decisions can be made [38].

Concussion prevention, detection, and treatment is another big area of interest, especially in American football. Concussions do a considerable more amount of damage when they go undetected and untreated. While only a single accelerometer or gyroscope needs to be used, the player greatly benefits by using an inertial fused sensor. Brain Sentry is a system that monitors spikes in gravitational force signals in the head area. The spikes are a strong precursor for a concussion and also serve as a hit counter over the course of a season [1]. The system can be improved by fusing sensors for additional readings. Once a concussion occurs, other areas such as the walking and running signature can be affected and then evaluated and fused with existing data.

Data fused while performing complex actions like throwing a baseball can measure the level of the user's technique, which is noted and compared to peers. Areas of improvement can be found and an individualized plan is constructed. One system, called Graspables, uses touch sensors embedded inside of a baseball. The sensors record the user's grip during a pitch. This information is saved, and the pitcher's grasp can be evaluated. It can also be used as a training aid for a new pitcher to learn the techniques of a more experienced player [63]. This system would not be able to recognize all of the pitcher's fingers if only one sensor was used.

In a sport like golf, club head speed is important. The faster the club head speed, the farther the ball travels. It is also important that technique remains consistent. However, club head speed is also affected by wrist rotation. One system uses inertial sensors on the body to create a body area network. These sensors provide feedback to a base system that allows a reconstruction of the swing to be made and analyzed [33]. Other sports, including basketball and baseball, have similar constraints. When a basketball player is shooting a free throw or a baseball player is pitching a fastball, having the same technique is important for producing the same outcome.

There are times in which the input range of the sensor may need to vary. Using pitching as an example, the player can throw fastballs or changeups in which their arm speed varies a great deal. However, accuracy of the readings is still important and would be lost if only a single range sensor was used. Instead, a version of the Sensemble system was adopted. This system was made with a wireless sensor with gyroscopes and accelerometer sensing high and low gravitational forces. The accelerometers are also multi-axis to increase the dimensions in which the forces are occurring. In order to eliminate noise in one study, a Butterworth low-pass filter was employed to remove erroneous readings at excessively high frequencies resulting in increased precision. This system was controlled wirelessly through a base station that acquires 5.6 seconds of 1 kHz samples to monitor data pitch-by-pitch [38].

CHAPTER 2

PERFORMANCE MONITORING FOR OLDER ADULTS

Through sensor fusion, new types of health related applications are enabled. This author has researched and implemented several applications that take advantage of sensor fusion in order to monitor the performance of older adults. By smartly monitoring their performance, we were able to create applications that automatically call for help when needed thus allowing them to live more independently and providing peace of mind. This suite of applications were developed for the Android platform using commercial smartphones. It consists of three applications: iFall, iWander, and BEAT. These applications help monitor falls, wandering, and bio-environmental data respectively [60].

2.1 iFall

The first application to be developed in this suite was iFall. With the number of seniors on the rise, falling is one of the greatest risks that this demographic faces. Falling is a leading cause of injuries as well as reason for admittance to nursing homes. The goal of this project was not to prevent falls, but to offer a cost effective solution to automatically monitor and alert loved ones in the event of fall. Thus, by alerting a third party, the amount of time the user may be on the ground, a termed referred to as a long-lie, would be greatly reduced allowing for a greater rate of recovery [59].

2.1.1 Sensor Fusion in Existing Fall Solutions

Before the mass emergence of smartphones, there were typically three options in which older adults had in order to issue alerts when a fall occurred. The three main methods were video, vibration, and push button alert systems. Out of the three, only one method, push button systems, has arguably seen wide spread success. However, all three solutions use some form of sensor fusion.

The first solution is to use video data. The user would have several cameras installed throughout their home in order to monitor all the rooms in which the user was located. In this case, the sensor fusion occurs in the fact that several cameras are needed in order to see all the living areas in which the user was in danger of falling. The most problematic areas include the bathroom and bedroom since many users are concerned about their privacy. In order to detect a fall using video data, algorithms are created that monitor how the user travels throughout the room. Data about where the user enters and exits the room along with places in which the user is stagnate, such as a chair, couch, or bed is combined in order to determine normal movements. In the event that a fall occurs, the user would be lying on the floor or against the wall. The camera would see that this is not typical activity of the user and could issue a fall alert with high confidence.

An alternative solution to home fall monitoring is to use vibration sensors embedded in the floor. Once again, several sensors have to be fused together in order to achieve full monitoring of all living areas. In this solution, the sensor monitors the vibration patterns of the user. Once normal readings are gathered, the system would be able to detect abnormal readings and to alert for help. In this case a fall reading, exemplified by a sudden spike, would be abnormal and contain a greater surface range and higher readings, as a result of a heavy human body falling to the floor rather than a light household item [43].

As previously mentioned, the solution that has seen the most commercial success is the push button alert system. In these solutions, the user carries or wears some sort of button or touch sensor that they can press in case of an emergency. One of the problems is that this button must be in range of another receiving device in order to make the call for help. As with the aforementioned solutions, this system will not work if the user is outside their home or in an area in which the sensors are not able to signal for help. In addition, the user must actively touch the sensor to start the call for help; there is no automatic solution. However, this solution is successful due the fact it is easy to install, easy to use, and is cheaper to purchase than the others. Of course one could fuse a hybrid of these solutions in order to achieve the greatest accuracy and reliability. The cost and practicality of this becomes a greater issue.

2.1.2 Accelerometers and Activities of Daily Living

The author's proposed solution depended on monitoring gravitational data. The sensor of choice for gathering this data was the accelerometer that existed in current Android smartphones. By

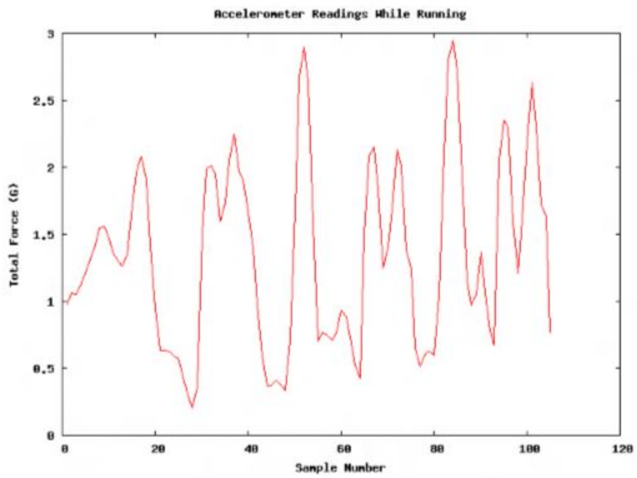


Figure 2.1: Total gravity force over time while running

monitoring this data, the phone can sense, like existing solutions, when a non-normal event has occurred and automatically call for help. The key in this solution is determining when this non-normal, or falling event has taken place. In order to create context, it is important to know the daily routines for the demographic.

For older adults, activities of daily living (ADL) rarely cross an upper threshold of 3.5 G. This is due the relatively low impact events that are most common in their lives. Any time an older adult experiences over 3.5Gs they may be at risk for injury due to the jarring nature of this amount of force. This upper threshold was derived by processing data from an accelerometer while it was attached to a subject whom was performing day to day activities. To attempt to classify ADL some initial processing on the accelerometer data was done. A typical accelerometer gives three outputs in the terms of G force. These three outputs correspond to the X, Y, and Z direction relative to the sensor. The inputs are combined into a total G force by performing the root sum of squares as shown in 2.1.

$$\sqrt{x^2 + y^2 + z^2} \tag{2.1}$$

Graphing the total gravitational force with respect to time creates waveforms with signatures that can be categorize which ADL was performed. 2.1 displays the signature of jogging or running. This is very similar to walking in that their sine wave has the same shape with the main difference

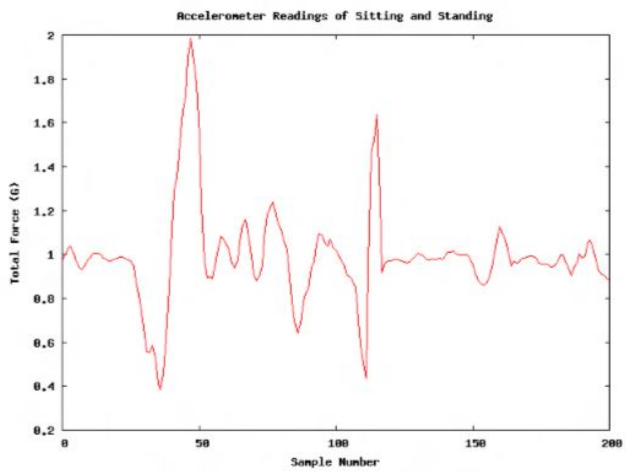


Figure 2.2: Total gravity force over time while sitting then standing

being the amplitude. 2.2 is another example that shows the signature for sitting then standing. Older adults at risk of falling typically perform these actions more gently in order to keep their balance.

Using an upper threshold as a sole metric for fall monitoring would result in a low confidence solution. Therefore it is important to identify exactly what a fall looks like in order to achieve a high success matching it. 2.3 shows a typical fall signature processed in the same fashion as above. The first part of the fall signature starts with a dip in total G force. This takes place when the accelerometer is in freefall and the total force on the sensor approaches 0G. The second part of a fall signature is a spike in the graph, above the ADL threshold. The peak in total G force is a result of the sensor coming in contact with the ground and experiencing a sudden stop. The result is a sudden, jarring force that tends to do damage to older adults. This damage may leave the unaccompanied adult on the floor, perhaps in pain or unconscious. This translates to the third part of a fall signature, the long-lie. This is captured on the graph as a long-flat line, around 1G in which there is very little motion. It is at this point in which the system must attempt to get help.

2.1.3 Touch Input and Social Monitoring

Once all three parts of a fall signature are met, the system suspects that a fall has occurred. However, touch input is used before issuing an alert to ensure a greater confidence. There are various scenarios that may look similar to a fall, but there is no need to issue an alert. Those issues

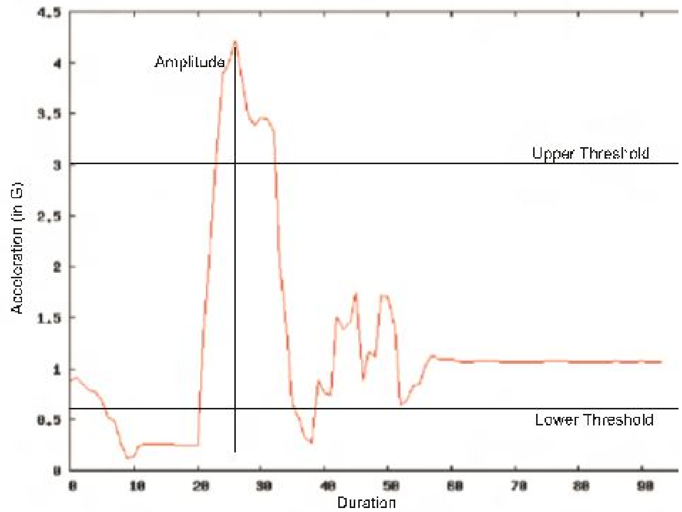


Figure 2.3: Total gravity force over time while falling

include: dropping the device (and leaving it on the ground), running and then coming to a sudden stop, and sitting down with excessive force. To avoid missing true positives, these cases were not accounted for specifically in the fall algorithm. Instead, another sensor was fused into the process.

Once a fall is suspected, the system issues a prompt to the user for touch input. The phone will ring, flash, vibrate, and perform typical notification actions in order to get the users attention. The system will then await for a simple touch input by the user for a specified amount of time, usually in order of magnitude from 30 seconds to 1 minute. If the alert was issued by mistake or the user did fall but is not in need of medical assistance, they are able to touch the device's screen to cancel the alert process. If they do not give any touch input, the final step of the alert is taken, an alert to social monitoring.

Social monitoring is a concept that the user has a social networking comprised of friends, family, and loved ones that are able to respond to alerts in an emergency. This network is automatically called by the phone and the phone places the call on speaker in order for the social network to evaluate the situation further and alert trained medical professionals if determined necessary. In this system, a single call is made to a Google Voice number set up by the user. The Google Voice number has the functionality to simultaneously forward the call to several people in the social network. Once someone has answered, the phone is placed in speaker mode and left to the social monitor to further evaluate. The alert has also been fused with additional sensors such as GPS via SMS in order to identify the user's exact location.

2.2 iWander

The second application, iWander, is designed to monitor performance for older adults with dementia. A side effect from this chronic condition is wandering. Having an early alert system can be lifesaving. This application fuses together GPS sensor data with contextual data to determine if the user is at risk of wandering. If wandering is suspected the system automatically issues an alert using social monitoring as previously described. This application is only intended to be used while users are on foot. Wandering while driving is outside the scope of this application [58].

2.2.1 GPS and Context Data

The application combines user specified information with GPS data and current weather to determine if the user is at risk of wandering. When the application is first started, the user supplies basic information such as level of dementia, safe location, and safe radius. The safe location is typically the user's home and can be automatically discovered when the user charges their phone. The safe radius is the distance that the user must travel away from the safe location before an alert is issued, similar to a geo-fence. Current weather conditions are also automatically gathered via the wireless adapter in the device.

All of the information acts as input for a decision making process that outputs whether the user is at risk of wandering. First, in order for any alerts to be issued, the user must be outside of the safe radius. Once outside the safe radius, the distance outside, duration outside, time of day, and weather are taken into account. Each of these pieces has an effect on the probability that the user is wandering and a relation can be created as shown in 2.4. As the distance outside the safe zone increases so does the probability for wandering. This is also the same for duration. Time of day impacts the probability based on daylight. If the user is outside during daylight hours, they are less probable of wandering. Next the weather is taken into account. Any time the weather conditions are outside of a comfort zone the probably of wandering is greater. Finally, the level of dementia has an overall impact on the wandering probabilities. Therefore, the probability of wandering for a medium level dementia user one mile outside their house at noon on a spring day is much less than a high level user four miles outside at nine pm on a cold night.

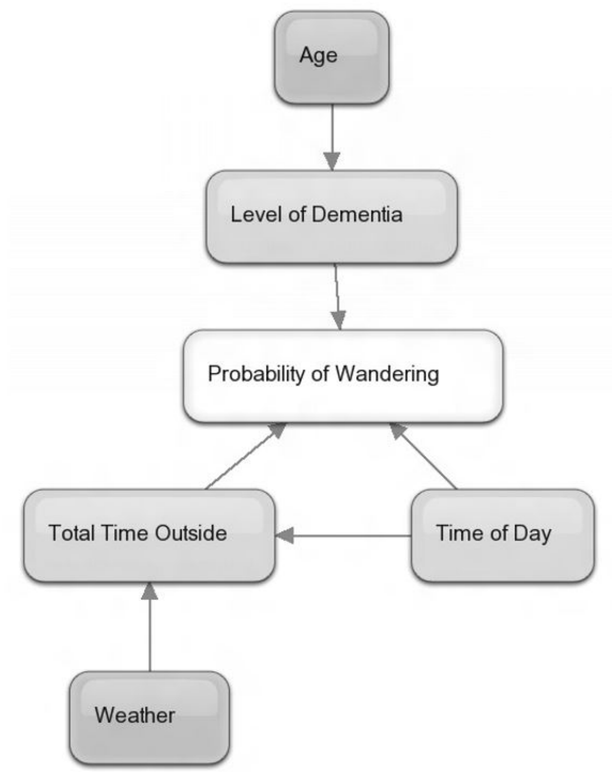


Figure 2.4: Contextual relations related to the probability of wandering

2.2.2 Learning through Touch Alerts

When an alert is issued it follows the same flow as described in social monitoring. The first alert goes to the user to filter any false positive. The user is able to manually cancel the alert in the form of a touch sensor. If the user does not touch the screen to cancel the alert, notifications are sent to the social network. It is here when this feedback is incorporated back into the system in order to increase accuracy. All information is given to a machine learning network that modifies the wandering probability for the given scenario based on any cancellation. As the system is used more frequently there is a larger data set and the accuracy increases.

2.3 B.E.A.T Bio-Environmental Android Tracking

BEAT is the final application in the medical monitoring suite for older adults. BEAT is an acronym for Bio-Environmental Android Tracking and is geared towards being a contextual computing framework. As the other applications in the suite gathered data, there was a need for a framework that collected, processed, and served information about the various inputs. BEAT was the framework that solved this problem. It would allow other applications to provide it data and/or rules. The framework would then serve queries about that data or issue notifications based on the various rules. Other applications can consume this data and developer smarter workflows and experiences [41].

2.3.1 Data Size for Sensors

One goal of BEAT was to gather data from a wide range of channels. These channels are intended to be a mix of biology and environment sensors. With the integration of Bluetooth on standard devices, there are a large number of medical devices that measure vitals such as heart rate, blood pressure, and blood sugar. This various data could all be feed into BEAT. In addition, there are also a number of environmental sensors that are currently on devices such as GPS and accelerometers. One concern for dealing with this data is the storage size.

The storage size is based on how much data is generated from the inputs. The data generated from the inputs is expected to be text data containing a small number of values. However, these values will be growing in relation to how often they are being polled. 2.1 shows an estimate of how many times over the course a year various sensors will be polled. An accelerometer is expected to

Table 2.1: Polling frequency of several common sensors

Reads per	Heart Rate	GPS	Accelerometer
min	3	2	180
hour	180	120	10800
day	4320	2880	259200
week	30240	20160	1814400
month	907200	604800	54432000
year	10886400	7257600	65318400

Table 2.2: Raw storage requirements in KB for various sensor

Data size	Heart Rate	GPS	Accelerometer
day	22	6	310
week	154	42	2170
month	4620	1260	65100
year	55440	15120	781200

be one of the highest frequencies, polling at three times per second. This needed to be at a higher frequency due the requirements of iFall's falling algorithm. However, the majority of sensors are expected to poll at a much less frequent rate.

After taking into consideration the polling frequencies, the next part to consider is the amount of data each poll will consume. Many of the sensors are expected to only consume a few bytes of data, with the accelerometer being an upper level case. 2.2 shows an estimate of the amount of storage space it would require to service all the polls in 2.1.

In addition, this text data came be further compressed using a number of popular compression algorithms. 2.3 calculates the storage requirements using a simple compression algorithm that stores the deltas between readings. The main point for illustration is that all of this valuable data about the user can be stored in a few gigabytes over their entire lifespan. By digitizing a person's life, countless possibilities are introduced by studying, achieving, and cross referencing this data. This leads the way for even smarter applications.

2.3.2 Contextual Applications

Contextual applications make use of the additional data to create richer experiences for the user. By using the BEAT service, this data can include readings from biology and environmental sensors. The applications previously mentioned, iFall and iWander, subscribe to BEAT and are considered

Table 2.3: Compressed storage requirements in KB for various sensor

Data size	Heart Rate	GPS	Accelerometer
day	6	3	150
week	42	21	1050
month	1260	630	31500
year	15120	7560	378000

to be context computing applications. Another example of a context computing applications that uses BEAT is Tempo Trainer. It is an application used for running that uses the heart rate data to adjust the tempo of the music that is playing to optimize a user's workout. If the user's heart is not following the optimal beats per minute range then a faster tempo song will play to signal to the user that a quicker pace is suggested. The opposite is also true if the heart rate is too low.

CHAPTER 3

PERFORMANCE IMPROVEMENT METHODS FOR ATHLETES

This section discusses several methods and exercises currently used to improve the performance of athletes on another level, not necessarily directly related to their sport. The first subsection introduces several commercial systems that are available in today's market that specifically force on sensory improvements. The next section discusses temporal occlusion and training the athlete to use a subset of visual information more efficiently. The final section explores the idea of video games providing a way for athletes to improvement the amount of visual information they can both process and retain.

3.1 Commercial Systems

This section introduces several commercial systems available to train the sensory circuits of athletes. Each system is currently available in today's marketplace and considered to be in the main stream. The highest profile system is the SPARQ Sensory Performance by Nike. This system is expected to have the highest visibility and adoption rate due to Nike's large advertising budget and established distribution channels along with several high profile professional athlete endorsements. The successive systems, Eyeport and High Tech Vision Training, were discovered after performing several search queries related to the subject. Both systems claim success, but take vastly different approaches in achieving performance gains.

3.1.1 SPARQ Sensory Performance by Nike

The Nike SPARQ Sensory Performance is a system that helps athletes train with the goal to "build a better athlete." This goal is achieved in three parts. First, the athlete performs several vision analysis exercises at Nike SPARQ Sensory Stations. These stations are comprised of interactivity touch screen devices that host ten different assessments which include: visual clarity, contrast sensitivity, depth perception, near-far quickness, target capture, perception span, eye-hand coordi-

Figure 3.1: Nike SPARQ Vapor Strobe Eyewear

nation, go / no go, hand reaction time and visual endurance. A Nike SPARQ Sensory Performance Profile is then created for the athlete outlining their test results. This data is compared to any previous scores as well as scores from the user's peers. A vision training routine is then constructed for that athlete to improve his or her skills. The evaluation stations retail for $85,000 and usually a 36-month lease.

After the training plan is made, Nike produces the Nike SPARQ Sensory Training Station, which, like the evaluation station, is constructed with wall-mounted interactive touch screen devices. Depending on the plan, several exercises are run that focus on one of four areas of development sensory skills, depth perception, eye-hand coordination, decision making, and split attention. These systems are retailed at $55,000 [46].

The second part of training requires Nike SPARQ Vapor Strobe Eyewear. This device looks much like a pair of lightweight ski goggles as shown in 3.1. The lenses in the Vapor Strobe Eyewear are actually tiny, curved LCD screens that have the ability to alternate between transparent and opaque at variable rates. The athlete then practices wearing these goggles. By reducing the amount of visual feedback the athlete receives, he or she is forced to use more of the information that is available. This method of training is called temporal occlusion. There are also settings to allow each eye to operate independently to work on depth perception. These units retail for $300 [12].

Nike funded researchers at Duke University to perform a study on the Vapor Strobe Eyewear, the goal of which was to determine whether visual cognition was improved by stroboscopic training.

In other words, could training with limited visual information generalize the athlete's visual learning ability to become more superior once they regain full vision? Researchers used 157 students from the Duke football and ultimate Frisbee teams to test the eyewear. After performing the Nike SPARQ Sensory Evaluation, subjects were split into two groups. Eighty-five subjects underwent vision exercises in the lab, and the remainder only did field drills for their sport without vision exercises. The results found that the athletes using stroboscopic training had the greatest positive impact in their central field of vision. They were able to more easily recognize objects and motion directly in front of them. Results could be measured in as little as two day of training. The study did not, however, yield significant results increasing the athlete's peripheral vision [3].

3.1.2 Eyeport by Vision Training System

Vision Training System created the Eyeport, which aims to exercise the muscles in one's eyes. Having strengthened eye muscles gives a person the ability to see and focus better. The unit, as shown in 3.2, consists of a long beam and glasses with one red and one blue lens. The user, while wearing the red-blue glasses, sits around 24 to 30 inches from the beam. This beam has embedded red and blue lights, which it flashes in different patterns. The human eyes respond differently to red and blue lights. Red causes the eye to focus and blue causes the eye to relax, a phenomenon called "chromatic aberration." By performing a series of exercises that has users follow alternative lights for ten minutes per day, vision strengthening is achieved. This system currently retails for \$239.95 [50].

The Pacific University College of Optometry performed a study evaluating the Eyeport system in which 31 participants performed 12 different tests evaluating oculo-motor function, visual reaction time, visual endurance, and general vision skills. The results provided evidence that the Eyeport vision training helped to improve users in the areas of vergence facility, reading performance, and timed depth perception. The positive effects were reported lasting up to three weeks after training ceased. All subjects in this test were visually fit college students [39].

3.1.3 High Tech Vision Training

The High Tech Vision Training System uses a machine called "The Cannon," shown in 3.3 a pitching machine that launches tennis balls between 60 and 100 miles per hour. The goal is to have users focus on the high speed, moving ball and also to see a target the size of a nickel. Each

Figure 3.2: Eyeport by Vision Training System

tennis ball has a number written on it in several spots and in different colors. The assumption is that once users are able to focus and see these numbers, they will be able to make better contact with the ball. In order to see the ball better, users must keep the ball in their central vision for the entire length of the pitch, from the time it leaves the pitcher's hand until the time is crosses the plate. If the ball crosses into one's peripheral vision, then it creates a curve-like effect, an optical illusion that can hamper one's attempt to successfully track the pitch. This system was used by the 2008 and 2009 NCAA World Series softball champions [66].

3.2 Temporal Occlusion

Oftentimes, high-level athletes train using "temporal occlusion," which is defined as "the selective editing of clips to provide a limited amount of visual information" [51]. The purpose of this training is to force athletes to analyze the limited information they do have in order to make a decisions. By removing information like the location of the ball or approach (depending on the specific sport), the athlete typically has to place more emphasis on secondary information such as the non-kicking/non-throwing leg/arm or other body parts. Ultimately, athletes must progress their observation skills in order to anticipate what is coming.

The image in 3.4 is an illustration of temporal occlusion for a serve in tennis. The athlete in training is provided these frames and then may be asked in which direction the ball will travel, what spin it will have, or what arc it will have [51]. While athletes may not by consciously aware of

Figure 3.3: The Cannon by High Tech Vision Training System

their improving observation skills, they are subconsciously gaining the experience needed to react and anticipate better. Typically these exercises have a definitive answer, the ball actually did land here or spun this way. It could be challenging to derive the outcomes. One technique that could be used to evaluate performance is to relatively compare athletes to one another. The top ranking athletes are then considered to be expert level providing an upper limit for comparison. This idea of expert level performance and evaluation is discussed in length in the upcoming Spatial Awareness section.

3.3 Video Games

Duke's Visual Cognition Laboratory was responsible for performing the study on the Nike SPARQ. In addition, they have several other areas of related research. The goal of their laboratory is to understand the relationship between what we see and what we know. This includes studying areas of visual search, multiple target search, perception, attention, and memory [3].

One of their studies was conducted to determine whether people who play action video games see the world differently. This study tested gamers and non-gamers' visual abilities. The goal was to determine if we can retain something in memory by varying the amount of time we see it. The

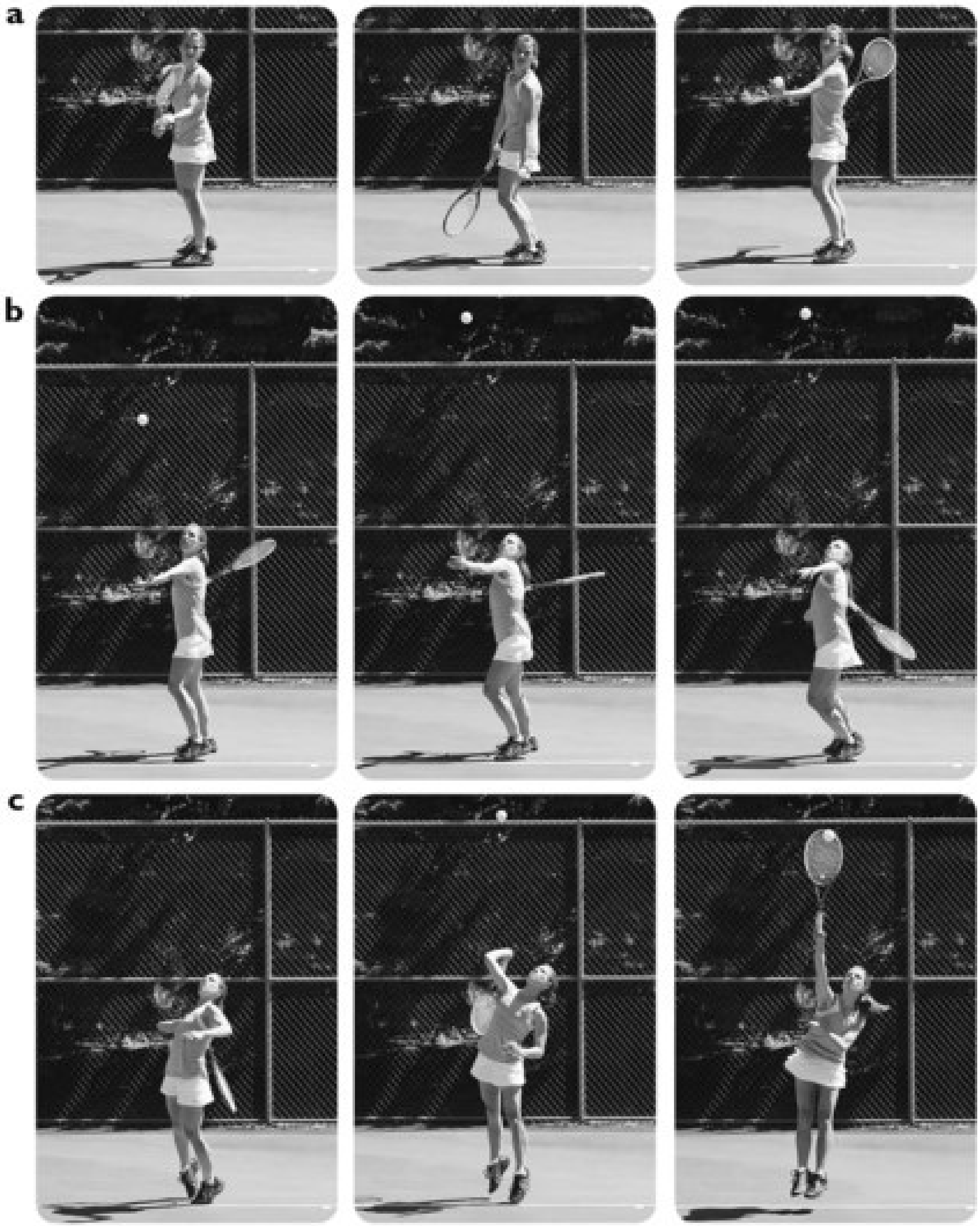


Figure 3.4: Example of temporal occlusion training with tennis serve

test flashed eight letters arranged in a circle for one-tenth of a second to the subjects. There was then a variable blank period in which all the letters vanished. Finally, an arrow appeared on the screen point to the location where a letter once was. The subjects were then asked to give the name of the letter that was previously at the location where the arrow is pointing. Results showed that the intense gamers beat the non-gamers every time, no matter how long the blank period was. However, there was not a difference between the two groups when it came to the rate of memory decay about the position of the letters. The final conclusion is that the intense gamers captured more visual information initially [2].

Because of their findings, this section was included as an illustration of the performance enhancement of athletes by using video games. The findings highlighted that hardcore gamers were able to capture and retain more visual information. Theoretically, this correlation should pertain to athletes as well. Therefore, if an athlete spends more time playing video games, they will exercise their visual circuit thus resulting in a better performance of their visual system. Note that not all video games are the same and may not produce desired results. For the purpose of this argument, only the games with rapidly changing visual and deeply intricate environments should be selected as training material. Games that are slow moving and static may not provide the level of engagement needed in order to see results.

CHAPTER 4

PERFORMANCE MONITORING USING VISUAL COGNITION

Visual cognition, a process by which the eyes interpret what they see and decode the information in the brain, can be improved by the use of phone-based sensory application systems. Routinely performed when people use their eyes to interact with the environment, this process is usually achieved without any perceived effort. It starts when information, in the form of light, enters the eye and is processed by the brain. The brain then uses this knowledge to make sense of the world as illustrated in the 4.1.

Sensory application systems essentially enable training of this visual cognition. The commonplace of smartphones helps put these sensor-based applications in the hands of everyone. The ability to see better is widely desired. It is so desired, in fact, that people are willing to pay for it. The sports industry, for example, directly benefits from improved visual performance. In response to these needs, application systems that improve vision are being commercialized. Applications can improve visual cognition in several areas including acuity, awareness, and reaction time. They enhance visual cognition by employing various techniques including temporal occlusion, focusing, and attention exercises. The success of these application systems can be measured by merging data from sensors and drawing complex conclusions.

4.1 Physiology of the Eye

4.1.1 Gathering Light

Turning vision into information starts with the eye. Information enters the body through the eyes in the form of light and passes through a frontal section called the cornea, which houses approximately two-thirds of the eye's optical power [32]. The cornea is curved, causing the light to refract and pass through the lens, which also has a curvature. The cornea and lens use their curvatures to focus the light precisely on the back of the eye, a layer of tissue called the retina, and more specifically on an area called the fovea. The process of gathering and focusing light on the

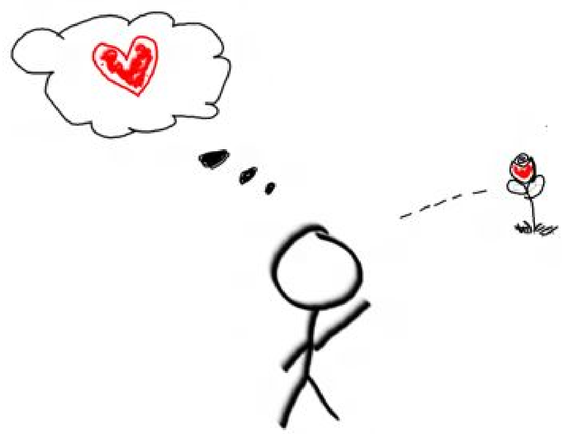


Figure 4.1: Making sense of the world through visual cognition

retina is displayed in 4.2. The bending of light to converge around the fovea is similar to the way a camera lens focuses light on film.

4.1.2 Processing Receptor Information

Once the light is properly focused, image processing can begin. The light enters the outer nuclear layer of the retina and reacts to photoreceptor neurons known as rods and cones. These neurons facilitate the low level process of converting light into electromagnetic signals of the brain. Cones are concentrated in the center of the fovea and are thus sensitive to stimuli located in the central visual field. Despite this area only being ten degrees of the entire visual field, the majority of the one's focus are spent in central vision. During daytime, in well-lit conditions, several hues of colors can be perceived in the central vision, a term called photopic vision. The perception of color is determined by the size of the color's wavelength and the three different types of cones that respond to them. These cones are called the S, M, and L cones referring to the short blue, medium green, and long red wavelengths to which they optimally respond. The rods, in contrast, are located around the perimeter of cones and used for scotopic vision. Scotopic vision occurs during night time under dim-lit conditions and thus lacks diverse wavelengths. This causes the sight in this area to be achromatic and only able to respond to one wavelength or color. These rods are a key factor in determining the movement, direction, and contrast of an object [24].

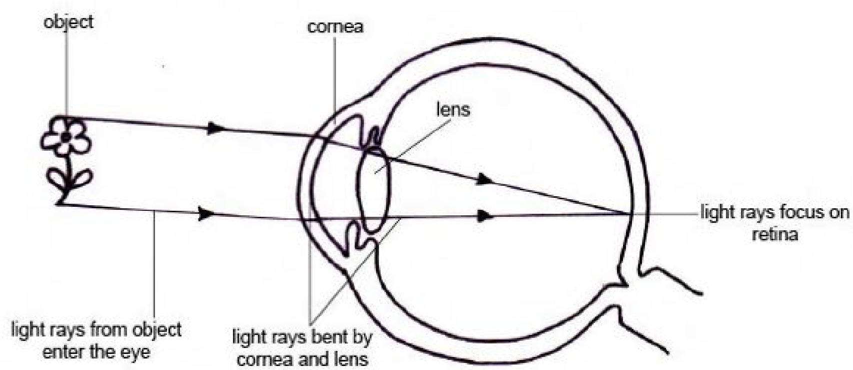


Figure 4.2: How the eye focuses light from an image on the retina

Despite responding to different wavelengths, rods and cones achieve the same goal of phototransduction in a shared fashion. Phototransduction is the process of transforming the light on the photoreceptors, rods and cones, into electric brainwaves. It starts with inactive Na+ channels in the photoreceptors. While inactive, in no light, these channels are open and release a substance called glutamate. When the photoreceptors are in the presence of light, they activate and have a reaction with a substance called rhodopsin, which causes the channels to close, thus stopping the flow of glutamate.

The ganglion cells, located at the bottom of the retina's nuclear layers, receive the varying levels of glutamate and respond. The level of response depends on which type of ganglion cell is processing the glutamate. There are two major types of ganglion cells, called the ON and OFF cells, which respond inversely to glutamate. ON cells respond more rapidly when glutamate is absent in the presence of light while OFF cells respond more rapidly when glutamate is present in the absence of light. There are also two minor types of ganglion cells called transient and sustained. The main difference between them is that sustained cells continue to respond rapidly in the presence of the stimuli, whereas transient cells only experience a spike in reaction during the onset and then calm back down. All types of ganglion cells, however, finish the process of phototransduction by responding in the form of generating electromagnetic brainwaves, often referred to as neuron "firing." In addition, the firing rate of neurons is affected by more than just a simple ON/OFF light source. Orientation, color, contrast, disparity, and movement direction all have an impact on the firing rate of neurons. The firing rate is needed for the neurons to complete their low-level processing responsibilities [10].

Because phototransduction is directly dependent on the presence of light, a wealth of information reaches the retina and causes it to apply adaptive filters. Throughout the day, several different light intensities activate the photoreceptors, which causes primary vision to shift back and forth between rods and cones. As described, each of the neurons outputs information describing different parts of the visual scene. For example, in daytime, when light is abundant, the cones in the central vision are used processing fine-grain details. Conversely, during the darkness of night, the rods in the peripheral vision system are primarily used, placing emphasis on disparity and movement direction. Under both conditions, the surface reflectance of an object must be calculated under varying light intensities in order for it to be perceived. Adaptation of light allows the retina to filter unnecessary information about intensity while keeping the important information about object reflectance. This entire filtering process must be completed in the eye or else there would be too many firing combinations for brain to handle [65].

4.1.3 Saccades

Eye movements are necessary in order to keep all of the neurons involved in phototransduction active. Without eye movements, these neurons would cease to fire, causing the image on the retina to fade and no longer be perceived. Even during voluntary fixations when focus does not appear to be changing, the eye is still subject to involuntary movements. These involuntary eye movements, called saccades, are important in the continuous action of phototransduction. Saccades only perform micro-movements; however, the receptors in the retina are so dense that even the slightest adjustment has a major impact [32].

Along with eye movements come lapses in vision. When the eye sweeps across a scene, the image is subject to motion blur. However, this motion blur is not perceived by the eye and the image still appears to be in high contrast. This has been tested by showing subjects different images of high and low contrasts. The results showed that when the high contrast image remained on the screen for an extend time after the saccade, the blurred image was not perceived at all. This led to a realization that the brain overwrites lower contrast images with high ones during a saccade [13].

Scene stabilization during a saccade remains fully unanswered. When the eyes move, so does the light and visual image on the retina. However, even when the eyes are moving, a scene appears to

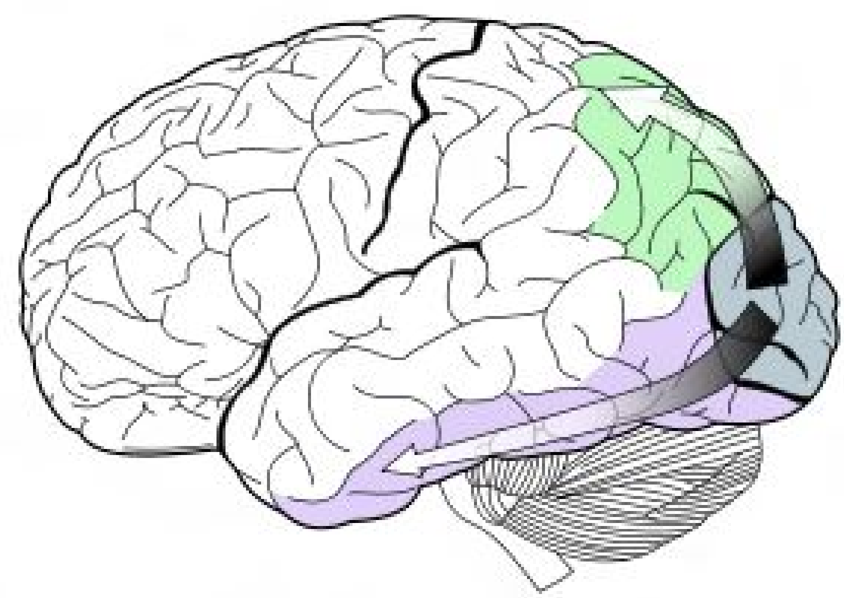


Figure 4.3: Ventral pathway (purple) and dorsal pathway (green) in the brain

be stable and does not jump. Part of the reason this happens is due to the neurons' reactions during the saccade. It has been shown that they can stop responding to the current visual stimulus and get ready to respond to a new one. In fact, these neurons can even begin to respond in anticipation of a saccade. However, the reasons for many of these responses are yet to be understood [9].

4.2 Physiology of the Brain

4.2.1 Contour Integration

When information leaves the retina, it travels down the optic nerve toward the brain, eventually reaching the visual cortex. The visual cortex begins the intermediate-level visual processing and then forwards the information down either the ventral or dorsal pathway. The ventral pathway is responsible for determining what the object is, while the dorsal pathway is responsible for determining where the object is. 4.3 shows the locations of the ventral pathway, purple, and the dorsal pathway, green.

To make sense of an object, the brain must first analyze and identify the object itself. The ventral pathway uses the firing patterns of the ganglion cells to detect all the edges, boundaries, and orientations associated with the object while the dorsal pathway contributes context taken from the movement of an object. The brain then assembles all the information about the light intensities, depth perception, color, and edges to detect the object's foreground, background, and shape. The process of assembling smaller amounts of information about an object into complete picture is known as contour integration [23].

4.2.2 Cognitive Influences

Once the brain has used orientation, color, contrast, depth, and movement information to detect an object, the next step is to classify it. This process takes part along the ventral pathway in the inferior temporal cortex of the brain, which is comprised of two sections, the apperceptive agnosia and the associative agnosia. The apperceptive agnosia is responsible for visually recognizing objects, while the associative agnosia is responsible for understanding the meaning of the objects. When one factors in all the different ways an object can be viewed, object recognition becomes increasingly complex. The same object can be viewed from various distances, colors, illuminations, and movements; however, the brain sorts this information and comes to a conclusion. Often times, this conclusion is based on past experiences. Prior experiences or memories of an object that enable high-level processing of an object can be referred to as cognitive influences [22].

4.2.3 Perceptual Attention

The brain needs to give an object attention in order to have a cognitive influence, but how much attention is needed in order to perceive a difference? In an experiment testing perceptual attention, two images were shown to a subject, each set displaying one of two differences in the scene in which an object could appear or disappear, change colors, or move. These modified objects were classified as either central or marginal. Through testing, objects were deemed to be of central interests if three or more observers noticed them. Objects were marginal interests if this number was less than three observers. While the general color and intensity of central and marginal objects were the same, the change in marginal objects averaged 20 percent more than the change in central objects. The two images were also presented in different fashions, the first being the flicker paradigm. Image A was displayed for 240 milliseconds followed by a blank 80-millisecond period. This was repeated again before switching to image A' and thus repeated. So the images were displayed as A A A' A'. The results showed that it took people significantly longer to detect the marginal changes, despite

Figure 4.4: Yarbus study of eye movements focusing on human faces in "An Unexpected Visitor" painting

the scope of the change being larger. The detection time was reduced by extending the display time for each image in an A A' A A' fashion, and was even further reduced by providing cues, or hints about differences [52].

It can be concluded that while the brain is able to classify information about a scene, not every part of the scene is given full perceptual attention. In fact, various objects attract attention differently. A study performed in 1967 by Yarbus attempted to discover what parts of a scene are given perceptual priority. A subject was shown a painting by Ilya Repin called An Unexpected Visitor, and while the subject looked over the painting, their saccades were observed. The results showed that while the subject's eyes observed the stimulus, special attention was given to the faces of the people in the painting. 4.4 shows the results of Yarbus's study. The left side is the stimulus, the right side shows the paths that the eyes took while observing it. During eye movements, the eyes tended to have more frequent, longer fixations and increased perceptual attention on faces [69].

4.2.4 Psychophysics

Speaking about reacting to visual information leads into the field of psychophysics, the study of the relationship between stimuli and sensation. This field explores relationships of the perceptual system and how one views the world. In computer science, study in this area contributed to the development of the lossy compression algorithm, which reduces the file sizes of audio or images by removing the information that is out of the detectable range of humans. For example, a music file can be lossy compressed by removing all of the sound frequencies below 20 hertz and above 20,000 hertz as between represents range of frequencies that humans can perceive. The result is a smaller file size that appears to be of similar quality as the original file.

One military study took a psychophysical look at sensor-fused images, captured by sensors and merged together. In this case, images of various scenes were combined from several military infrared and i2 night vision sensors into one master image. The goal of this master image was to provide the operator with additional information in order to enhance their awareness. The researchers wanted to determine if sensor-fused images always achieved their goal over single images that contained less information. The results showed that fused imagery did not enhance the performance of a target object recognition task. However, it did aid with the tasks of judging scene orientation and scene recognition. The study arrived at the conclusion that sensor-fused images are task dependent and do not improve performance in all areas. This can be compared to a similar process in which the retina filters out information depending on the abundance of light [34].

4.3 Measuring Neurological Performance

4.3.1 Visual Acuity

Visual acuity is clearness, acuteness, or vision and relates to how sharp and focused an object is on the fovea. In other words, it is the smallest retinal image that can be seen by a person. If the light is not focused in this central visual area, then the object appears blurry and therefore unable to be perceived. Blurry vision is often times a result of refractive errors. These errors can occur in the lens of the eye, which scatters the light and does not allow it to properly converge on the fovea. Since the sensitive cones are used for central vision, they are unable to properly perform their function, resulting in a lack of visual performance. This is typically the reason for prescribing corrective lenses. These lenses manipulate the light, depending on the problem, to allow it to correctly focus on the proper area. Acuity can be broken down into two subcategories, static and dynamic visual acuity. Dynamic visual acuity is based on moving stimuli whereas static visual acuity is based on stationary stimuli. However, there is debate among experts in the field on the relationship between the two [56].

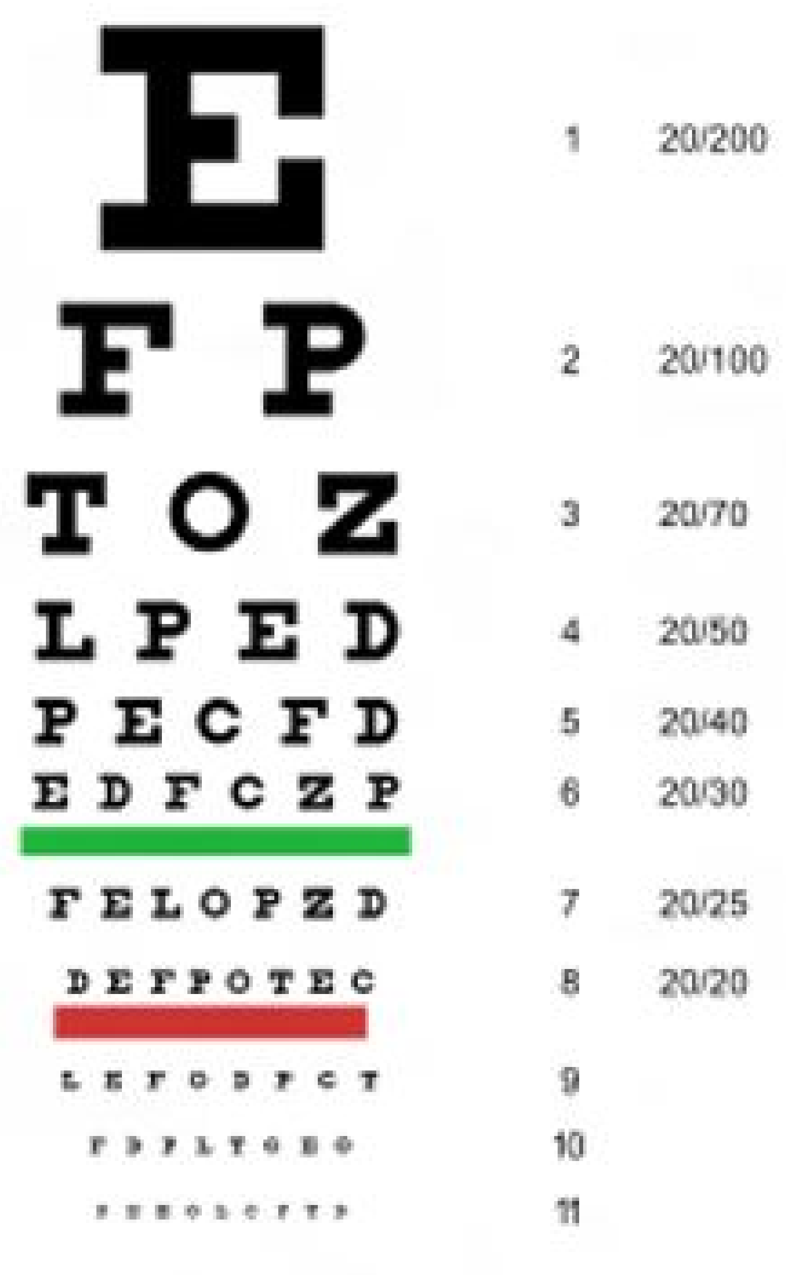


Figure 4.5: Snelling chart used to determine visual acuity

Visual acuity is typically expressed as the minimum visual angle or minutes of arc. A minute of arc is equivalent to one sixtieth of one degree, which can be used as a measurement of the spatial resolution of the visual processing system. A traditional way for testing and calculating visual acuity is the Snellen chart, displayed in 4.5, which contains a set of symbols called optotypes. These symbols, printed in black ink and placed on a white background, have a font with special geometric properties that determine their size and spacing. They are arranged across eleven lines, with each successive line displaying a larger number of smaller letters. Each line has symbols that are a size factor 1.2589 different from the neighboring lines [56]. During vision acuity tests, a person views the chart from a distance of twenty feet. Normal acuity, commonly referred to 20/20 vision, is the ability to read an optotype when it is subtended 5 minutes of arc. The optotypes that are 20 feet away appear to be 20 feet away. A person with vision impairments might experience 20/40 vision. In this case, objects that are 20 feet away appear to be 40 feet away.

4.3.2 Visual Evoked Potential

Visual evoked potential is an electrophysiological voltage that occurs in the brain after a stimulus is presented. As discussed in the previous sections, when visual stimuli is presented to a subject the image is processed in the retina, passed through the optic nerve into visual cortex, and down transferred the ventral and dorsal pathways. During this process, the brain emits electromagnetic signals, brainwaves, which can be recorded by averaging readings from electroencephalographic sensors attached to the scalp in various areas depending on the part of the brain being observed. This potential not only varies across several areas of the brain, but also varies when the visual stimuli is altered.

Electrodes used for recording brain activity during the test are recommended to have silver-silver chloride or gold disc surfaces. These are mounted to the scalp over the areas that the researcher wishes to monitor, which are typically the primary visual cortex and inferior temporal cortex. Researchers have debated over the precise amount of time it takes to record visual evoked potential from the onset of the stimulus. However, studies have shown that the first evidence of visual evoked potential in the primary visual cortex can be seen between 40 and 70 milliseconds after stimulus presentation and peak latency between 60 and 100 milliseconds [45].

There are common stimuli used for testing visual evoked potential, luminance stimulation, and pattern stimulation. Luminance stimulation is tested by presenting the user with a uniform flash of light, which should cover at least 20 degrees of the visual field. It thus covers the entire central visual field and crosses into the peripheral. The test should be conducted in a dimly lit room, and the strength of the flash along with the background's luminesces should also be recorded. Results for this class of potential testing tend to vary with different subjects.

The other class of testing is pattern stimulation. For these tests, subjects are presented with a checkerboard-like pattern of black and white spots. The procedure is similar to the first test, except that while viewing, the checkerboard pattern is reversed. This occurs back and forth with measurements while noting the beginning of the reversal onset. Pattern reversal potentials have relatively low variance among populations; however, visual evoked potentials as a whole seem to have age-dependent results [57].

4.3.3 Spatial Awareness

The definition of spatial awareness has been debated in the past and has been given alternative terms such as situation awareness. However, one of the most common definitions for spatial awareness is the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projections of their status in the near future." It is the totality of observing one's entire environment, processing the information, and then being able to predict what will happen. Spatial awareness has also been described as expert level performance. Typically, experts have a greater knowledge base and more experience that allows them to use long-term memories and better observations skills in order to understand and predict outcomes at a higher level [17].

There are a number of ways to measure spatial awareness, including explicit measures, implicit measures, and subjective measures. The majority of these tests attempt to analyze and grade a person's decision-making process. Explicit measures include techniques such as retrospective and concurrent measures. For retrospective measures, the subject is asked to recall events and describe their decision-making process after an event has occurred. Concurrent measures have the subject answer these same questions during the process of the event; however, this additional task may increase the subject's mental workload, which in turn decreases their overall performance [20].

Another mode for gathering explicit measures is utilizing the freeze technique, when the user is presented with information and then the information is stopped or paused. During this point of the simulation, the user is asked questions and evaluated. This technique is a hybrid of the retrospective and concurrent measures. Situation Awareness Global Assessment Technique (SAGAT) is a tool that helps implementation and evaluation of this technique and breaks the decision-making process down to three distinct levels, perceived data, comprehension, and projection respectably. This nonintrusive system was reported to produce accurate data that can be validated [18].

Measures of spatial awareness can also be found implicitly. One method of gathering implicit measurements is through external task measures, when data is greatly altered or removed from the simulation. The subject is then graded on their responses and decision-making process with the alterations. Another implicit method is embedded task measures, when the subject is assessed on the performance of subtasks that are highly dependent on the overall situational goals [21].

Lastly, subjective measures can be used to determine the level of situational awareness. In this class of measures, there are three main methods used to determine results. First, the subject is asked to rate themselves on their level of awareness. Theoretically, the subject knows their level of expertise best. Comparative self-ratings are another method, which requires the subject to review all of their self-assessments across several trials and rank them against each other. The last technique, which is unbiased, is observer ratings. In this instance, the observer is assumed to be an expert rather than being neutral to the situation, and so they are able to pull from their level of expertise and actually judge a third party [19].

4.4 Quantifying Cognitive Response

4.4.1 Reaction Time

Reaction time (RT) is defined as the time that elapses between a stimulus and the response to it. To be more specific, it is the summation of a sensory lag, an energy or intense processing lag, and a lag which depends on attentional, cognitive, and motivational factors. Interest in the theory of RT has been ongoing since Berger and Cattell began investigations in 1886 [8]. Pre-motor time, the time between the reaction stimuli to the first appearance of muscle action potential, has even been monitored using EMG machines. Since the first half of the 19th century, researchers have started spending even more time trying to understand how RT works [64]. Not everyone has the same RT to a given stimulus or event, and individuals often times have varying RTs to different types of stimuli.

However trivial a simple RT paradigm may seem, there still exist several different stages to RT, especially when trying to perform experiments in the lab environment. The first stage during an event is a warning signal that can range anywhere from a blinking light, sound, or announcement by the proctor. Next is the foreperiod, the amount of time between the warning stage and the reaction stimulus. This leads to the reaction stimulus, the point at which an event occurs that prompts the subject to respond. Many different simple and complex stimuli have been researched, ranging from showing a simple light to recognizing an image respectively. Now comes the response, which can also be simple like pressing a button or complex, like moving to a certain region. Lastly is the inter-trial interval, which is the amount of time between either the next warning signal or reaction stimuli [44].

4.4.2 Individual Variance

The interdependence of these events is very complex, because changing any individual event has a direct effect on the RT. A study on the foreperiod found that the fastest RTs occurred with constant foreperiods of 100-150 milliseconds. This study also confirmed, as one may assume, that faster reaction times can be achieved if the subject is better able to time the reaction stimulus due to constant foreperiods [44].

In one study, reaction and movement tests were performed on a group before and after an acute bout of stretching of the lower limbs. The study concluded that after the stretch, condition reaction time increased by 4.0% and movement time increased by 1.9%. The results can be attributed to the stretching, which caused an increase in muscle length, resulting in a delay of body signals [40].

As mentioned, one can expect various RTs based on various types of reaction stimuli. In Osaka's study, results showed that RT decreases as a function of increasing target size. Therefore, the bigger the visual reaction stimulus is, the faster the RT. The length of the stimulus also affects RT. If the length of the flash is short, it may take the subject extra time to realize that an event occurred, resulting in an increased RT. In one study, it was estimated that length affected RT on the scale of .002-.010 seconds [7]. The brightness of luminance of the stimulus, a factor with perhaps the greatest impact on RT, causes visual variations for an individual [68].

Perhaps bigger and brighter stimuli invoke quicker RTs for the same reason that audible stimuli do. It has been shown that when visual stimulation is combined with auditory stimulation, the RTs are faster than when visual simulation alone is manipulated. Auditory stimuli (especially loud stimuli), along with larger and greater luminance, have an automatic alerting property. As a result, this alerting property causes the subject to have a decreased RT, even if just the warning signal was auditory and not the stimuli [4].

Discussion of decreased RT naturally incites the question: what causes increased RT? Besides introducing opposite conditions of the stimuli aforementioned (meaning large, bright, loud would change to smaller, dimmer, and silent), are there any additional circumstances that may cause a lengthened RT? The addition of a second stimulus can inhibit the simple visual reaction time. This can, once again, be contributed to complex stimuli taking increased processing time. In fact, Merkel and later Hick showed that reaction time can be a linear function of the number of stimulus alternatives [67].

Hick's experiment indicates that in more complex scenarios, subjects are able to decrease their reaction time to presentations of reaction stimuli, increasing the number of incorrect responses. This can be best described as simply the guessing technique. A common conclusion is that delayed stimulation, on a small scale, does not have an effect on simple reaction time response. There is, in fact, a disjunctive procedure which causes the reaction to be complex and therefore result in longer reaction times [26]. Ray Hyman attempted to systematically vary the number of stimulus alternatives and ran three trials in which the stimuli presentation was altered. In the first test there were several stimuli, each with an equal probability of being the reaction stimulus. The results showed that the RT did not see a significant increase. The second trial was set up much like the first except the stimuli had a varying frequency of occurrence. They were not given equal probability and yielded similar insignificant results. Lastly, the third trial introduced sequential dependencies within the stimuli. These simple dependencies made the reaction phase complex enough to have a significant impact on the inflation of reaction time, around a 1% time increase [28]. In other cases, however, it has been shown that a logarithmic equation can best relate the increasing number of choices with the increase in reaction time.

4.4.3 Population Variance

Just as the presentation of different stimuli cause varying reaction times, so too do different people. One study showed that the mean RT for individuals to detect an auditory stimulus is around 160 milliseconds. This number increases to 190 milliseconds in order to detect a visual stimulus [11].

Another study attempts to draw conclusions about visual processing length. Subjects were flashed a 384 by 256 pixel-sized image for 20 milliseconds. After seeing the visual stimulus, they immediately had to classify whether the image shown was of an animal or not. Premotor times were found as early as 150 milliseconds. By 325 milliseconds, the motor activity of the right hand shows clear lateralized differences [65].

Reaction time has proven to be even greater for people with mental disabilities, mainly those with brain damage. These people have even slower RTs for complex tasks. If a subset of people have slower RTs, then there must exist a subset of people that have faster RTs. A study was performed on sprinters who attended the Beijing Olympics. After the reaction time of all their starts was collected, results showed that the mean RT was 166 milliseconds for males and 189 milliseconds for females. However, one out of 1,000 starts could be as fast as 109 milliseconds and 121 milliseconds, respectively [6].

In one study comparing the reaction time of soccer athletes to non-athletes, the visual stimulus was one of several sizes of rings. By increasing the ring size, both the direct and peripheral vision can be tested. These rings were placed at different intervals to simulate varying distances, yet the results showed that there were no differences in the RTs for these fields of vision. A point of interest, is that the premotor times of the athletes were significantly shorter than the non-athletes, which suggests that athletes' muscles are faster and have higher perceptual abilities, allowing them to respond to the test fields of vision quicker. In a more general case, researchers have found that centrally located or direct stimuli invoke faster reaction times than ones located peripherally. In addition, increasing the viewing angle also increases the RT of peripheral vision more than centrally located vision [70].

Another study of sports players was performed in which expert soccer goalkeepers were given a joystick, shown a video of a penalty kick, and asked to move in the direction of the ball. In the case of soccer, the expert goalies are able to better predict ball flight just by observing the kicker's approach to the ball. While the expert keepers saved more shots, Savelsbergh et al also noted that they waited longer before initiating a response and made fewer corrective movements. According to the study, expert athletes tend to have more efficient search algorithms when it comes to locating the ball. There are fewer visual fixations of long duration that are less important to the movement. In soccer, experts tend to focus on more informative body parts like the head, kicking leg, non-kicking leg, and ball areas. Novices spent longer times looking less informative part such the trunk, arms, and hip [54].

A similar study was conducted analyzing the batter and pitcher scenario of cricket. Expert batters only focused on certain parts of the pitch like the ball release and bounce about 200 milliseconds before crossing the plate. By using this predictive information properly, expert batters have more pursuit tracking than novices [62].

CHAPTER 5

PROCEDURE FOR PERFORMANCE IMPROVEMENT IN ATHLETES

This dissertation proposes a new human computing interface to assist athletes in strengthening their vision by performing vision exercises. The results from the exercises fused inputs from several sensors in order to measure the athlete across several area such as correctness and speed. Problems with single sensor systems are addressed in a cost efficient matter while accurately processing measurement quickly. Correct movements are verified by using the users' skeletal data as input to a novel motion detection algorithm. Custom inertial sensors were created and mounted on the athlete to determine reaction time via a proposed reaction time algorithm. The end goal is improve the user's reaction time to complex visual events.

5.1 Custom and Commercials Sensors

There were a number of sensors used in the both the experiments and trials. These devices range from pre-built commercial devices, like the Kinect, to custom fabricated hardware using smaller, common chips. This section describes the various sensors including how they were used and what part they played in gathering the critical data for the project.

5.1.1 Microsoft Kinect for Windows V2

The Microsoft Kinect, shown in 5.1, is a device that provides data from several sensors including cameras and microphones. The camera was the primary sensor utilized in order to obtain video of users while performing various trials. The Kinect for Windows V2 SDK was used to interface the device and refine the data. It provided the key function of extracting the user's skeletal coordinates from onboard sensors. Their process for determining skeletal positions is based off depth calculation and machine learning. A large number of training images were collected in order to become the basis of the machine learning algorithm. There has been work published providing details of specifics in [55].

Figure 5.1: Microsoft Kinect V2 Sensor

Figure 5.2: Custom build inertial measuring device side and front view

5.1.2 Custom Inertial Measuring Device

Custom hardware was created in order to monitor gravitational data to determine reaction time. There were several requirements for the hardware. The device must be able to provide accurate data at a very high speed while being small enough to inconspicuously attach to the user. In additional the cost of creating the device must be low. The end result consisted of joining together several commercial devices including: a Teensyduino (Teensy Arduino), Triple Axis Accelerometer, Bluetooth radio transceiver, and a Lithium Polymer battery pack. The images in 5.2 are the resulting prototype hardware as fabricated by Michael Mitchell of The Mobile Lab @ FSU [42]. The left image is a side view of the device while the right image is a frontal view. These images were taken next to a standard quarter in order to give a perspective on sizing. In addition, a twist tie was used to secure the battery to prevent it from dangling during testing.

Figure 5.3: Teensyduino Hardware

Teensyduino. The Teensyduino, shown in 5.3, is an Arduino compatible microcontroller with an ATMEGA32U4, 8 bit AVR 16 MHz AVR. The unit is programmable via AVR cross-compiler toolchains and the AVRdude command line utility, or through the Arduino IDE. All firmware flashing is done via the standard "Mini-B" USB port. The cost was $16.

This device was chosen over a traditional Arduino microcontroller for its smaller footprint, and ease of prototyping and programming. For our future prototype, we plan to migrate the system to use a dedicated ATMEGA microcontroller, to further reduce the size of the device, as well as to cut down on the overall cost of the hardware [49].

Triple Axis Accelerometer. An accelerometer was needed to generate the inertia data. A Triple Axis Accelerometer Breakout MMA7361 model board, shown in 5.4 was used. This particular chip houses a Freescale MMA7361L three-axis analog MEMS accelerometer. It was chosen because of its features across several areas such as low power requirement, ± 1.5g measurement range, high frequency, small size, and price. The low power enabled it to be connected to a low cost battery that provided several hours of monitoring. At the time of purchase, the chip cost around $10 and had dimensions of 0.90 x 0.50. Once the chip connected, a data frame was measured to be received around every 1.5 MS [16].

Bluetooth Radio. While conducting trials, the device needed to minimally invasive. In order to achieve this, the device needed to be wireless to allow the user free range of motion. A

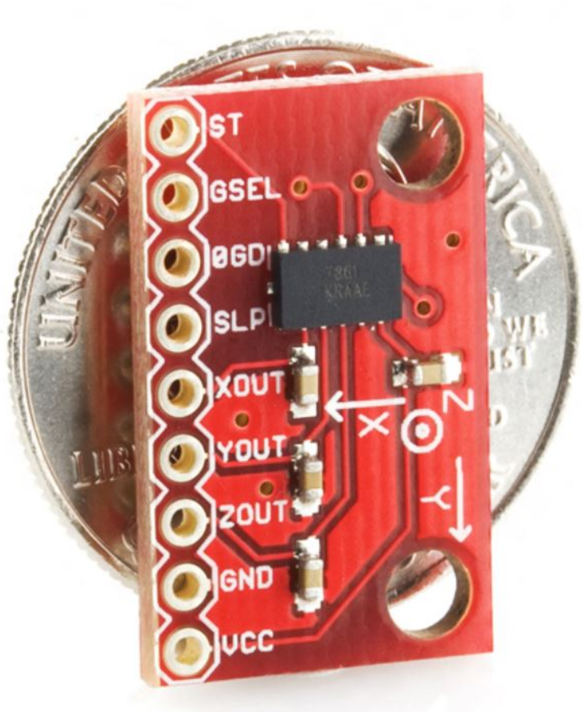


Figure 5.4: Triple Axis Accelerometer Breakout - MMA7361

Figure 5.5: SparkFun Bluetooth Modem - BlueSMiRF Silver

Figure 5.6: Polymer Lithium Ion Battery - 110mAh

Bluetooth radio chip was integrated to provide this. The actual chip, shown in 5.5, is a BlueSMiRF, FCC Approved Class 1 Bluetooth Radio Modem. It operates as a serial (RX/TX) pipe between connected devices. Bi-directional serial communication received over the Bluetooth interface is forwarded over the hardware serial interface, and communication over the hardware interface from the Teensy is propagated over the Bluetooth radio. The unit draws its power from the LiPoly battery through the VCC and GND lines of the Teensy microcontroller [15].

Polymer Lithium Battery. For power supply the rechargeable Polymer Lithium Ion battery was used. Several sizes could have be used based on how long the device needed to function. In this case the 110 mAh battery displayed in 5.6 was sufficient. One charged lasted for the 2-3 hours which was sufficient to conduct the trial, and was recharged at the end of the day [14].

5.2 Creating a Fast Reaction Time Algorithm

The main goal of using this hardware was to devise an algorithm to accurately determine reaction time on the millisecond scale. In order to achieve this, several incremental steps were made in a sandbox environment. The following sections are going to describe the steps that were taken to achieve this goal.

5.2.1 Program Framework

The first step was to create the framework for both administering the tests and gathering feedback. This program was written in C# using Visual Studio 2013. The program provided several key functions needed in order to gain the insight for forward progression. The first key function was administering the test. This administered test was a simple reaction time test that attempted to remove any complex cognitive tasks. The user hit a button when ready and the program waited a random period of time, anywhere between 4-15 seconds, before displaying a reaction stimulus. The reaction stimulus was merely displaying the text "Go" on the screen in black text and a moderate font size. Once again, this acted as a simple prompt in order to have the user move as fast as possible without ordering them to think a great deal.

5.2.2 Skeletal Reaction Time Algorithm

The Kinect for Windows device was used to gather data for constructing an algorithm that determined the user's reaction time based on their skeletal position. This device possessed the framework that allowed for easy computation of the user's skeletal position based on a deep machine learning algorithm. This algorithm is based off depth calculation and millions of training images. A previous section on the Microsoft Kinect for Windows V2 provides additional details of this proprietary algorithm.

Choosing the Correct Skeletal Point. The first step in developing this algorithm was to choose which skeletal points to focus on. There were many different options to choose from, with all choices being displayed in figure 5.7. Since this study was geared towards athletes, the points chosen needed to ensure that the user made a very deliberate, athletic move. At first, the hands were selected as they seemed like the obvious choice. The majority of athletes use their hands both constantly and deliberately to make highly athletic moves. After analyzing the data however, the Kinect seemed to lose track of these points often enough to deselect them as a candidate. Once the points were lost, the Kinect either made guesses as to where the points most likely were, or it stopped providing that data entirely.

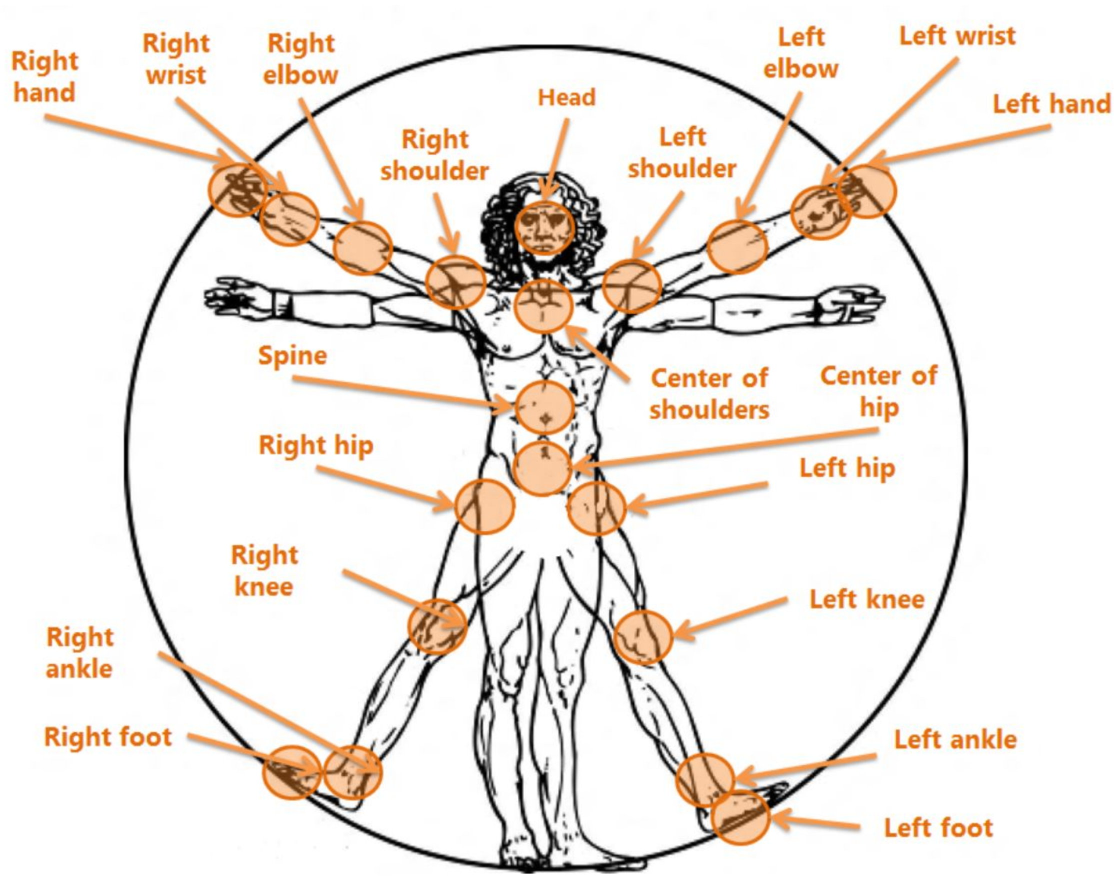


Figure 5.7: Kinect for Windows skeletal points

The next choice were the wrists. They provided virtually all same the benefits as the hands, but with additional reliability. However, it was found that working with the wrist data did not appear to be ideal. Wrist data was highly variable since they are appendages. Often times the users swung their wrists/hands around their body causing big jumps in the data. This swinging of the arms was such a natural movement that it also proved hard to determine direction since typically users would instantly move their arms in any direction when the reaction stimulus appear and then make corrective adjustments. In addition, due to the restricted distance between the user and the Kinect, the wrists sometimes went out of range of the Kinect's camera and it was unable to provide accurate data once again.

The next, and final chosen, point was the center shoulder. This point proved to be highly reliable. If this point was not visible to the Kinect, then no points on the skeleton were visible. Since several core muscles were involved to move this body part, it also fit the requirement of being a highly athletic move. It was also found that this point did not generate as much background noise during the reading as the extremities since typically users are unable to constantly swing their chest all over the place. As a bonus, it was easier to focus on a single body point rather than multiple ones.

There were some other points that seemed similar to the shoulder center that were not used. The spine and hips center could have also been used instead of the shoulder center. However, after testing the movement of those parts it was easier for the users to control the shoulder center rather than these other options. Users were able to grasps the center motions easier than trying to move their spine or center hips. Lastly, the head was not used for similar reasons as the arms and legs. The core body parts were favored over any extremity.

Fixed Circular Threshold. Once the skeletal point was selected the stream was fed into the test program to extract the data. This data was then graphed using gnuplot to get a better visual understanding of it. Figure 5.8 is a graph of the center shoulder point for a single trial run. This trial run consisted of several reaction movements, which can be seen in each of the loops away from the center point (0, 0). The x and y axis are relative points which the Kinect generates in order to place the point in a Cartesian plane. Both x and y on this graph related to the user moving sideways and up/down respectively. The scale was generated from the Kinect and left untouched at this point

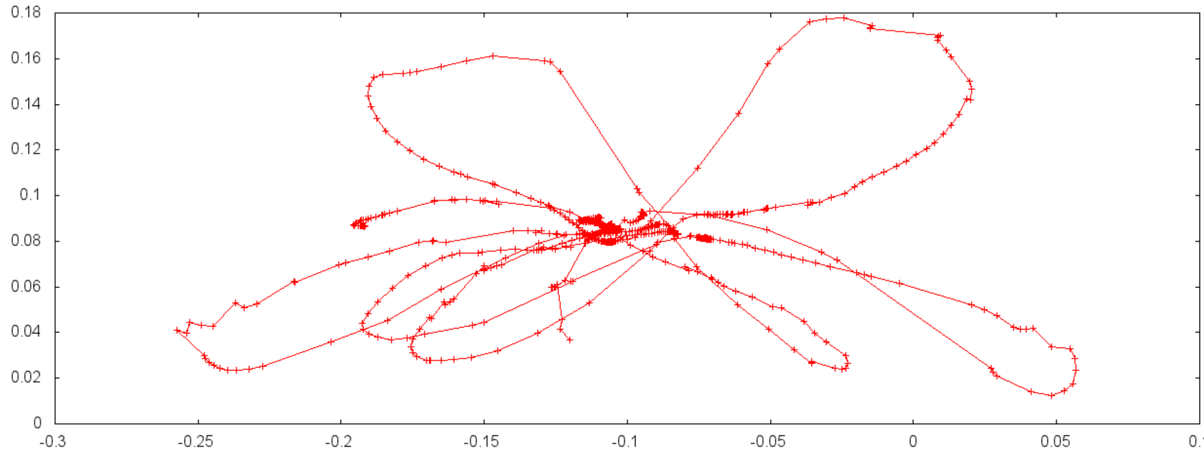


Figure 5.8: The graphed skeletal points of the center shoulder

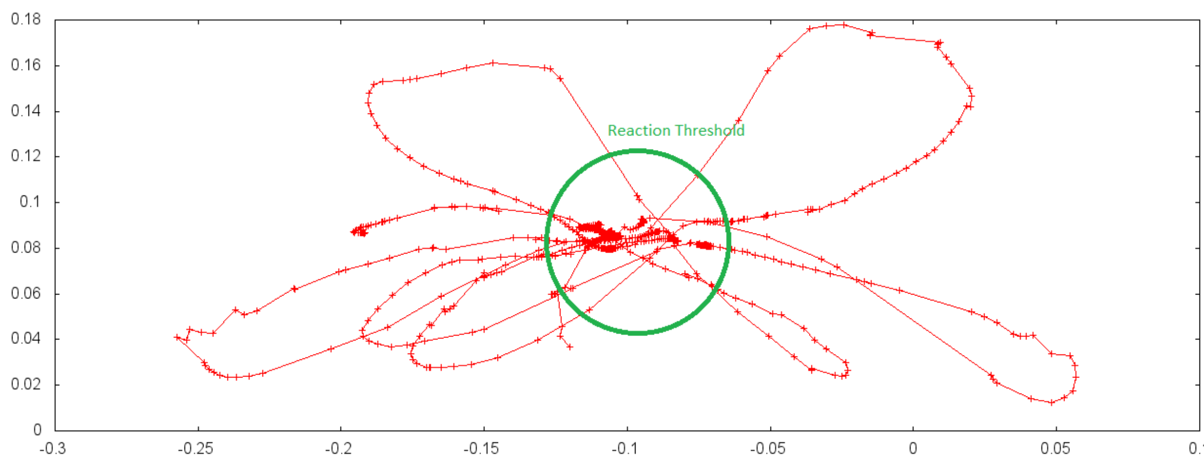


Figure 5.9: Proposed reaction time threshold using the center shoulder of the Kinect skeletal data

The initial algorithm attempted to use these points to create a threshold. This threshold was a circle around the center point as seen in figure 5.9. The idea is the user starts inside the green circle. Once the reaction stimulus occurs a timer starts. When the user moves outside of the circle, the timer stops and that time is used as the reaction time. However, this algorithm proved to have several flaws. The first issue was deciding the radius to use for the circle. A smaller circle lead to faster, more accurate reaction time however it risked having several false positives. A larger circle would reduce those false positives, but the user would have to physically travel a greater distance. This travel time was included in the reaction time thus not providing the truest data. Another issue included that certain measures would have to be taken in order for the user to start in the exact center of the circle. If the user was not in the exact center of the circle, then their reaction time would be bigger or smaller depending if they moved to near or far side of the threshold. For these reasons, this algorithm was not sufficient.

Distance Algorithm. After coming up short on the fixed circular threshold algorithm a new algorithm had to be devised by keeping the data in the current form it was difficult to visualize an alternate method. Since each data point was literally a point in a Cartesian plane the classic distance formula as in 5.1 was applied.

$$\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{5.1}$$

The results were graphed again and shown in figure 5.11. This graph shows the distance between two points against the linear time in milliseconds. On this graph it is easier to see the individual reaction attempts made in a single trial. The data is agnostic as to where the user starts relative to the Kinect sensor enabling a flexible environment.

By reducing several variables in the data, another threshold was chosen that provided a faster and more correct reaction time. The threshold that was chosen is the green line in figure 5.12. This threshold would be triggered if the difference between any two points were greater than the given value. Picking the threshold was a trade-off between speed and false positive. The smaller the value was, the less frames were needed to detect the movement. Less frames also meant less time delay and a faster reaction time. However, a smaller value also meant the algorithm was more sensitive to even the slightest movement. Being too sensitive would cause many false positives which hinder reliability. After several attempts with difference threshold values, .01 seemed to work the best. It allowed the user to make minor movements to adjust their balance and position while being small enough to quickly detect an athletic movement.

5.2.3 Accelerometer Reaction Time Algorithm

The accelerometer reaction time algorithm was devised after the skeletal one so many of the same concepts were applied from the beginning. However, the first step was to extract the data from the tri-axial accelerometer. A formula was then applied to the data in order to get the total gravitational force that the device experienced over a linear time. This data was then graphed and checked. Instead of creating a threshold with this data, the previous experience from the skeletal reaction time was used and the difference between points were plotted. From that data a threshold was selected in order to create the accelerometer reaction time algorithm.

Calculating Total Gravitational Force. Before the data could be processed, it needed to be extracted from the device. The device was configured to return every data point in the format time, X, Y, and Z. Time was replaced by the system time on the device in nanoseconds. Due to the buffering on the device, this time had to be used because the framework received a bulk package of points. Therefore it was not possible to log timestamps as the data was received. The X, Y, and Z points were the acceleration in each of those directions.

Those X, Y, and Z points were then used as parameters to equation 2.1 to calculate the total gravitational force on the device. The three values of the points were used as the series for the equation. Each point was squared, then all were summed together, and then the square root was taken in order to derive the final value. Figure 5.10 is a graph of the result for a single repetition in a trial over time. In this graph, it can be deduced that the user's reaction movement was downwards.

The downwards first movements can be characterized by the initial decline in force. This decline is the period of time in which the user moves towards the ground, sending the device into a "free-fall" like state. It is then followed by a large increase in force. During this period, the user has finished their downward movement and is coming back up towards a the initial ready position. Thus, the device is experience a large amount of gravitational force. Figure 5.13 displays the reverse, in which the user's reaction movement is upwards. The data quickly raises first while the user is moving up thus experience additional gravitational force. This is followed be a smaller free-fall period, and the force approaches zero. The second increase in data is simply the user recoiling themselves and

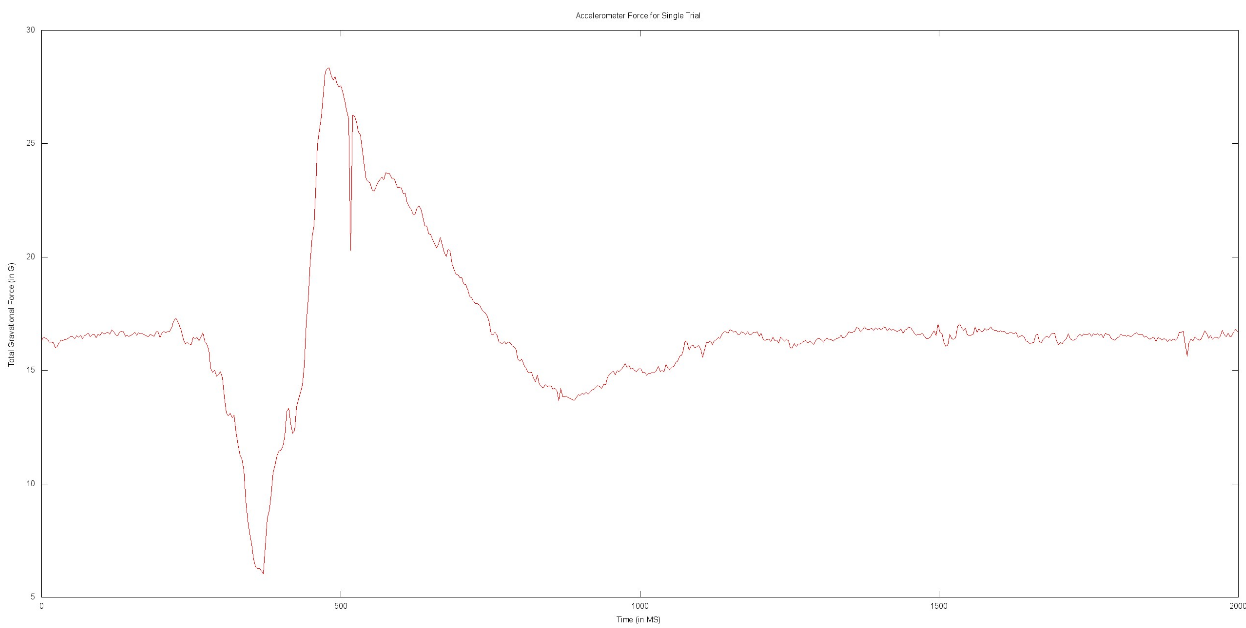


Figure 5.10: The total gravity over time for a single repetition in a trial where the reaction movement is downwards

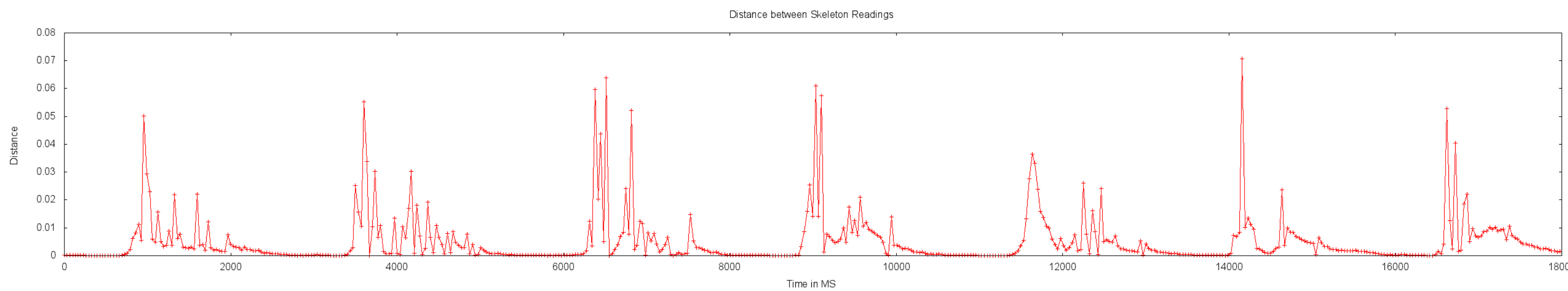


Figure 5.11: The distance between two skeletal points against time in milliseconds

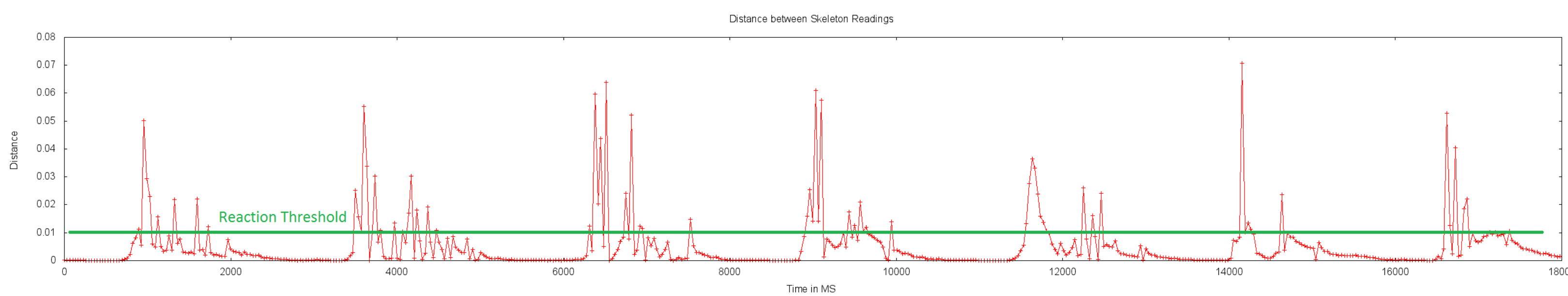


Figure 5.12: The distance between two skeletal points with a reaction threshold

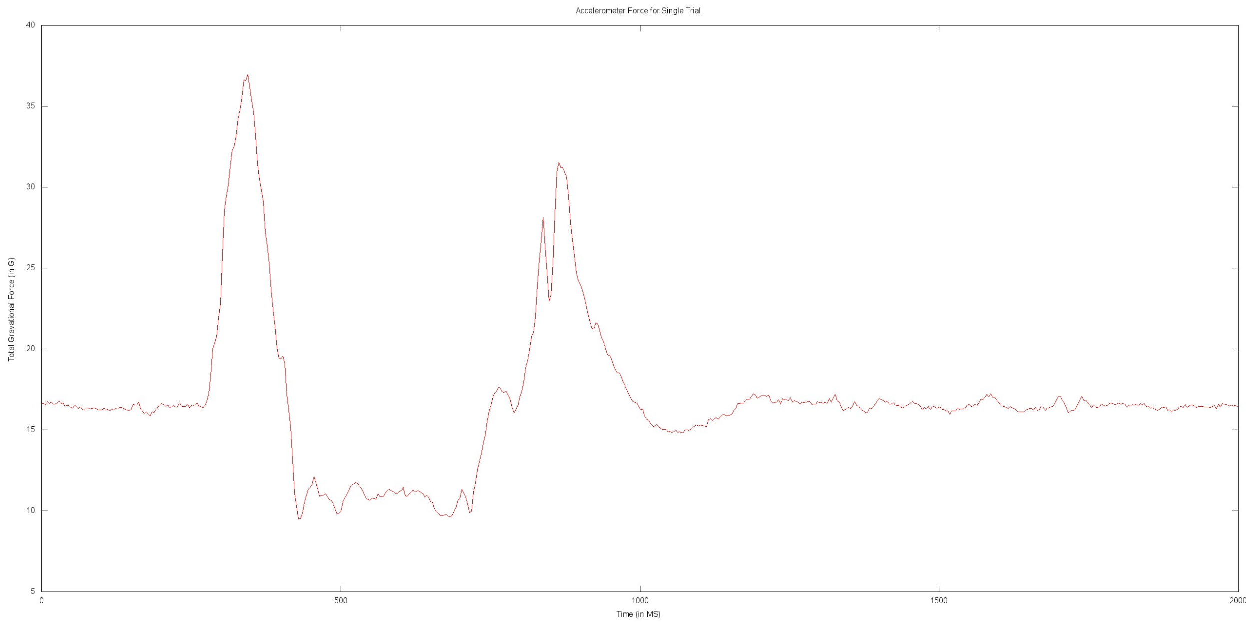


Figure 5.13: The total gravity over time for a single repetition in a trial where the reaction movement is upwards

bouncing their knees to get in position for the next repetition. In both graphs, the gravitational force is slightly shifted. When the user is at rest, the lines on the graph are flat. The readings would ideally be 1G at this resting state. In these cases they are around 16. This is simply due to the configuration of the device sensitivity. For all intensive purposed, 16 on the vertical scale is the same as 1G, thus the device is at rest.

Distance Algorithm. Following the same process as used in the skeletal reaction time algorithm, the difference in total gravitational force was plotted in order to determine a threshold. Figure 5.14 graphs the delta values for an entire trial. Each trial consists of a number of individual repetitions. In this case, the data shows that the user performs roughly 7 repetitions. These repetitions can be counted by denoting how many spikes are in the graph. However, it must be noted that successive peaks may be part of the same reaction and not unique. Quick successive peaks can be caused by the user recoiling or regaining their balance after performing a reaction. To realize this, it was helpful to take a micro look at the data. Figure 5.15 is the delta between each two total gravitational force against time in milliseconds for a single instance. The figure displays a closer, zoomed in, representation of the data. This graph was derived from the total

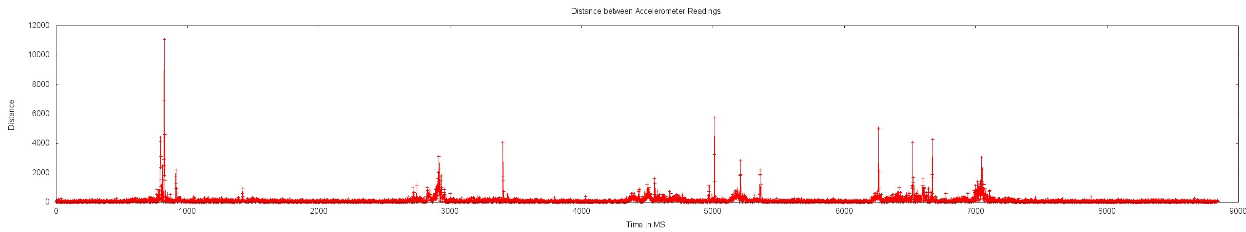


Figure 5.14: Delta between total gravitational force for a single trial

gravitational force as given by 5.10. As in that graph, this data was captured when the user made an initial downwards reaction movement. The threshold that was chosen to trigger the reaction time is drawn and labeled on the graph at a difference of 1, a value that was chosen after seeing more data.

Figure 5.16 graphs the difference between force while the user performs the upward reaction movement. Like the previous example, this graph uses the data from 5.13. After comparing both the upwards and downwards difference graphs it shows that the user's reaction time was slightly faster on the up first movement. This is only a single instance, but this result seems likely in other instances and can be explained. The user tends to have an easier time breaking the threshold by extending their legs as opposed to bending them. It would appear that in order to help fix this issue, the threshold could be lowered to catch the initial small amount of downwards movement however, it would come at a cost.

Choosing the Threshold. Just like the value in the skeletal algorithm, the accelerometer reaction time threshold value is a trade-off between speed and false positives. There is also the factor that the initial direction in which the user moves tend to show results favoring upward movements. The value selected, 1, was chosen after several test runs with lower values. Once the threshold was below 1, the algorithm had numerous false positives. These false positives were a result of small user movements. The main problem was the user was not intentionally moving and was indeed trying to keep their balance. The graphed data was a single instance in a highly controlled environment. When implementing this algorithm in the training environment, many more movements due to fatigue and body repositioning were found.

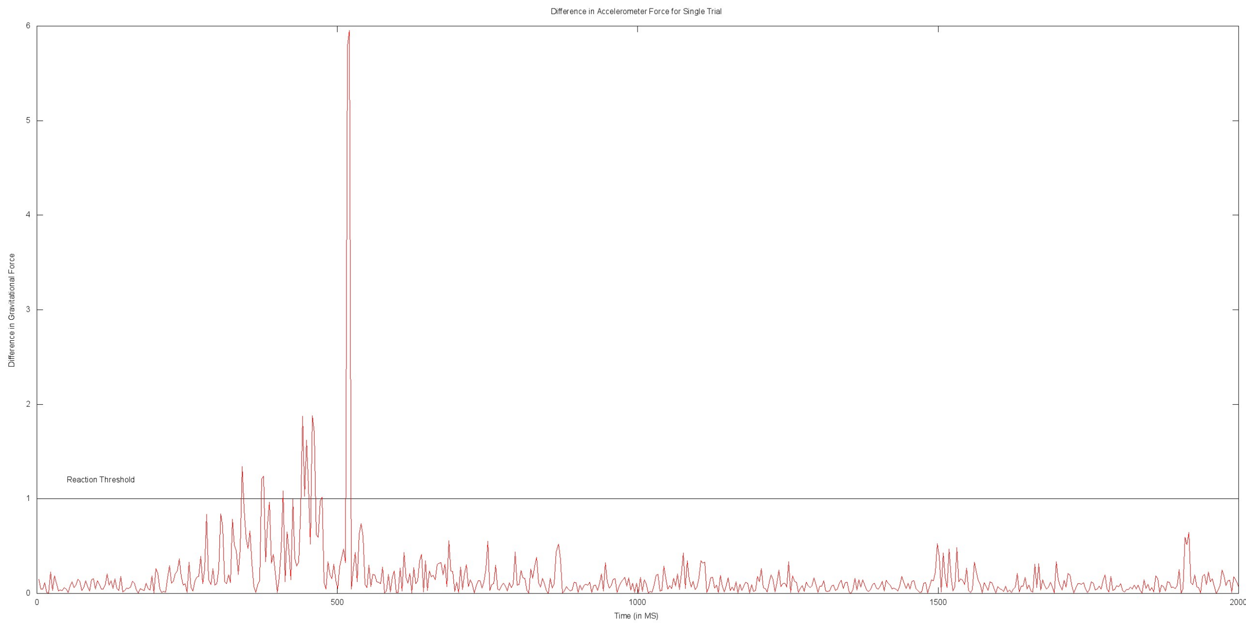


Figure 5.15: Difference in total gravitational force between two points during downwards reaction movement

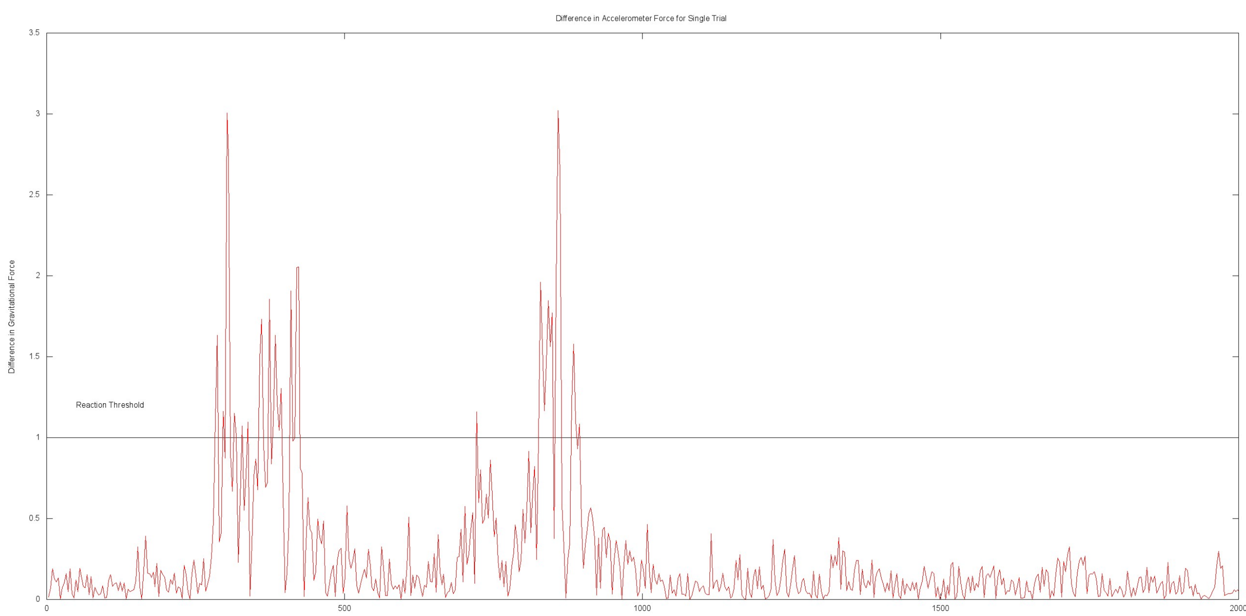


Figure 5.16: Difference in total gravitational force between two points during upwards reaction movement

5.2.4 Sensor Fused Reaction Time Algorithm

Now that a reaction time algorithm was created for both sensors, skeletal and inertial, the last step was to fuse the two together. In order to achieve this, both sensors had to be graphed on the same plane. By skewing the results using constants, it was a relatively straight forward process. In the following examples, the skeletal data was multiplied by a constant of 30000 while the gravitational data was multiple by 300. These constants were selected to make both data sets share the same range, and thus be easily visualized on the same graph. The threshold values for both algorithms are also kept and received a multiplication factor.

Figures 5.17 and 5.18 show two examples of both the skeletal and gravitational data graphed in the same range. The deltas are calculated as previously described and the horizontal axis remains the linear time in milliseconds. The vertical axis is the difference between two adjacent points and does not have a fixed unit of measurement. The reaction threshold is now a common number, 300 in these cases, so it can provide for a better visualization of when the reaction time for each data set occurs. In these graphs the green line is the inertial data and the red line is the skeletal data. One, and perhaps the most important, visual characteristic of the data shows the accelerometer triggering the reaction threshold first. While these are only two single instances, several trials were performed and with the same results. The delta between the two reaction triggers varied roughly between 30 to 100 milliseconds, however the green line was constantly first to cross. This is important because a high speed reaction time algorithm is a major goal of this project.

Other characteristics of this data were also realized, such as the inertial data being more varied than the skeletal. The skeletal data stays flat-lined around zero until movement occurs, while the inertial data fluctuates a great deal. This can be explained by the following items. First, the inertial data is coming in at a much higher rate. Inertial data received a frame around every 1.5 milliseconds while the skeletal was around every 60 milliseconds. Because of this higher framerate the data appears nosier. Another main reason can be attributed to the Kinect for Windows SDK. They automatically provide smoothing functions as part of their machine learning data while no such smoothing was applied to the inertial data. Lastly, the accelerometer was more sensitive to movements than the Kinect camera and therefore reflected more variance.

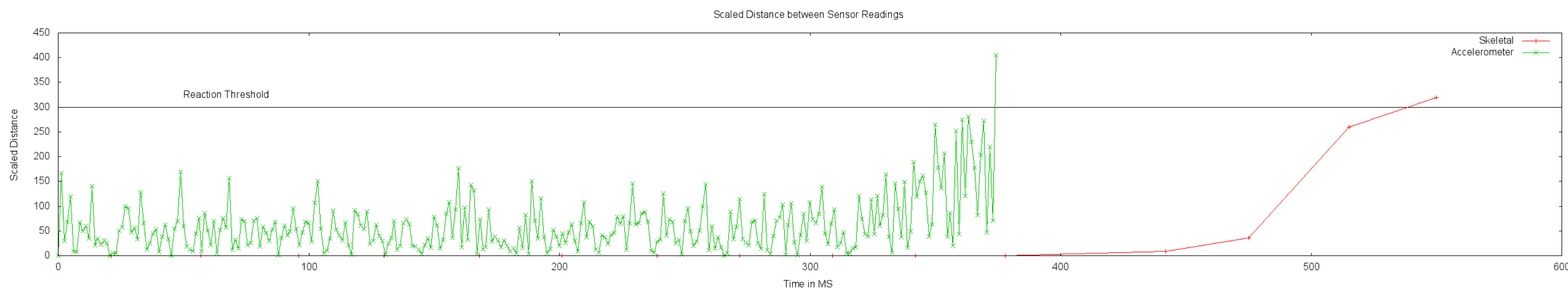


Figure 5.17: Example of a single repetition in which sensors are fused together to create a reaction time algorithm

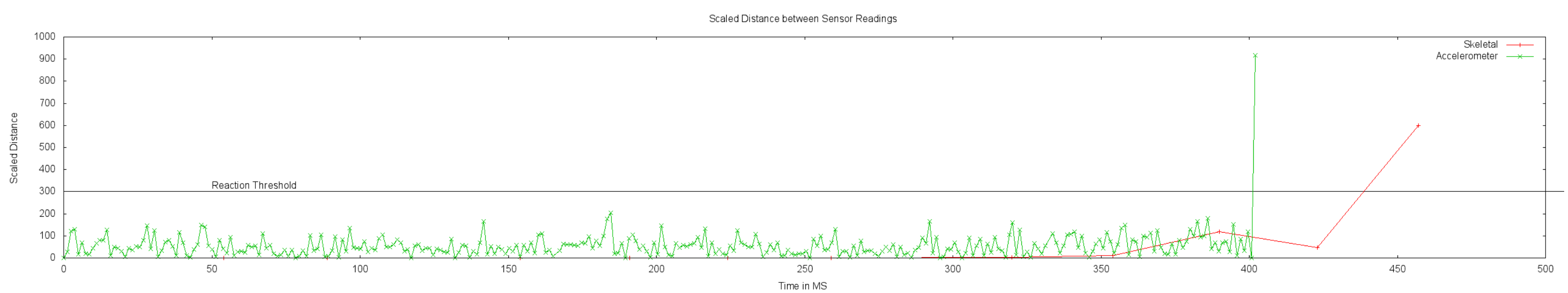


Figure 5.18: Another example of a single repetition in which sensors are fused together to create a reaction time algorithm

5.3 Vision Training Trials

5.3.1 Recruiting Athletes and Time Commitments

The first step in this process was to recruit student athletes that wanted to be involved with this study. A third party approached the men's and women's rugby teams at Florida State University and explained the study. They were informed the goal of the study (to improve visual performance), time commitments, and general training routines.

This total length of this study ran for six weeks both on the Florida State University campus. The first week was used to get the athlete's baseline measurements. This involved measuring their initial visual evoked potential (VEP) performed by Orsillo Vision and Optical [48]. The next four weeks were used to train the athletes. Each training session was held at Florida State University's Dunlap Training Facility and lasted about thirty minutes occurring twice a week, which summed to four hours total training time. Lastly, the final week was used to gather post VEPs from the athletes. Both the pre and post VEPS used the same procedure and equipment.

5.3.2 Drills and Exercises

During the four week trial, the athlete's completed several training exercises. Each exercise was specially designed to strengthen several areas of the athlete's vision. The areas focused on were reaction time, spatial awareness, and peripheral vision. The goal of these exercises was to show a decrease in reaction time and increase in spatial awareness and peripheral vision. All of the training exercises were performed on the Florida State University campus within the Vision Training Clinic housed in the Albert Dunlap Indoor Practice Facility. For the purposes of this study, the terminology between drills and exercises are synonymous.

Hand Dot Drill. The hand dot drill consisted of touch sensitive LED board. The LED board was mounted on a wall with the center being roughly six feet off the ground, for the majority of the athletes this was slightly above eye level. The LED board contained thirty-two LED lights with one center dot and the others arranged in the three circular patterns of three different diameters, with the biggest diameter being approximately twenty four inches as displayed in figure 5.19. Once one lighted dot was touched, another dot lit up randomly on the board. They were permitted to use two hands with the constraint that if the dot was on the left side of the board they had to use their left hand and vice versa with the right. If the lighted dot fell on the center line they were allowed to use either hand. Athletes had one minute to touch as many lighted dots as they could and their final score was the total of how many dots they touched. During the course of the training the athletes performed this exercise twice per session.

Foot Pedal Drill. The foot pedal drill also used the same LED board as in the previous section. In addition, it used four of the one foot long pressure sensors laid out in a square pattern with the length between each opposite side being approximately four feet apart. There were only four LED lights that illuminated on the board: the top most, the bottom most, the right most and the left most. Once one appeared the athlete had a set amount of time to touch the corresponding foot sensor as demonstrated in figures 5.20 and 5.21. If they were successful, they received a point and a different LED position lit up. If they exceeded the amount of time they heard a buzz and still had to touch the corresponding sensor in order to light the new LED; however, they did not receive a point. They performed this exercise twice per session with increasing difficulty as they improved. The test was made more difficult by decreasing the amount of time the athlete had to touch the foot sensor before their effort did not count. The initial timeout period started at one second and every successive level decreased this time by one tenth of a second.

Balance Board Drill. The main board had the same foot long pressure sensors attached to the underside of it along all four sides. The board was then wrapped in material to hold the sensors in place and to provide the athlete a way to gain traction. The final result was a board that enabled the athlete to go to a down, up, left, right, or neutral position. Like the foot pedal drill, the athlete had to move to the corresponding position based on which light was lit; however, instead of stepping with their feet they had to rock in that direction on the balance board as displayed in figures 5.22 and 5.23. The timeout period was also the same as the previous drill. This exercise was performed twice per session and the difficulty was increased as the athlete improved.

Crosshair. The crosshair exercise was designed to train reaction time and the peripheral vision of the athlete. A large projection screen was split into four quadrants similar to a Cartesian plane. A single character appeared in the middle intersection of the screen, which randomly cycled through a subset of characters. At the same time there were several balls of different colors and sizes orbiting the intersection at a variable constant speed. When the target character ball appeared the athlete had to move towards a target ball. When the exercise first began the target character and ball were denoted as shown in figure 5.24. The ball would lie in one of four general quadrants to

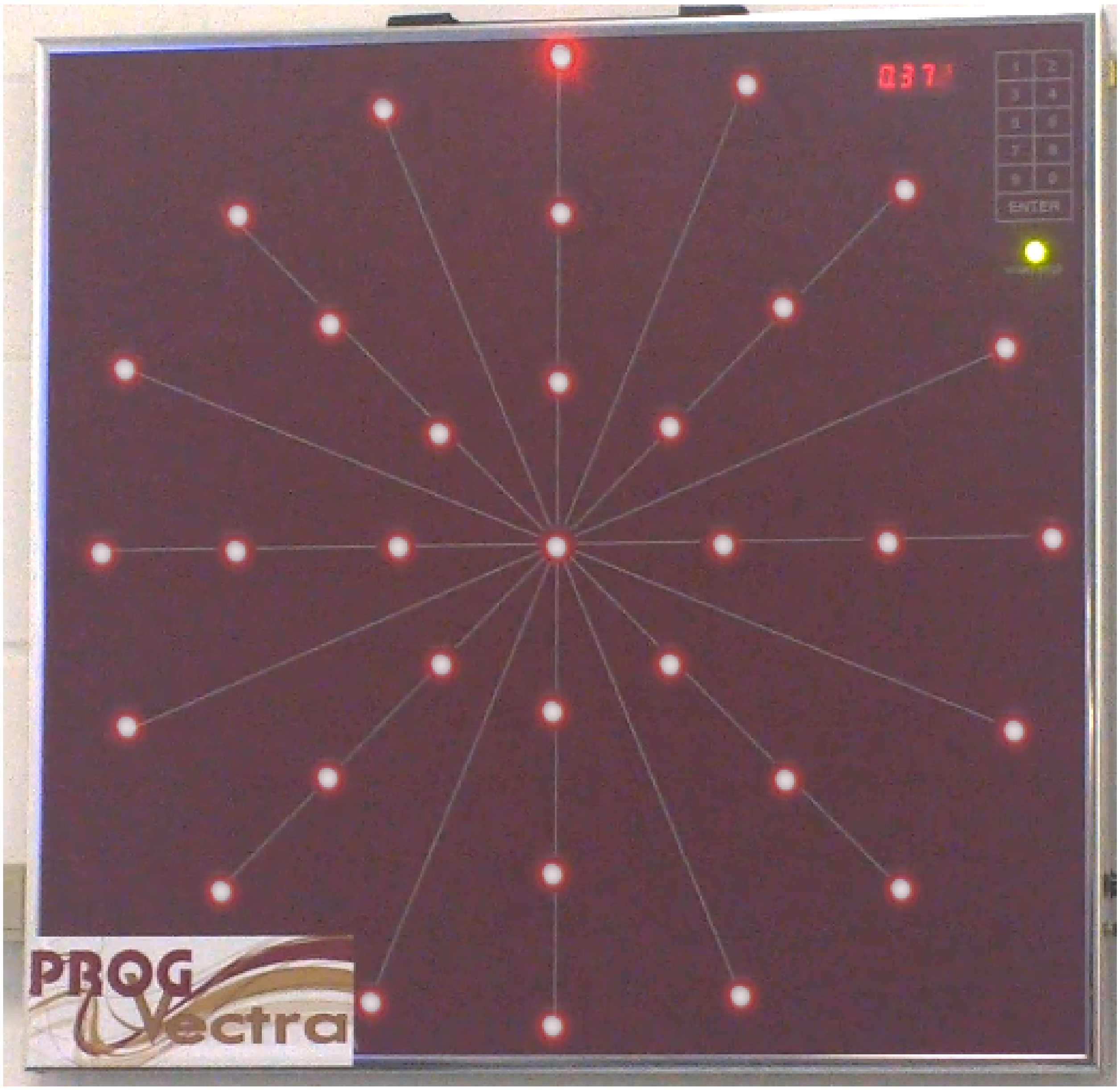


Figure 5.19: LED board used for hand dot drill with all LEDs lit

Figure 5.20: Right position of Floor Pedal Drill

Figure 5.21: Front position of Floor Pedal Drill

Figure 5.22: Balance board front position

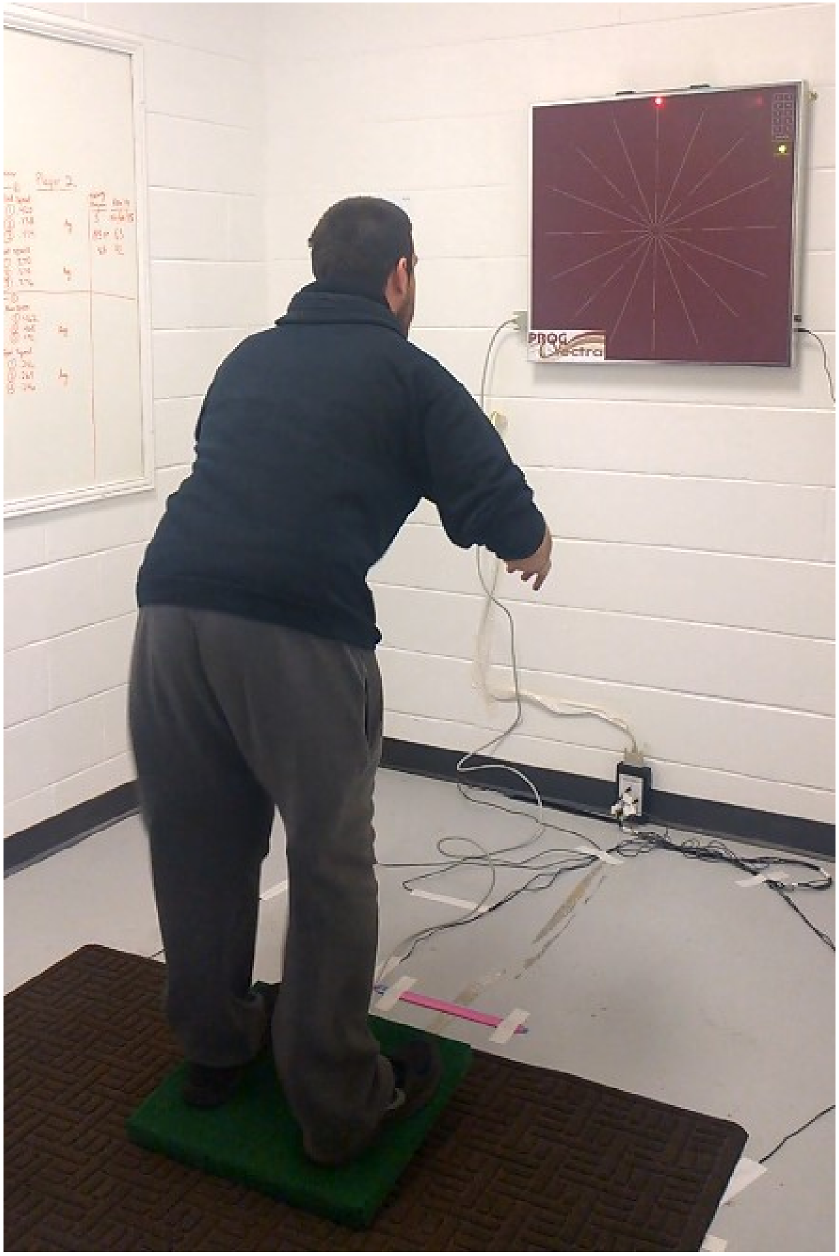


Figure 5.23: Balance board back position

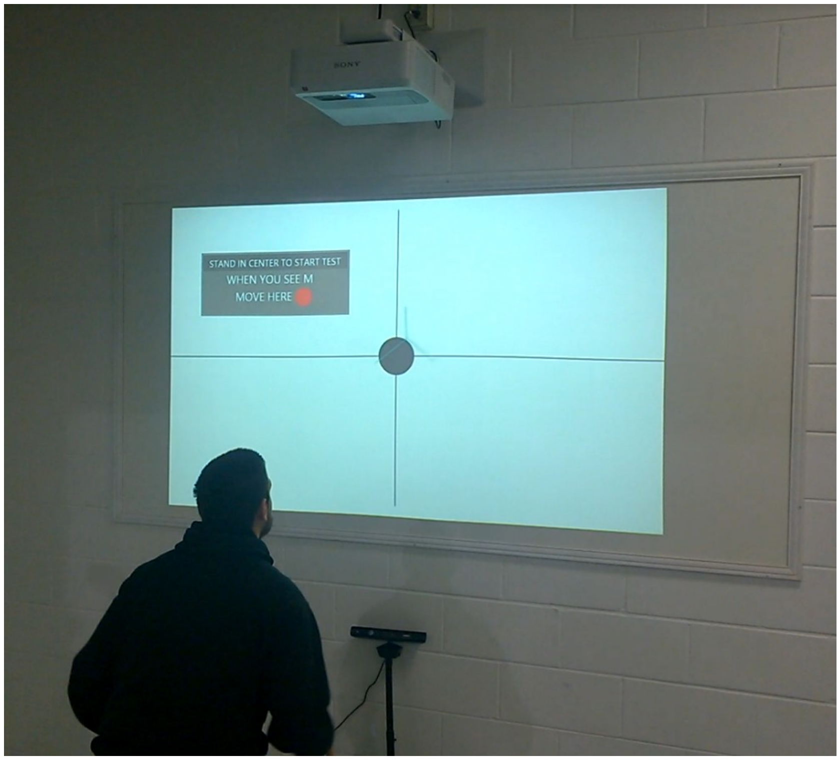


Figure 5.24: Athlete in start position receiving target character and ball

which the athlete moved. This was the up-left, up-right, down-left and down-right quadrants. The background of the test also alternated between a light and dark background every second. Example screen shots of this exercise are shown in figure 5.25 and 5.26.

A Microsoft Kinect, was used to gather results from this exercise. The Kinect was used to determine if the athlete moved to the correct target quadrant. This was achieved by using the Kinect's skeletal tracking feature to extract the location of the athlete. A movement tracking algorithm, described in another section, was then used decide which quadrant the athlete's initial movement was towards. If their movement was correct, the quadrant flashed green to notify the athlete as displayed in figure 5.27 (note: exercise in figure has different configuration than described). However, if their movement was not correct then nothing happened. In addition to tracking movements, the Kinect also video recorded the session in order to be reviewed and evaluated.

A tri-axial accelerometer was used to gather the reaction time of the user. Before the exercise, this device was attached to athlete's chest using an elastic ace bandage. During the exercise, the

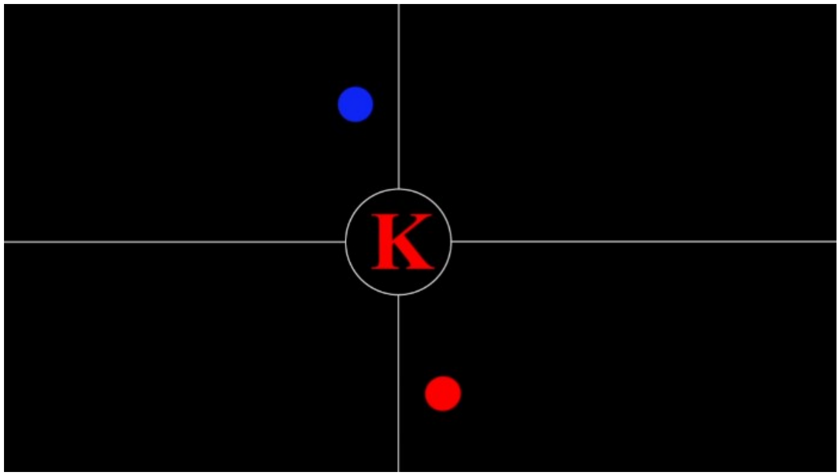


Figure 5.25: Crosshair exercise screenshot with dark background

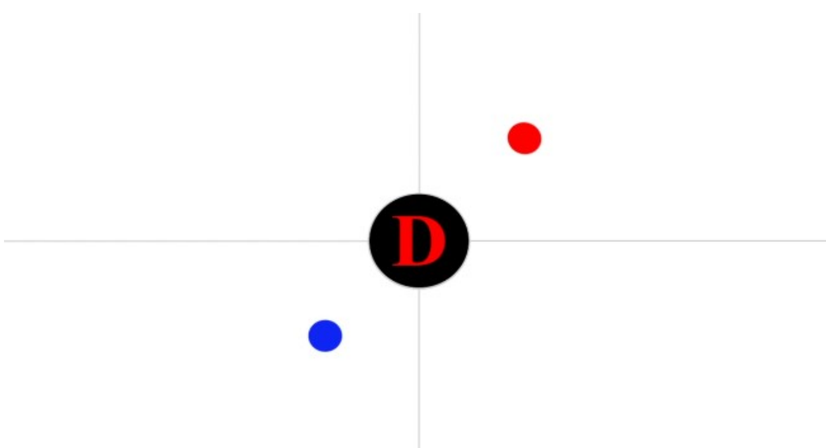


Figure 5.26: Crosshair exercise screenshot with light background

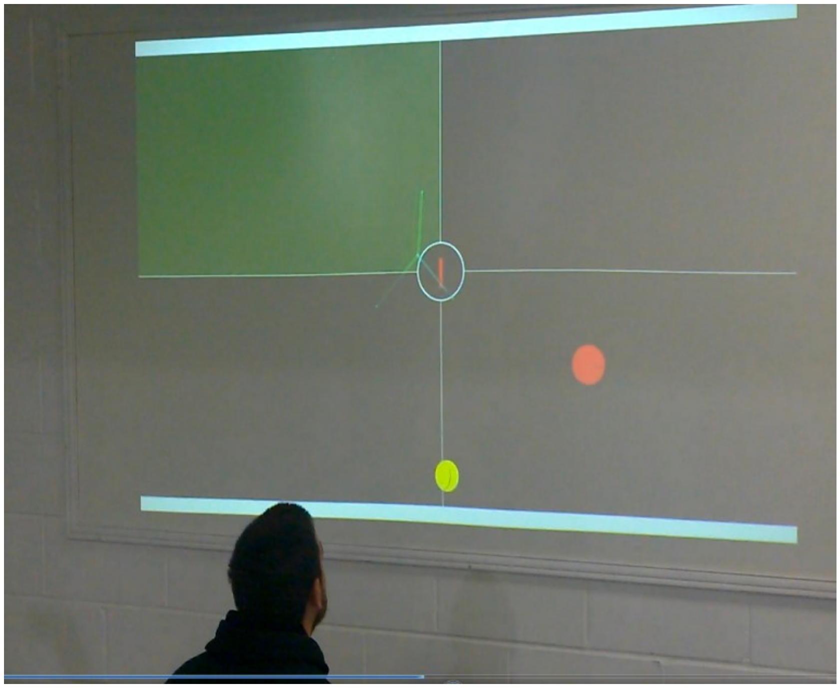


Figure 5.27: Athlete receiving feedback for correct movement

device transmitted information to the base station via Bluetooth. The sensor fused reaction time algorithm, described in previous section, was then used to determine the time, in milliseconds, in which the athlete started to respond to the stimulus. All of the visual objects on the screen had several individual properties such as orbit size, ball size, color, ball speed, ball direction, character set, character speed, target character frequency and background images. These properties were used to increase the difficulty of the exercise. Overall, there were two different property configurations. The first configuration was intended to be an easier, introductory exercise. It consisted of one red ball with a diameter of seventy five pixels that rotated on a 675 pixel orbit at .3 revolutions per second. The character set included all 26 alphabetical letters that changed every 500 milliseconds. The target character was the letter 'A' which appeared randomly about 40% of the time. The athletes performed this exercise every session, once with the target ball rotating clockwise and then once counter clockwise in order to exercise both eyes equally.

Once the athlete performed at a sufficient level the configurations were modified to increase the difficulty. The ball color was changed to yellow and the size was reduced to a 45 pixel diameter. The speed of the ball was increased to .45 revolutions per second and the orbit diameter was increased to 750 pixels. The character set remained the same with all 26 letters as well, but added an alternating background and the target frequency at 40%, but the target character was changed to 'M.' This exercise was also performed twice: once with the ball moving clockwise and once with the ball moving counter-clockwise.

Eye maze. The eye maze exercises were a series of puzzles, in image format, that the athlete had to solve while being timed. They consisted of four letters, A-D, and four numbers, 1-4, both in sequential order, with the letters and number vertically aligned opposite of each other. Each letter had a solid line that matched up to a random number on the opposite side of the image, therefore there were four lines each matching to a different letter/number pair. The goal of this exercise was to verbally announce what those pairing were as quickly and accurately as possible. To begin the exercise, the athlete started with their back turned to the projector screen and then an eye maze was displayed. On the athlete's mark, they turned around and began to announce what the pairings were. Their solutions were noted and graded by a proctor as well as the time it took to come up with the solution, which determined by the proctor using a stopwatch. After the test the athlete turned their back, a new eye maze was display, and the procedure was repeated. The athletes were instructed to begin the opposite way for every new test. For example, if they started with an A then they would be instructed to start with D for the next maze. Each session the athlete completed eight mazes, each slightly more difficult than the previous. To increase difficulty the lines in the maze became longer and contained more changes in slope as demonstrated in figures 5.28, 5.29, and 5.30.

Number Flash. The number flash exercise consisted of nine, five digits numbers that appeared in series. A dot in one of the nine ordinal positions directed the athlete where to look as displayed in 5.31. After the dot was displayed for roughly 300-500 milliseconds it disappeared and was replaced by the number as shown in 5.32. Once the number was displayed, the athlete had to recite the number digit by digit. All numbers were flashed in one of nine ordinal positions which were comprised of a three by three grid as laid out in 5.33. The length of time that the number was displayed on screen varied depending on the difficulty. The athletes performed this exercise twice per session with an initial difficulty of 100ms. Halfway through the trials, the difficulty was increased and the numbers were displayed for 50ms.

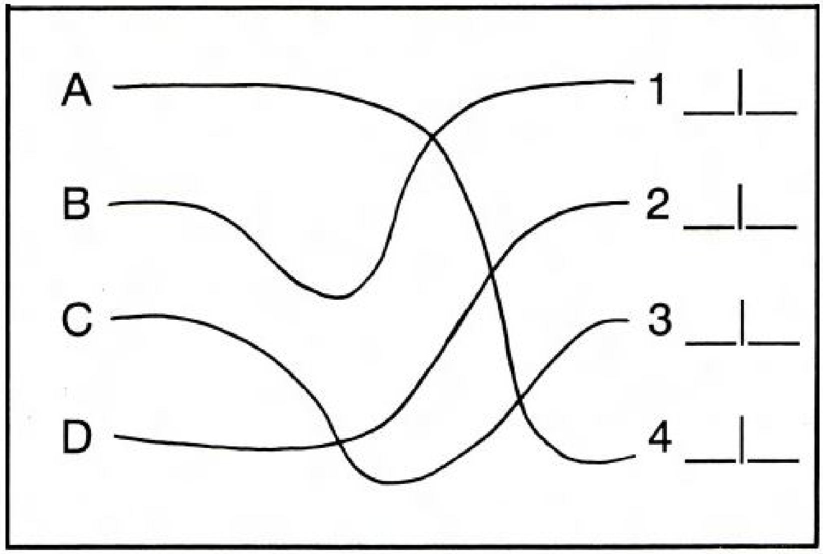


Figure 5.28: Eye maze at easy difficulty

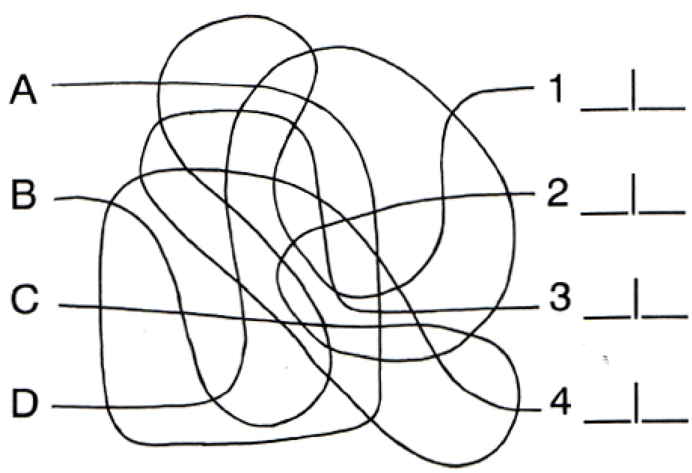


Figure 5.29: Eye maze at medium difficulty

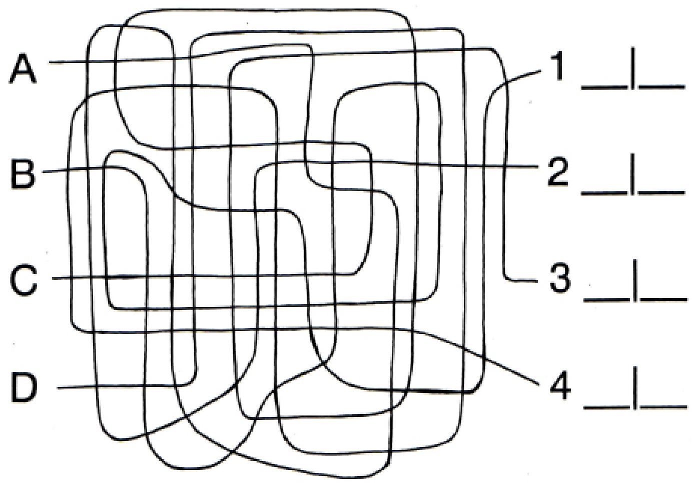


Figure 5.30: Eye maze at hard difficulty

Figure 5.31: Dot in ordinal vision position to direct athlete's gaze

Figure 5.32: Number flash to be verbally recited

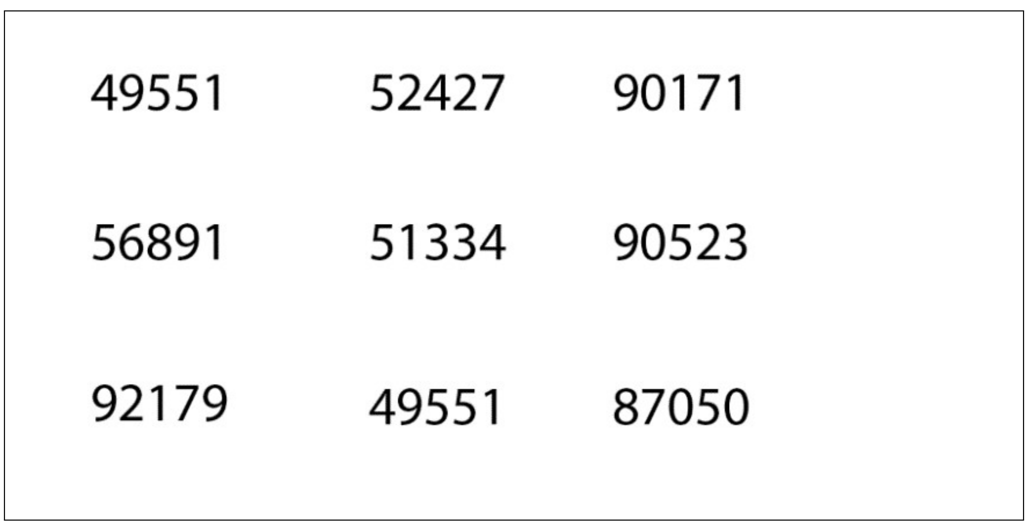


Figure 5.33: The ordinal positions where the numbers were flashed

5.4 Measuring Success

5.4.1 Visual Evoked Potentials

First, all athletes received an eye exam to evaluate the need for corrective lenses. If corrective lenses were prescribed, they were required to wear them while measuring their visual evoked potential (VEP). The athlete's VEP was measured both before and after training. These measurements were taken using a Diopsys Nova-VEP machine [30]. To gather these readings an unaffiliated technician prepared the athlete's skin on their forehead, temple, and the back of their head (on the outside of their visual cortex). This was achieve by first cleaning the areas with alcohol pads and then applying an electrode gel. The purpose of the gel was to promote conductivity between the skin and the electrodes, which were placed over the three mentioned areas. The athlete was then sat at a distance of approximately three to four feet away from a nineteen inch monitor at eye level. Lastly the ambient light in the testing room was dimmed.

Once the athlete was prepared several VEP tests were ran. All tests lasted for fifteen seconds and involved a thirty-two by thirty-two checkerboard pattern that alternated its squares between light and dark. There were two different types of tests that were performed to evaluate the athlete's response to both dark and light contrast. The dark contrast test depicted its black squares at 85% contrast, while the light contrast test depicted its black squares at 15% contrast which appeared light grey squares. Both styles of tests were ran several times and gathered information on the oculus sinister (OS) (left eye), the oculus dexter (OD) (right eye), and the oculus uterque (OU) (both eyes) by having the user cover and/or uncover the opposing eye. Each subtest was repeated until a reliability index, which was determined by the Diopsys machine, was over 70%.

After the tests were complete, the machine displayed how strong the athlete's visual system was. Strength of the visual system was composed of two main metrics, latency and amplitude. Latency, displayed as milliseconds, indicated how long it took the checkerboard information to travel from the retina to the visual cortex, in the form of electrical signals. A smaller latency is considered to be a stronger system. The second metric is amplitude, measured in microvolts. This metric measured how well the athlete's neural structure conducted information along their visual pathway. In this metric, larger readings are considered to be working more [29].

5.4.2 Mind-Foot Speed Test

The Mind-Foot Speed Test was used to gauge a measurement of how fast the athlete was able to respond to a given stimulus. This test consisted of two pressure sensors and a LED board. The sensors were about a foot long and placed on the ground approximately four feet apart. Once the athlete's foot was firmly planted on one, sensor they would direct their attention to the LED board as shown in figure 5.34. At a random time interval, an LED light would light up in a constant position. When this stimulus occurred, the athletes had to move their foot to the other sensor as fast as possible, displayed in figure 5.35. This process occurred several times until three normal results were recorded and then the athlete switched side to use the opposite foot. Normal results were considered to be results where the athlete was able to perform the test correctly without technical issues or miss stepping on the sensors. Each results yielded two measurements. The first was the amount of time, in milliseconds, for the athlete to remove their foot from the sensor once the stimulus has occurred. This term was named mind speed since it was the total amount of time it took the athlete to recognize and to react to the stimulus. The second measurement was the amount to time, also in milliseconds, it took the athlete to reach the opposite sensor once their foot was removed from the first. The term for the second measurement was named foot speed. These tests were only performed twice, during the athlete's first session and last session.

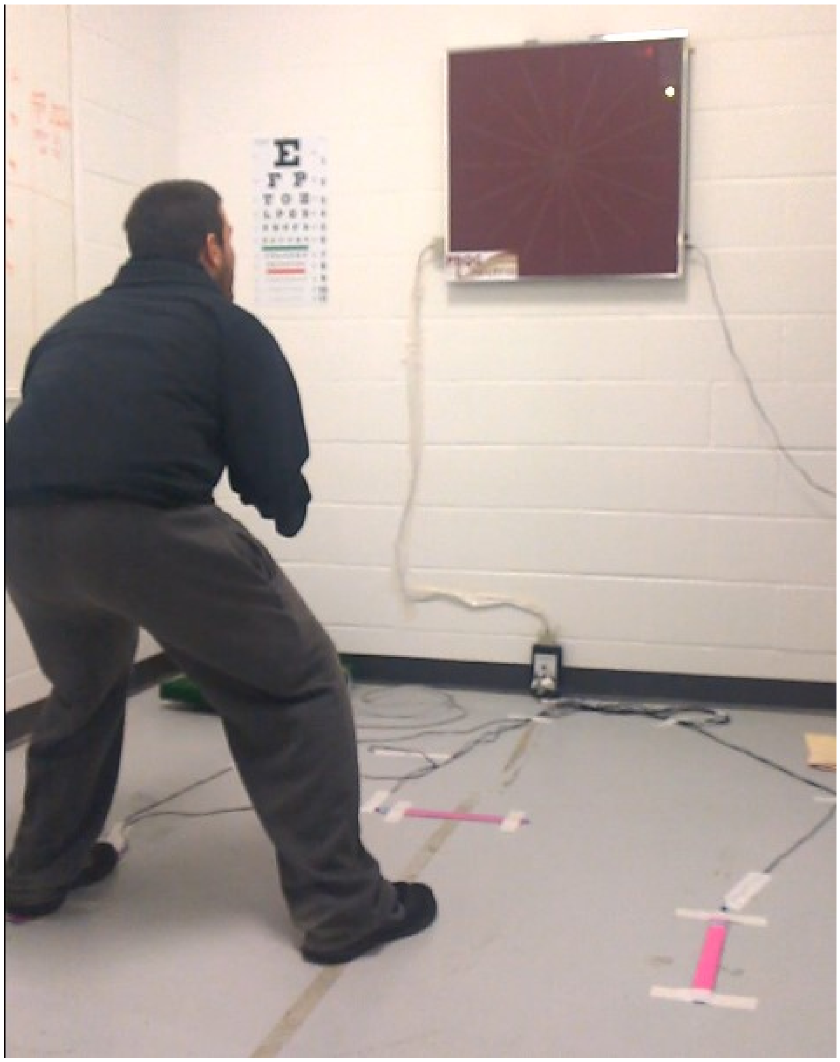


Figure 5.34: Starting position in Mind-Foot Speed Test

Figure 5.35: Ending position in Mind-Foot Speed Test

CHAPTER 6

RESULTS

This section introduces and discusses the results of the trials, exercises, and tests described in the previous section. A highlight of this section is the inertial sensor results since they describe the findings of the reaction time algorithm which was a major contribution of this project. This is followed the VEP results, which are important in linking the proposed training program with a stronger and more efficient visual circuit. The before and after results for the Mind-Foot speed test are detailed next. These results are an extension of the VEP. They include the neurons in the optical path that render the visual image, also the neurons in the brain path that process and classify the image and the signals to the muscles to complete a movement. The section is then rounded out with noteworthy findings for several individual exercises in attempts to measure progress.

6.1 Inertial Sensor

While performing the cross hair exercise, the athletes wore the custom built accelerometer device as previously described. This device recorded tri-axial accelerometers readings at a frequency of around 320 hertz. The readings for each exercise attempt were recorded and separated into each individual repetition. These results were then processed using 2.1 to calculate the total gravitational force and then graphed against the elapsed time, in milliseconds, from onset of the reaction stimulus. A compilation of every repetition recorded for all players is depicted in figure 6.1. After overlaying all the data, certain characteristics and patterns can be realized in order to help compute a reaction time.

One of those patterns is seeing motion before the stimulus was shown. Since the goal is to calculate reaction time, any reading in which the user was already moving before the stimuli's onset was disregarded. Thresholds were deducted by examining the data's totality and by selecting values that did a reasonable job at preserving its common pattern. When the time is between 0 and 100 milliseconds the total gravitational force should be between 1.2G and 1.9G. Any data that does

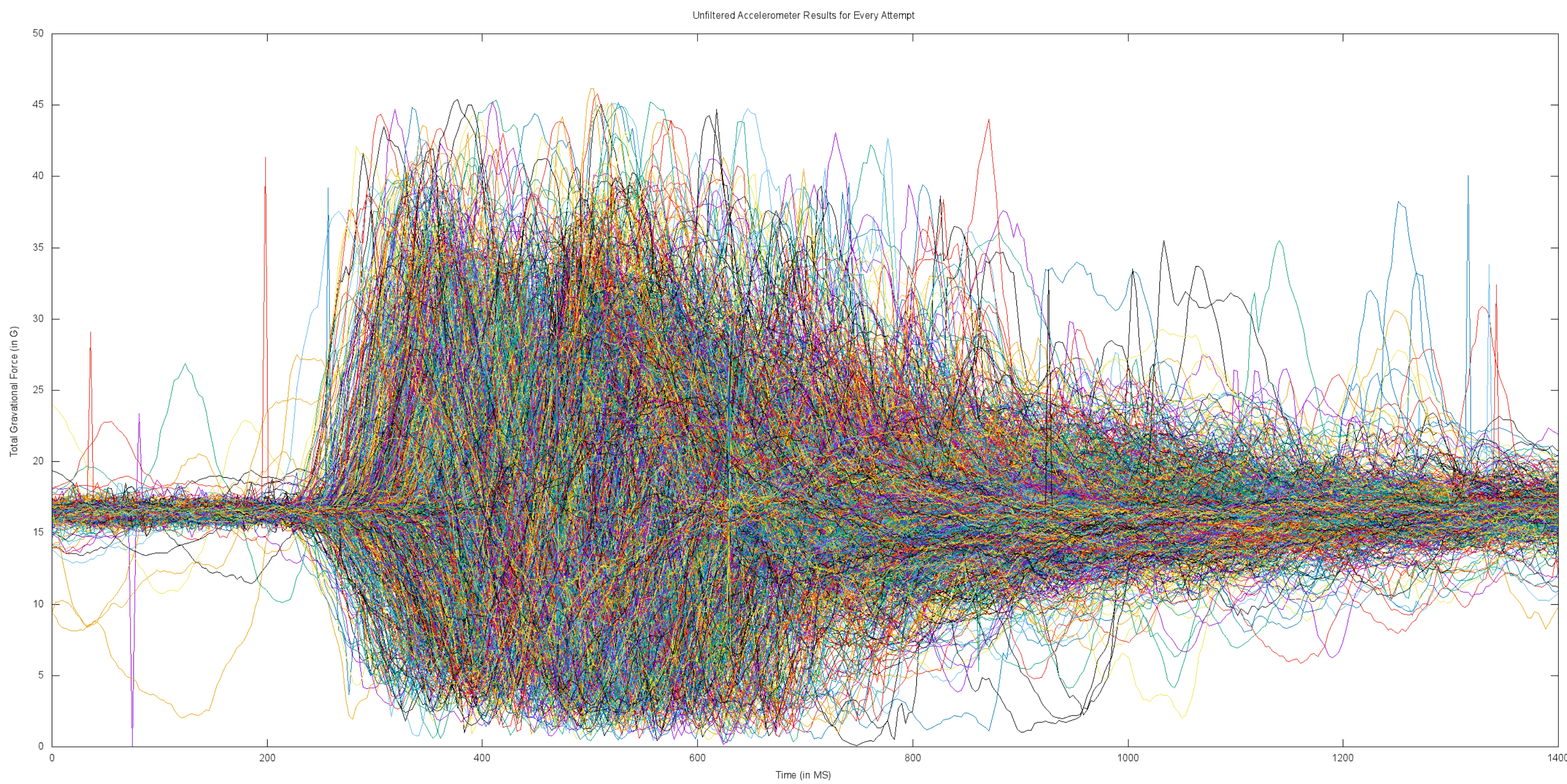


Figure 6.1: Accelerometer results for every repetition performed on during the cross hair exercise

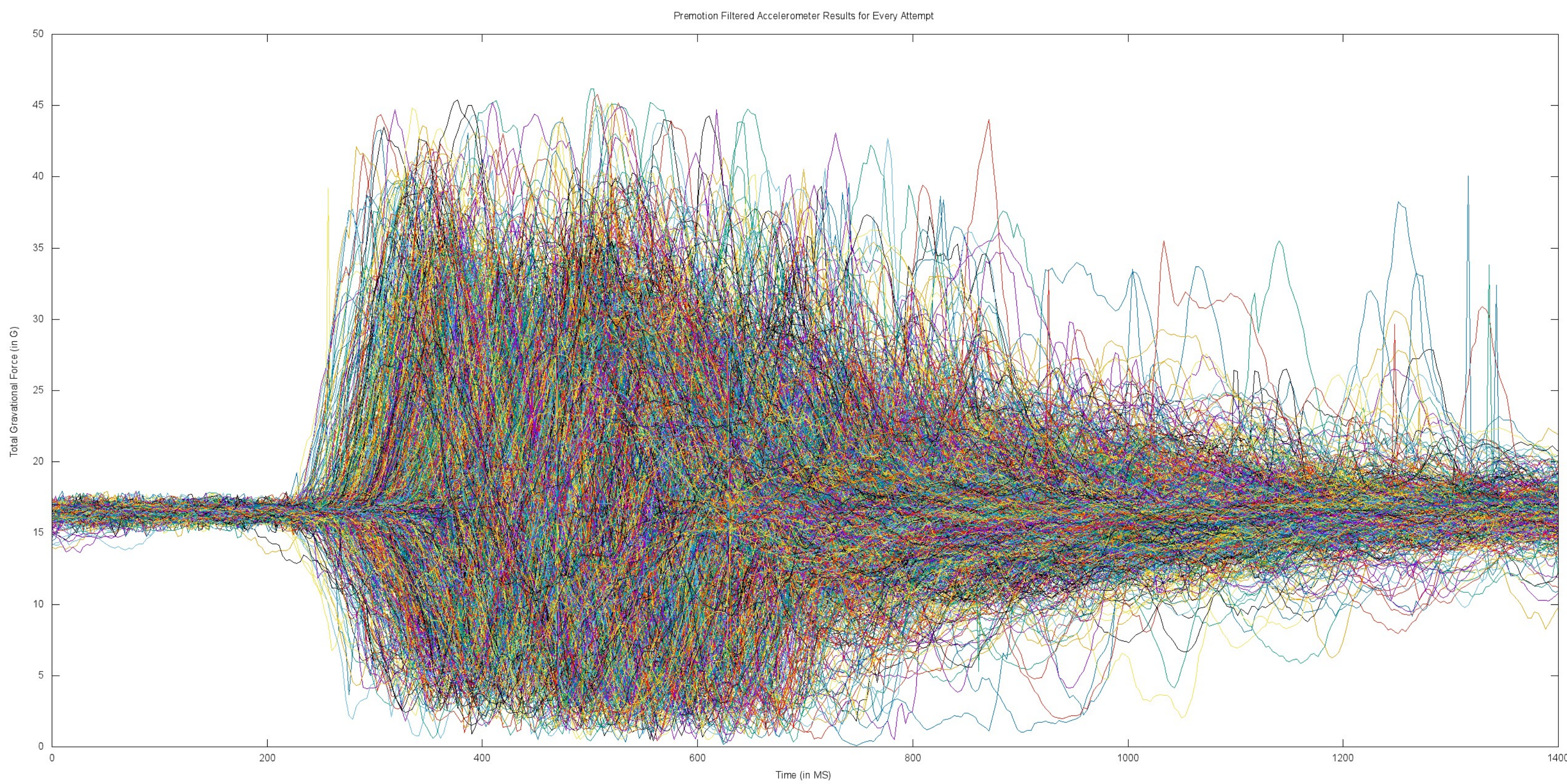


Figure 6.2: Accelerometer results for every repetition performed on during the cross hair exercise with pre-motion filtered applied

not meet this requirement was removed. Figure 6.2 is the graph of all trials after the pre-motion filter was applied. The main characteristic of this data is the flat-line of data between time 0-200 milliseconds before the user starts their reaction. In theory, the VEP measurements previously described indicate that the user requires a measurable amount of time before they can even begin to process any images. Therefore, they should be physically unable to begin their reaction before that time.

6.1.1 Signature Movements

Figures 6.5 and 6.6 are subsets of the previous graph and depict all the data for every trial on an individual athlete basis. To reiterate, this is all the captured data without the pre-motion filter applied. During the implementation several issues arose such hardware or I/O error that may have rendered several pieces of data unusable. These errors were relatively minor, followed no specific pattern, and were fixed as soon as possible. The graphs provide a large amount of detail and announce certain characteristics. Only a small number of these features will be discussed.

One feature is that each individual appears to have a movement signature unique to them. For example, the movements between player 2 and player 16 look vastly different. Player 2 appears to have more erratic movements that span several hundred milliseconds while player 16 has small, quick movements and faster stabilization. Several data points need to be collected in order to realize this, however the results are fairly clear. These variances are due to the fact that each athlete achieved their reaction movements following different patterns. This was one variable that was not constant across individuals. Each athlete was asked to move in one of the four Cartesian directions described in the setup section of this exercise. In addition, they may have received a tutorial from either the framework or the administrator of the exercise; however, fine grain detailed movements were not described and the athletes were left to make their own decisions about how to move. Perhaps if these additional movement details were provide it may have normalized some of the data. The normalization is theorized to be minor and would certainly include a significant amount of repetition and correction on the athlete's part.

It is worth reminding that each reaction movement started either in up or down direction as described in the Accelerometer Reaction Time Algorithm section. This is important to keep in mind because these graphs show the difference in directions and how the individual handles them. For example, player 7 has two different movement patterns for reaction up and down. Their data hints towards a lack of rhythm and repetitive movements as indicated by the scattered peaks and various waveforms. Player 6, on the other hand, has very symmetrical and repetitive movements. Their graph has very few outliers, and the vast majority of their waveforms follow a rather distinguished pattern. While no definitive, optimal waveform is indicated one hypothesis is that the user with the more repeatable movements may achieve a higher level of success in a lesser amount of time. The proposed hypothesis is purely based off neuroplasticity, outlining that the human body becomes more efficient handling repetitive movements. This example can be lightly compared to a golf swing. Typically, the player with the same repeatable swing tends to achieve greater success.

Another method is proposed to determine which signature is optimal. This proposal was inspired by methods used to rank spatial awareness. In this method, an expert level athlete is identified and their signature is considered to be optimal. This athlete can be determined by performance on other tests, judgement by peers and coaches, or further data analysis. While this method is not concrete, it provides a baseline from which to compare others.

6.1.2 Reaction Time

The data from the cross-hair exercise was processed using the methods in the previously detailed sensor fused reaction time algorithm. From the fused sensor data, reaction times were calculated for all trials where the repetition was determined to be valid. A valid data point was only recorded if it was properly captured (free from I/O or hardware errors), passed the pre-motion filter as previously described, and triggered the reaction threshold. Figures 6.3 and 6.4 display this resulting record for the first and second half of players respectively. The vertical axis is the reaction time for each repetition in milliseconds, while the horizontal axis is the repetition number. Therefore the horizontal axis provides a linear sense of time in which the points towards the right of the graph occurred at a later time than those on the left. The vertical axis is normalized across all graphs to provide an easier way to visually compare different athletes. However, the number of repetitions may have varied between players and can be seen by the length of the purple line.

Ideally the results would definitely capture the athletes' progression to better performance. This ideal graph could be visualized as a linear line with a negative slope in such that every reaction time is less than the previous. However, the resulting graphs do not follow this idealized trend. Instead, the reaction times are varied, both positively and negatively, producing a rather jagged line. In practice, this variance is to be expected. It is unrealistic to expect humans to perform in a

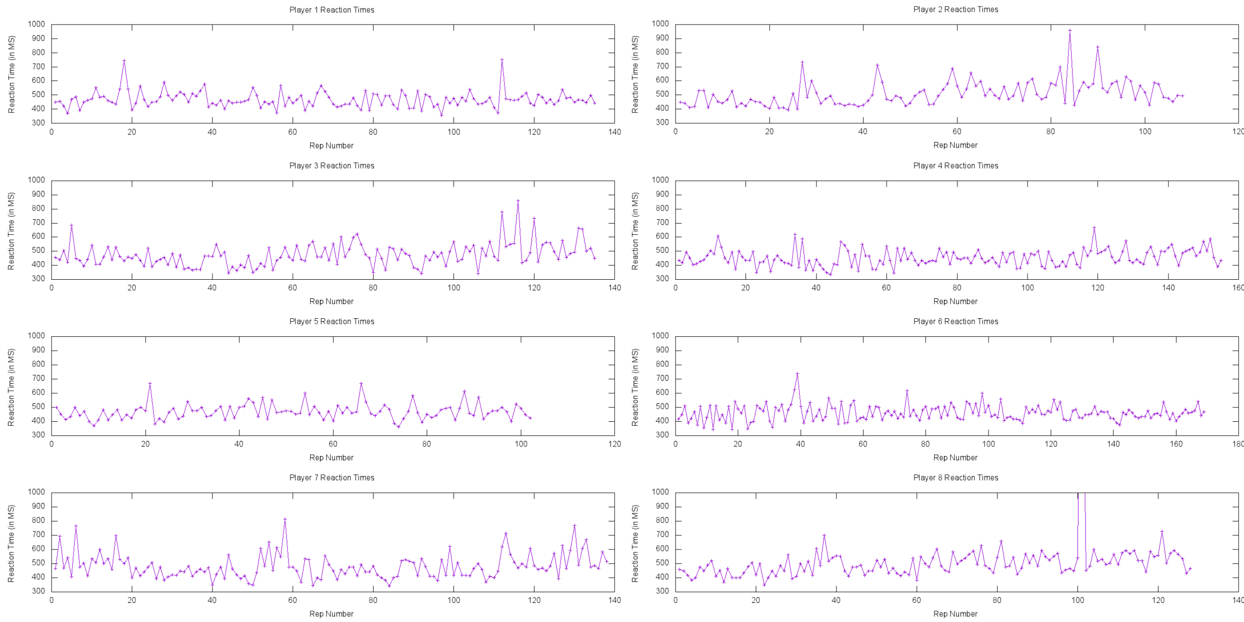


Figure 6.3: Calculated reaction times during trials for first half of players

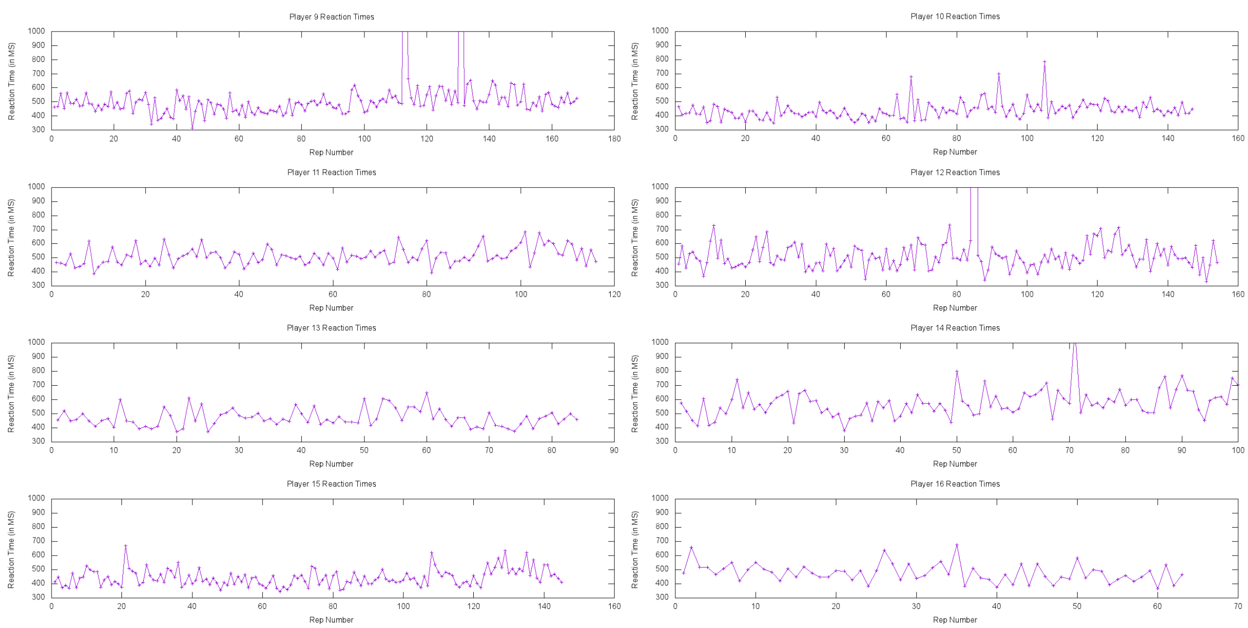


Figure 6.4: Calculated reaction times during trials for second half of players

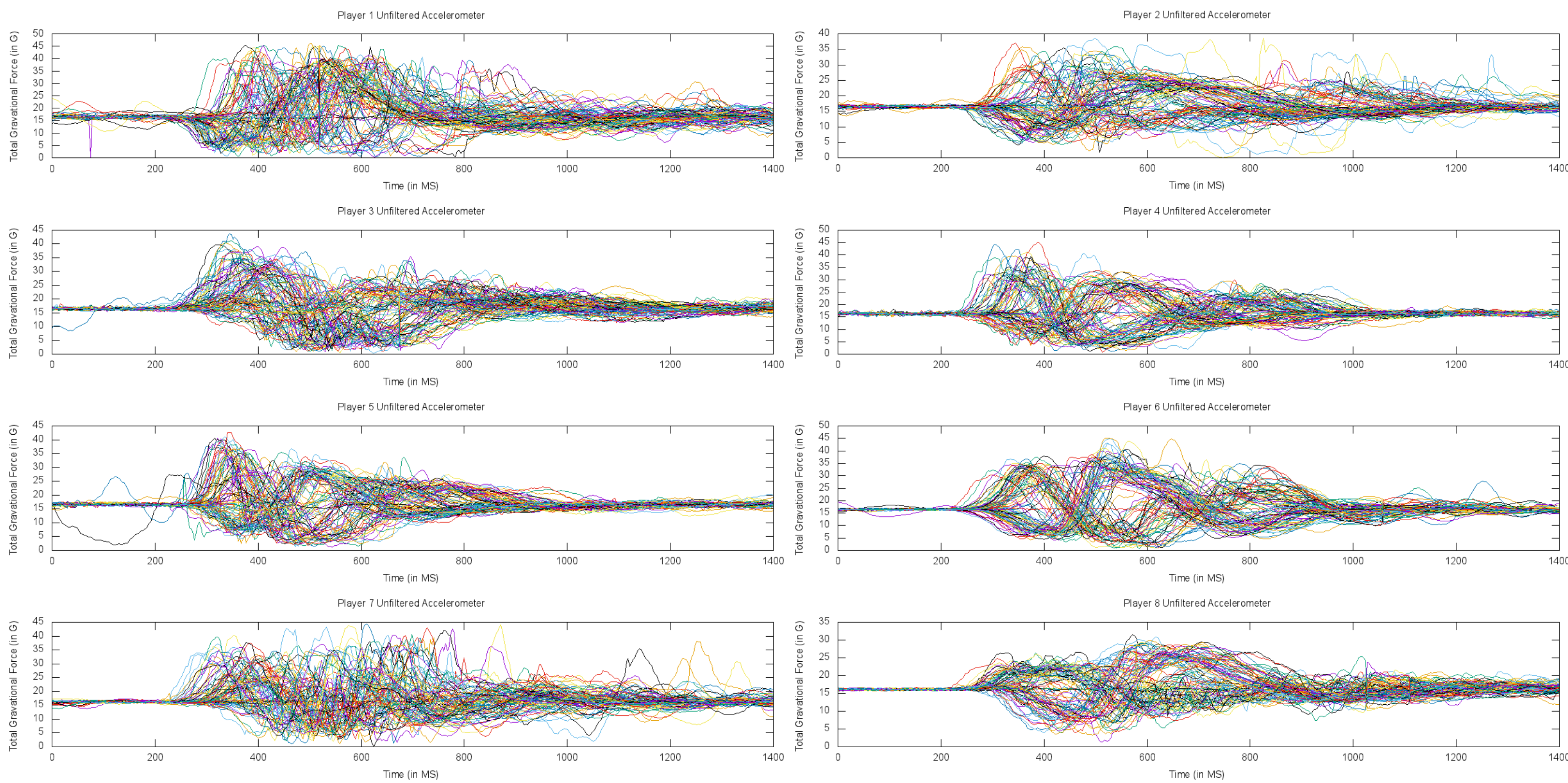


Figure 6.5: Total gravitational force during all trials for first half of athletes

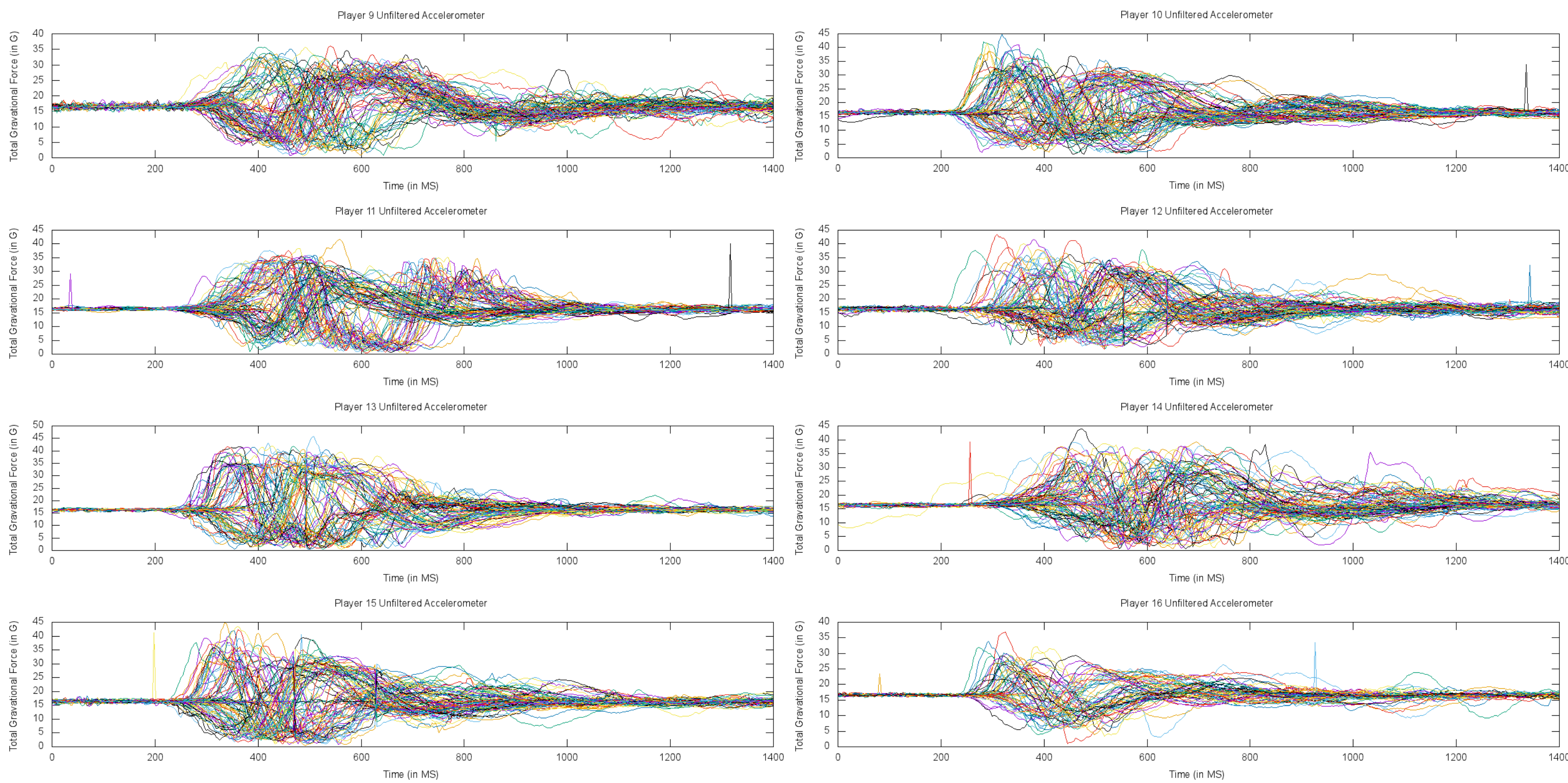


Figure 6.6: Total gravitational force during all trials for second half of athletes

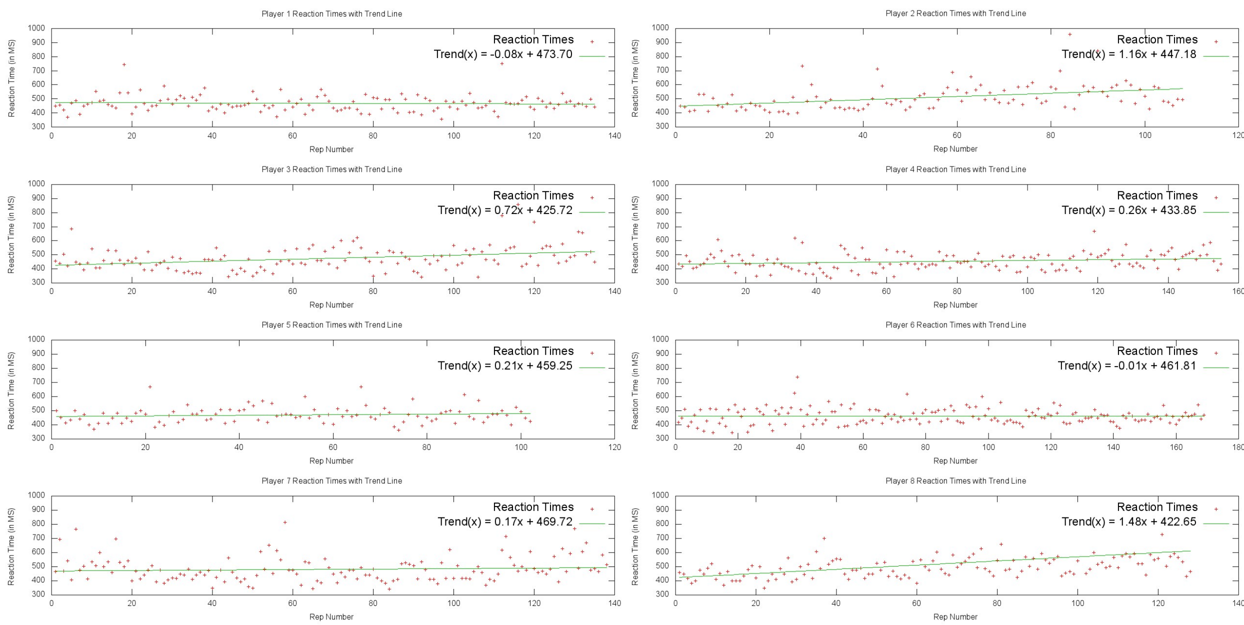


Figure 6.7: Calculated reaction times with trend line for first half of players

robotic fashion achieving consistent results down to the millisecond for a large number of actions. Instead the ideal result can be modified to include an overall downward trend.

Figures 6.7 and 6.8 are the same reaction time graphs as recently discussed with an added trend line calculated for each data set. The equation for each trend line is included in the top right of the corresponding graph in order classify the slightest change. As stated, the desired trend line would possess a negative slope indicating the athlete's overall reaction time is decreasing. The minority of graphs do not contain this trend. In fact it would appear that the majority of athletes digressed as the trial proceeded. This conclusion is misleading because it does not take into account the increasing difficulty of the exercises. As previously described in the Cross Hair Exercise section, once the athlete demonstrated the ability to perform the exercise with little or no errors, the difficult of the exercise was increased in several ways. This inherited method of proctoring the exercise did not take this information into account which, altered the results enough to yield a graph that did not follow the desired pattern. Yet, the derived equation can still be used as a relative comparison method between athletes to if the minimum slope is considered to represent the fastest progressing individual. If this study were to be conducted again, this is a key area to remedy.

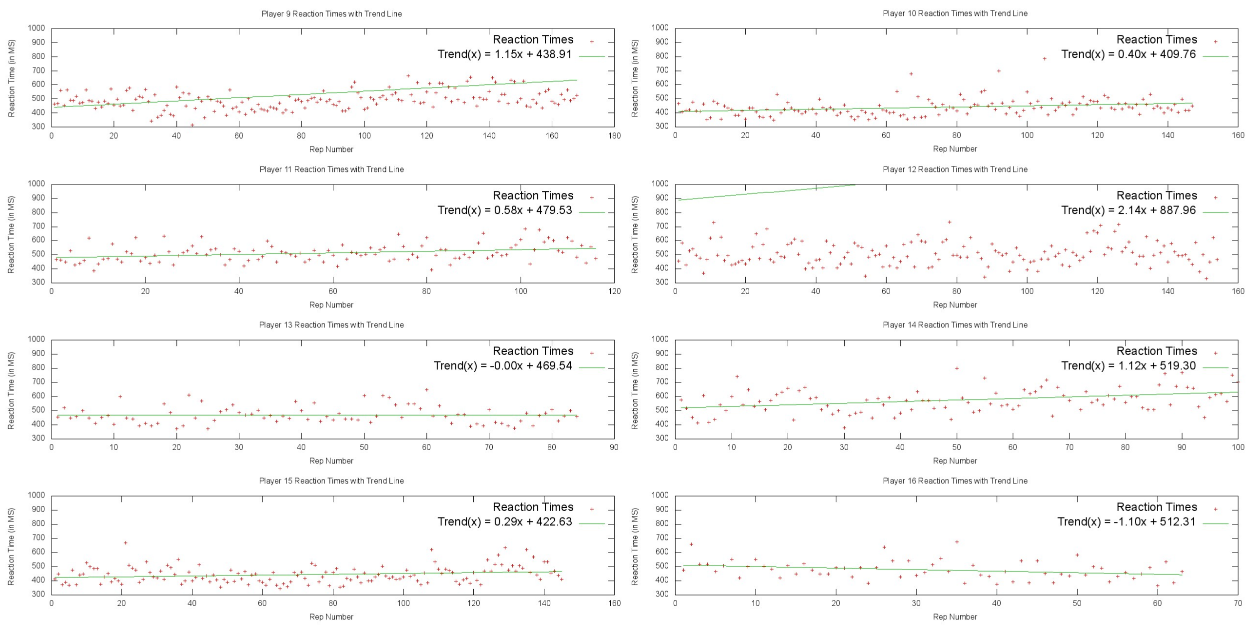


Figure 6.8: Calculated reaction times with trend line for second half of players

6.2 VEP Results

Every athlete, with the exception of player 5 who was withheld due to injury, in the study underwent a Visual Evoked Potential (VEP) measurement before and after vision training. There were several tests performed and the results are shown figure 6.1. VEP tests fell into two main categories, light and dark contrast. The top of the table denotes if the test was at 15%, light contrast, or 85%, dark contrast. Both contrasts had a checkerboard like pattern, however the dark contrast appeared black and white (like a chessboard) while the light contrast had white and light grey boxes. The tests were then divided in readings that occurred pre training and in readings that occurred post training. For each test, there were two main measurements that were recorded, delay in milliseconds, and amperage in microvolts. These two measurements are the most significant because they determine how fast the image is getting to the athlete's visual cortex, the delay, and how efficient it is, the amplitude. These two measures were also recorded for the oculus sinister (OS), oculus dexter (OD), and oculus uterque (OU). These terms signify whether the measurements are referring to the left, right, or both eyes respectively.

According to the Diopsys manufacturer, the time it takes the electrical signal to travel from the retina to the visual cortex occurs around 100 milliseconds. Any delay under this time would be considered an outstanding score. The pre-VEP measurements in table 6.1 indicate that none of the athletes started below this latency, with the exception of player 2 whom was not able to get a reliable reading for his left eye at 15% contrast. The manufacturer also mentions that a normal amplitude at 85% contrast with this test configuration should be expected to be above six microvolts [29]. Several of the athletes did not start above this mark.

Table 6.2 shows the difference in the pre and post VEP results. The highlighted cells range from red to green depending on if the desired result was achieved. The shades of green and red indicate the significant difference in the results. For the delay measurement, the desired result was to have a lower latency and thus a smaller reading on the post VEP. If the number listed in the table is positive, it will be highlighted green to show the amount of time the latency was decreased. For the amplitude, the desired result was to get more information to the visual cortex which is an increase in measures for the post VEP.

While the majority of athletes experienced gains, several of them showed digressions in some areas. There could be several variables contributing to these digressions such as sleep, stress, focus and other outside factors. In cases where the digressions seem extreme, such as players 3, 4, 7, 9, and 13, there still benefits. Player 3 recorded 10.15 microvolts less for his 15% amplitude in both eyes, but each individual eye showed progress. The left benefited more than the digression amount. Players 7 and 13 experienced the opposite result. Each individual eye showed a loss, however both eyes together showed a positive. Player 4 recorded lower scores for the OD and OU while gaining in the OS. Note that player 4 also recorded the same amplitude pattern for 15% and 85%. Player 9 was only one of two athletes who recorded all negative scores. Player 9's 85% amplitude was decreased across the board while his 15% scores were all increases.

Despite the fact that several athletes recorded negative scores on the post vision training VEPs, the majority were positive. Table 6.3 shows the percentage of athletes that showed gains in their post VEP tests. The cells were highlighted green if the percentage was over the majority, 50%. They were highlighted red if they were below this threshold. There was one category in which the majority of athletes performed worst, the 15% amplitude with both eyes. One explanation for this

Table 6.1: VEP results before and after training as broken down by left, right, and both eyes for low and high contrast

	Contrast	15%						85%					
		Pre-VEP			Post-VEP			Pre-VEP			Post-VEP		
Player	Result Type	OD	OS	OU	OD	OS	OU	OD	OS	OU	OD	OS	OU
1	Delay (ms)	123	131.8	130.9	117.2	115.2	112.3	119.1	118.2	121.1	114.3	108.4	109.4
	Amp (uV)	5.56	6.04	6.61	5.31	11.24	7.59	12.9	10.64	12.83	9.38	12.16	10.71
2	Delay (ms)	113.3	0	108.4	119.1	0	101.6	106.4	107.4	107.4	105.5	109.4	104.5
	Amp (uV)	6.38	0	9.29	8.65	0	18.84	7.87	9.35	15.36	12.6	13.09	16.45
3	Delay (ms)	109.4	118.2	111.3	93.7	110.3	99.6	105.5	111.3	108.4	106.4	110.3	110.3
	Amp (uV)	7.64	9.04	17.61	12.5	19.91	7.46	18.65	18.88	30.84	18.75	19.97	35.01
4	Delay (ms)	114.3	112.3	96.7	108.4	116.2	97.6	113.3	107.4	116.2	108.4	99.6	114.3
	Amp (uV)	13.43	10.35	13.34	7.12	14.04	3.52	13.28	12.38	20.8	11.11	16.01	19.31
6	Delay (ms)	127.9	117.2	115.2	103.5	117.2	112.3	112.3	109.4	115.2	105.5	110.3	107.4
	Amp (uV)	11.05	4.94	8.29	6.71	6.09	10.85	10.28	11.82	15.5	4.85	7.73	16.03
7	Delay (ms)	120.1	123	113.3	119.1	118.2	108.4	110.3	110.3	100.6	110.3	108.4	105.5
	Amp (uV)	10.26	12.14	11.87	8.57	5.26	12.94	10.21	11.77	8.99	11.96	11.16	7.91
8	Delay (ms)	117.2	119.1	107.4	114.3	117.2	109.4	105.5	107.4	105.5	104.5	105.5	104.5
	Amp (uV)	13.94	11.91	10.79	10.91	11.39	11.41	12.77	15.3	19.02	20.71	20.65	20.64
9	Delay (ms)	120.1	125	111.3	123	112.3	113.3	118.2	111.3	110.3	121.1	106.4	111.3
	Amp (uV)	7.63	6.41	8.12	8.38	13.64	8.3	8.46	9.32	12.64	7.92	4.66	5.16
10	Delay (ms)	118.2	122.1	116.2	116.2	117.2	119.1	117.2	119.1	115.2	117.2	117.2	118.2
	Amp (uV)	5.99	5.47	7.25	8.87	5.66	5.77	17.03	15.12	14.04	13.63	14.52	13.02
11	Delay (ms)	123	126	116.2	110.3	113.3	104.5	112.3	115.2	121.1	112.3	111.3	110.3
	Amp (uV)	11.09	7.49	11.6	8.95	6.95	8.92	20.86	21.34	22.13	22.92	23	27.76
12	Delay (ms)	112.3	126	110.3	113.3	111.3	90.8	106.4	101.6	109.4	105.5	102.5	104.5
	Amp (uV)	5.14	3.38	6.51	10.38	4.39	4.16	8.74	13.22	15.87	11.57	7.25	16.32
13	Delay (ms)	111.3	102.5	112.3	114.3	113.3	110.3	112.3	109.4	113.3	111.3	104.5	118.2
	Amp (uV)	6.26	5.6	9.59	9.18	8.7	8.13	10.28	8.31	14.37	9.53	5.22	12.5
14	Delay (ms)	107.4	113.3	113.3	113.3	112.3	113.3	109.4	109.4	111.3	108.4	110.3	111.3
	Amp (uV)	5.57	4.17	5.47	5.54	6.02	12.04	14.03	12.54	15.57	11.24	13.3	13.36
15	Delay (ms)	104.5	111.3	107.4	108.4	109.4	98.6	111.3	106.4	106.4	99.6	106.4	109.4
	Amp (uV)	4.39	4.75	7.98	7.25	8.22	7.67	8.6	7.31	11.46	9.3	10.82	9.23
16	Delay (ms)	126.9	126	117.2	95.7	122.1	122.1	115.2	117.2	118.2	113.3	112.3	112.3
	Amp (uV)	6.21	8.45	9.47	16.75	14.58	5.09	11.76	10.64	14.98	22.35	20.85	13.08

Table 6.2: Difference in VEP results

	Contrast	15%			85%		
Player	Result Type	OD	OS	OU	OD	OS	OU
1	Delay (ms)	5.8	16.6	18.6	4.8	9.8	11.7
	Amp (uV)	-0.25	5.2	0.98	-3.52	1.52	-2.12
2	Delay (ms)	-5.8	0	6.8	0.9	-2	2.9
	Amp (uV)	2.27	0	9.55	4.73	3.74	1.09
3	Delay (ms)	15.7	7.9	11.7	-0.9	1	-1.9
	Amp (uV)	4.86	10.87	-10.15	0.1	1.09	4.17
4	Delay (ms)	5.9	-3.9	-0.9	4.9	7.8	1.9
	Amp (uV)	-6.31	3.69	-9.82	-2.17	3.63	-1.49
6	Delay (ms)	24.4	0	2.9	6.8	-0.9	7.8
	Amp (uV)	-4.34	1.15	2.56	-5.43	-4.09	0.53
7	Delay (ms)	1	4.8	4.9	0	1.9	-4.9
	Amp (uV)	-1.69	-6.88	1.07	1.75	-0.61	-1.08
8	Delay (ms)	2.9	1.9	-2	1	1.9	1
	Amp (uV)	-3.03	-0.52	0.62	7.94	5.35	1.62
9	Delay (ms)	-2.9	12.7	-2	-2.9	4.9	-1
	Amp (uV)	0.75	7.23	0.18	-0.54	-4.66	-7.48
10	Delay (ms)	2	4.9	-2.9	0	1.9	-3
	Amp (uV)	2.88	0.19	-1.48	-3.4	-0.6	-1.02
11	Delay (ms)	12.7	12.7	11.7	0	3.9	10.8
	Amp (uV)	-2.14	-0.54	-2.68	2.06	1.66	5.63
12	Delay (ms)	-1	14.7	19.5	0.9	-0.9	4.9
	Amp (uV)	5.24	1.01	-2.35	2.83	-5.97	0.45
13	Delay (ms)	-3	-10.8	2	1	4.9	-4.9
	Amp (uV)	2.92	3.1	-1.46	-0.75	-3.09	-1.87
14	Delay (ms)	-5.9	1	0	1	-0.9	0
	Amp (uV)	-0.03	1.85	6.57	-2.79	0.76	-2.21
15	Delay (ms)	-3.9	1.9	8.8	11.7	0	-3
	Amp (uV)	2.86	3.47	-0.31	0.7	3.51	-2.23
16	Delay (ms)	31.2	3.9	-4.9	1.9	4.9	5.9
	Amp (uV)	10.54	6.13	-4.38	10.59	10.21	-1.9

Table 6.3: Percentage of athletes that showed gains in post VEP tests

Contrast	15%			85%		
Eye Type	OD	OS	OU	OD	OS	OU
Delay (ms)	60.00%	73.33%	60.00%	66.66%	66.66%	53.33%
Amp (uV)	53.33%	73.33%	46.66%	53.33%	60.00%	60.00%

Table 6.4: Averages and gains for VEP testing

	Delay (ms)						Amp (uv)					
	15%			85%			15%			85%		
Eye	OD	OS	OU	OD	OS	OU	OD	OS	OU	OD	OS	OU
Pre	116.59	119.56	112.49	111.65	110.73	111.97	8.04	7.15	9.59	12.38	12.53	16.29
Post	111.32	114.68	107.55	109.57	108.19	110.09	9.00	9.72	8.85	13.19	13.36	15.77
Gain	5.27	4.88	4.95	2.07	2.55	1.88	0.97	2.57	-0.74	0.81	0.83	-0.53

outlying result could be the configuration of the testing environment. For post VEP testing there were additional staff members in the testing room which added to the noise level.

The data indicates that the majority of the athletes improved. Table 6.4 explores the averages and exactly how much was gained in post VEP testing. The left columns label the total average for pre and post testing, while the top rows label the types of tests. Overall, there were several significant gains in this four week training period. The average decreases in latency for the 15% contrast was almost five milliseconds. The 85% contrast saw improvements of nearly two milliseconds. The fact that players 3 and 4 performed very low on the 85% OU was still out weighted by the improvements in the other athletes. The amplitude shows that the average case for each the left eye and right eye was improved, however both seemed to take a minor recession. This could once again be the additional staff members in the testing room when gathering the final VEP measurements. An important note is that the amplitude of the 15% contrast in the OS rose over 2.57 microvolts. This number is very significant since the manufacturer suggests six was an average threshold. A gain of this size could be expected when taken into account that the majority of the athletes were right eye dominate. Since the left eye was the weaker of the two, it started with the most earning potential.

6.2.1 Amended Observations

The previous observations were preserved to document the thought process. But, after further analysis several new conclusions were drawn and the hypothesis was modified. The first conclusion modifies the initial hypothesis in which the greater the voltage or amplitude implies more information travelling to the visual cortex resulting in a stronger system. It would actually be beneficial to show a reduction in the voltage. A decrease in voltage could mean that the visual system is performing the same amount of work with a reduced amount of energy. This means that the athletes have become more efficient than previously thought. The data from table [**?**], shows that each eye has an increase in voltage, while both eyes together have a decrease in voltage. The reason for the single eye having in increase in voltage could be due to the fact that the entire vision system is operating at half capacity, one eye is not providing information. Thus, the open eye is attempting to capture more data to make up for its closed counterpart. In this case, a greater voltage would result in a stronger system. On the other hand, when both eyes are open they are providing the expected level of information. Here, a lesser voltage would the information is processed more efficiently resulting in a stronger system. This analysis leads to the conclusion that average results for all players follows a new, ideal pattern.

It was observed that 15% contrast yielded better gains than 85% contrast. To reiterate the difference in contrast, 15% contrast appeared as light grey while 85% appeared as dark black. The significance of color explains what part of visual system each contrast is intended to measure. The 15% contrast measures low light, peripheral vision, while the 85% measure direct vision. In modern times, humans typically use their direct vision much more frequently than peripheral. This is evident in developed cultures that spend a greater amount of time reading and looking at smartphones as opposed to wandering the outdoors hunting for food. By not exercising peripheral vision, there is greater potential to experience gains with a limited amount of effort. The greater gain of peripheral vision is what was observed during the study.

In addition to limited use of peripheral vision, there may have been limited use of the OS (left eye). The study observed that the OS appeared to have the biggest increase in voltage and decrease in delay. For the majority of the athletes, the OD (right eye) was their dominate eye. This means that, on average, there were greater gains in the non-dominate eye. Extending from the hypothesis that there is greater potential in the weaker system, this observation would appear follow that pattern.

6.3 Mind-Foot Speed Test

The results for the Mind-Foot Speed exercise are displayed in table 6.5. Each athlete received a sufficient change to warm up with the exercise in order to become familiar with it. After a warm up of about 3-5 trial runs their next three results were recorded. If any of those three results were invalid, like the athlete missing the start/stop pad, then it was thrown out and reattempted. The athletes' initial scores from their first day of training is in the left hand column, while the scores from the last day of training are on the right and marked with the prime symbol. All times listed are in milliseconds and were automatically calculated from the hardware unit. The ending scores from player 5 were omitted because he suffered a serious injury and could not complete training. The bold row at the bottom of each player is an average of their three scores in the corresponding columns. The highlighted cells are the differences between the initial and ending averages with the faster times colored green and the slower times colored red. While the desired result was faster times in all categories, as displayed in players 14-17, this did not occur. However, the average scores did decreased by 61.6% with no athlete showed a degradation in all four areas.

$$\sum(x - \bar{x})^2/(n - 1) \tag{6.1}$$

There are additional ways to determine success besides average scores. Table 6.6 displays the variance among the mind-foot speed results in table 6.5 using 6.1. The left side of this table displays the initial variance in milliseconds while the left side is the ending variance. The cells highlighted green show that the ending variance was smaller than the initial, while those in red are the opposite. By this metric 71.66% of athletes showed a decrease in variance. By lowering this variance the athlete would respond in a more predictable manner, which could be a desired result in sports.

The last metric used to analyze this exercise comes by looking at the entire motion together, rather than the mind and foot segments separately. Table 6.7 displays the sum, in milliseconds, in

Table 6.5: Initial and ending results for the Mind-Foot Speed Test in seconds

Player	Mind L	Foot L	Mind R	Foot R	Mind L'	Foot L'	Mind R'	Foot R'	Player	Mind L	Foot L	Mind R	Foot R	Mind L'	Foot L'	Mind R'	Foot R'
1	0.162	0.930	0.408	0.516	0.480	0.252	0.408	0.276	9	0.246	0.552	0.414	0.348	0.414	0.288	0.444	0.270
	0.306	0.570	0.318	0.504	0.456	0.282	0.444	0.264		0.180	0.522	0.402	0.276	0.408	0.276	0.450	0.258
	0.420	0.510	0.360	0.438	0.456	0.246	0.438	0.252		0.360	0.346	0.408	0.406	0.420	0.276	0.390	0.234
Avg	**0.296**	**0.670**	**0.362**	**0.486**	**0.464**	**0.260**	**0.430**	**0.264**		**0.262**	**0.473**	**0.408**	**0.343**	**0.414**	**0.280**	**0.428**	**0.254**
					-0.168	0.410	-0.068	0.222						-0.152	0.193	-0.020	0.089
2	0.378	0.300	0.336	0.294	0.330	0.258	0.384	0.300	10	0.390	0.348	0.408	0.330	0.366	0.330	0.426	0.306
	0.342	0.252	0.444	0.312	0.402	0.312	0.312	0.288		0.444	0.276	0.420	0.306	0.396	0.348	0.366	0.324
	0.384	0.252	0.372	0.288	0.378	0.288	0.378	0.288		0.432	0.282	0.450	0.282	0.390	0.354	0.408	0.324
Avg	**0.368**	**0.268**	**0.384**	**0.298**	**0.370**	**0.286**	**0.358**	**0.292**		**0.422**	**0.302**	**0.426**	**0.306**	**0.384**	**0.344**	**0.400**	**0.318**
					-0.002	-0.018	0.026	0.006						0.038	-0.042	0.026	-0.012
3	0.426	0.330	0.462	0.426	0.456	0.348	0.408	0.276	11	0.390	0.348	0.396	0.384	0.432	0.366	0.426	0.330
	0.438	0.408	0.444	0.300	0.432	0.342	0.414	0.324		0.426	0.306	0.414	0.426	0.414	0.332	0.414	0.342
	0.426	0.366	0.426	0.330	0.462	0.360	0.444	0.306		0.408	0.354	0.270	0.498	0.420	0.342	0.408	0.282
Avg	**0.430**	**0.368**	**0.444**	**0.352**	**0.450**	**0.350**	**0.422**	**0.302**		**0.408**	**0.336**	**0.360**	**0.436**	**0.422**	**0.347**	**0.416**	**0.318**
					-0.020	0.018	0.022	0.050						-0.014	-0.011	-0.056	0.118
4	0.282	0.312	0.306	0.346	0.372	0.372	0.360	0.354	12	0.318	0.306	0.240	0.468	0.372	0.270	0.396	0.348
	0.294	0.336	0.394	0.294	0.318	0.390	0.312	0.330		0.330	0.294	0.964	0.288	0.336	0.246	0.384	0.252
	0.336	0.276	0.300	0.294	0.330	0.396	0.306	0.336		0.294	0.282	0.264	0.252	0.348	0.246	0.348	0.258
Avg	**0.304**	**0.308**	**0.333**	**0.311**	**0.340**	**0.386**	**0.326**	**0.340**		**0.314**	**0.294**	**0.489**	**0.336**	**0.352**	**0.254**	**0.376**	**0.286**
					-0.036	-0.078	0.007	-0.029						-0.038	0.040	0.113	0.050
5	0.378	0.264	0.162	0.510	N/A				13	0.336	0.276	0.354	0.276	0.288	0.336	0.324	0.324
	0.426	0.270	0.390	0.264						0.324	0.312	0.378	0.324	0.360	0.324	0.318	0.318
	0.390	0.270	0.378	0.306						0.324	0.282	0.552	0.252	0.330	0.312	0.294	0.312
Avg	**0.398**	**0.268**	**0.310**	**0.360**						**0.328**	**0.290**	**0.428**	**0.284**	**0.326**	**0.324**	**0.312**	**0.318**
														0.002	-0.034	0.116	-0.034
6	0.444	0.342	0.450	0.384	0.426	0.300	0.414	0.306	14	0.420	0.306	0.546	0.324	0.348	0.312	0.372	0.294
	0.372	0.354	0.414	0.336	0.462	0.336	0.450	0.288		0.396	0.312	0.396	0.312	0.432	0.253	0.372	0.258
	0.384	0.354	0.408	0.336	0.420	0.372	0.444	0.276		0.438	0.288	0.414	0.300	0.354	0.282	0.384	0.258
Avg	**0.400**	**0.350**	**0.424**	**0.352**	**0.436**	**0.336**	**0.436**	**0.290**		**0.418**	**0.302**	**0.452**	**0.312**	**0.378**	**0.282**	**0.376**	**0.270**
					-0.036	0.014	-0.012	0.062						0.040	0.020	0.076	0.042
7	0.408	0.408	0.438	0.456	0.798	0.438	0.402	0.408	15	0.360	0.294	0.414	0.318	0.348	0.270	0.360	0.258
	0.405	0.486	0.432	0.576	0.456	0.396	0.420	0.366		0.366	0.396	0.366	0.300	0.348	0.264	0.330	0.264
	0.426	0.420	0.486	0.504	0.396	0.414	0.426	0.366		0.348	0.300	0.360	0.288	0.348	0.312	0.324	0.288
Avg	**0.413**	**0.438**	**0.452**	**0.512**	**0.550**	**0.416**	**0.416**	**0.380**		**0.358**	**0.330**	**0.380**	**0.302**	**0.348**	**0.282**	**0.338**	**0.270**
					-0.137	0.022	0.036	0.132						0.010	0.048	0.042	0.032
8	0.408	0.396	0.444	0.312	0.420	0.336	0.474	0.330	16	0.456	0.369	0.480	0.390	0.360	0.384	0.390	0.366
	0.414	0.336	0.468	0.354	0.450	0.324	0.162	0.624		0.498	0.372	0.468	0.342	0.348	0.324	0.378	0.318
	0.420	0.342	0.402	0.288	0.456	0.354	0.540	0.348		0.438	0.642	0.474	0.342	0.324	0.342	0.336	0.348
Avg	**0.414**	**0.358**	**0.438**	**0.318**	**0.442**	**0.338**	**0.392**	**0.434**		**0.464**	**0.461**	**0.474**	**0.358**	**0.344**	**0.350**	**0.368**	**0.344**
					-0.028	0.020	0.046	-0.116						0.120	0.111	0.106	0.014

Table 6.6: The variance of the three scores in Mind-Foot Speed Table in seconds

Player	Mind L	Foot L	Mind R	Foot R	Mind L'	Foot L'	Mind R'	Foot R'
1	0.01672	0.0516	0.00203	0.00176	0.00019	0.00037	0.00037	0.00014
2	0.00052	0.00077	0.00302	0.00016	0.00134	0.00073	0.0016	4.8E-05
3	4.8E-05	0.00152	0.00032	0.00433	0.00025	8.4E-05	0.00037	0.00059
4	0.0008	0.00091	0.00277	0.0009	0.0008	0.00016	0.00088	0.00016
6	0.00149	4.8E-05	0.00052	0.00077	0.00052	0.0013	0.00037	0.00023
7	0.00013	0.00176	0.00088	0.00365	0.04703	0.00044	0.00016	0.00059
8	3.6E-05	0.00109	0.00112	0.00112	0.00037	0.00023	0.04076	0.02716
9	0.00829	0.01239	3.6E-05	0.00424	3.6E-05	4.8E-05	0.00109	0.00034
10	0.0008	0.0016	0.00047	0.00058	0.00025	0.00016	0.00095	0.00011
11	0.00032	0.00068	0.00616	0.00332	8.4E-05	0.00031	8.4E-05	0.00101
12	0.00034	0.00014	0.16913	0.01339	0.00034	0.00019	0.00062	0.00289
13	4.8E-05	0.00037	0.01168	0.00134	0.00131	0.00014	0.00025	3.6E-05
14	0.00044	0.00016	0.00671	0.00014	0.0022	0.00087	4.8E-05	0.00043
15	8.4E-05	0.00328	0.00088	0.00023	4.6E-33	0.00068	0.00037	0.00025
16	0.00095	0.02457	3.6E-05	0.00077	0.00034	0.00095	0.0008	0.00059

Table 6.7: The sum of mind and foot average results for the left and right side in seconds

Player	Left	Left'	Diff	Right	Right'	Diff
1	0.966	0.724	0.242	0.848	0.694	0.154
2	0.636	0.656	-0.020	0.682	0.650	0.032
3	0.798	0.800	-0.002	0.796	0.724	0.072
4	0.612	0.726	-0.114	0.645	0.666	-0.021
6	0.750	0.772	-0.022	0.776	0.726	0.050
7	0.851	0.966	-0.115	0.964	0.796	0.168
8	0.772	0.780	-0.008	0.756	0.826	-0.070
9	0.735	0.694	0.041	0.751	0.682	0.069
10	0.724	0.728	-0.004	0.732	0.718	0.014
11	0.744	0.769	-0.025	0.796	0.734	0.062
12	0.608	0.606	0.002	0.825	0.662	0.163
13	0.618	0.650	-0.032	0.712	0.630	0.082
14	0.720	0.660	0.060	0.764	0.646	0.118
15	0.688	0.630	0.058	0.682	0.608	0.074
16	0.925	0.694	0.231	0.832	0.712	0.120

the average scores of the mind and foot motions for both the left and right side. The highlighted columns are the difference in sums between the initial and ending trials. The green cells show a faster time, which is the desired results. Overall, 63.33% of athletes showed improvement. It is also important to note that several of the athletes showed great improvement, such as players 1, 12, 14, and 16. Their improvement was more dramatic than the few athletes that showed degradation, such as player 8. Furthermore, all of the cases in which one side was improved and the other side digressed, the improvement out weighted the digression. This lead to an overall faster motion, despite the fact the athlete was slower on part of the exercise.

Another note regarding digressions in this metric is that they did not occur on the right side exclusively. There are two cases in which the right side of athletes digressed, player 4 and player 8.

In both of these cases, there was also a regression on the left side. A possible explanation is that the majority of the athletes were not used to leading with their left foot. Their natural motion is to take the first step with their right foot. Due to this unfamiliar motion, it may have added to a slight delay causing a negative difference while the familiar right side saw gains.

6.4 Drills and Exercises

6.4.1 Hand Dot Drill

The athletes performed this drill a combined 213 times and averaged 13.31 attempts. The individual results are displayed in table 6.9, with the top 10% of scores highlighted. Figure 6.10 is a graph that shows these results. The minimum score was 69 by player 3 and the maximum score was 128 by player 13. The average score was 101.85. Each player's average is displayed in the Table 11. Comparing average scores could be one metric to determine the top performers. In this case, the top performers were player 1, player 6, player 14, and player 13, who held the highest score of 166.75. Oppositely, the lowest performer was player 16 with only 91. It is important to note that the majority of attempts were performed in pairs. Each session, the athlete completed the exercise twice and their scores would appear in succession.

Another metric to rate players can be most improved. In order to determine this metric, a linear regression was used. This linear regression, shown in figure 6.9, is a rate of improvement per attempt. It also emphasizes that all athletes improved in their succeeding attempts. According to the regressions, player 14 was the most improved earning, on average, 3.46 more dots each time he completed the test. Conversely, player 3 was the least improved athlete earning, on average, .77 more dots per attempt. It is important to note that this regression only works to a certain degree due to the athletes eventually reaching a plateau. Due to the limited sample size, this upper limit is yet to be determined. An example of this case may be seen in player 1. player 1 attempted this exercise 14 times and achieved his second highest score on attempt 6. However after his peak of 121 in attempt 10, then next 4 attempts were slightly lower.

6.4.2 Number Flash

The results for the number flash are shown in table 6.8. Results are grouped by individual athletes and are in chronological order of their attempts. Therefore, the top row for a player is

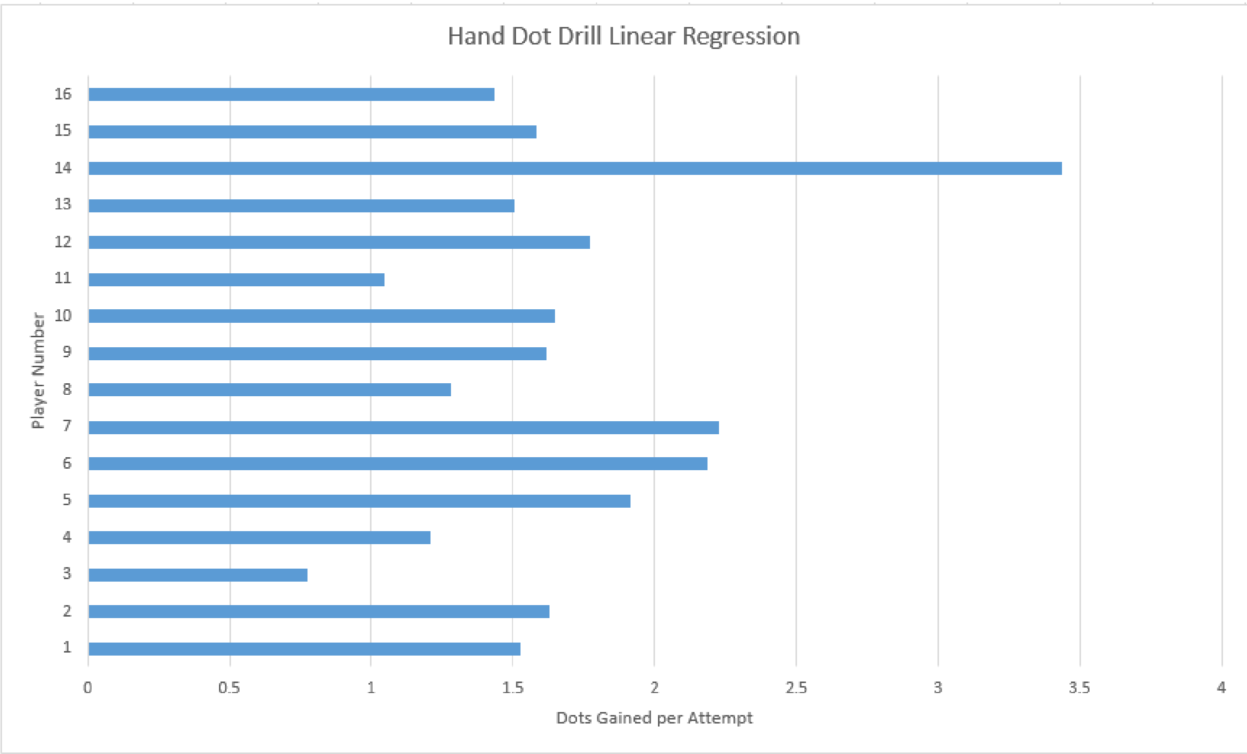


Figure 6.9: Regression for Hand Dot Drill

Table 6.8: The results of the number flash exercise by attempt

Time (MS)	# Incorrect	Time (MS)	# Incorrect	Time (MS)	# Incorrect	Time (MS)	# Incorrect	Time (MS)	# Incorrect
Player 1		Player 4		Player 7		Player 10		Player 13	
500	0	500	1	500	0	500	0	500	0
250	0	100	5	250	0	250	0	250	3
100	6	100	0	100	4	100	2	100	3
250	0	250	3	250	2	500	0	250	0
100	4	100	5	100	3	250	1	100	4
100	2	250	1	250	0	100	4	250	0
50	1	100	3	100	0	250	0	100	4
100	0	100	1	250	1	100	4	100	1
50	0	50	4	100	0	250	0	50	1
100	0	100	0	100	0	100	2	100	0
50	0	50	4	50	0	100	1	50	0
				50	0	100	0	100	0
						50	0	50	0
Player 2		Player 5		Player 8		Player 11		Player 14	
250	0	100	0	500	1	500	0	500	4
100	4	250	0	250	5	250	0	250	3
250	1	100	0	100	8	100	2	100	3
100	0	250	0	250	1	250	0	500	0
250	0	100	0	100	7	100	1	250	1
100	0	100	0	100	2	250	0	100	5
100	2	50	0	50	3	100	0	100	3
50	0			100	1	250	0	50	2
50	1			50	2	100	1	100	3
100	1							50	3
50	0								
100	1								
50	0								
100	0								
50	0								
Player 3		Player 6		Player 9		Player 12		Player 15	
500	0	500	1	500	0	500	1	500	0
250	1	250	2	250	2	250	2	250	2
100	5	100	3	100	7	100	3	100	3
250	1	250	2	500	2	500	0	100	1
100	6	100	3	250	4	250	1	50	1
250	1	250	0	250	8	100	6	100	0
100	3	100	3	500	3	250	2	50	1
50	3	100	1	500	1	100	3	100	0
100	3	50	0	250	4	250	0	50	0
100	0	100	0	100	5	100	4		
50	1	50	0	100	4	100	2		
100	0	100	0	100	4	50	4		
50	2	50	1	50	4	100	2		
100	0					50	0		
50	1					100	1		
						50	0		
						100	2		
						50	1		

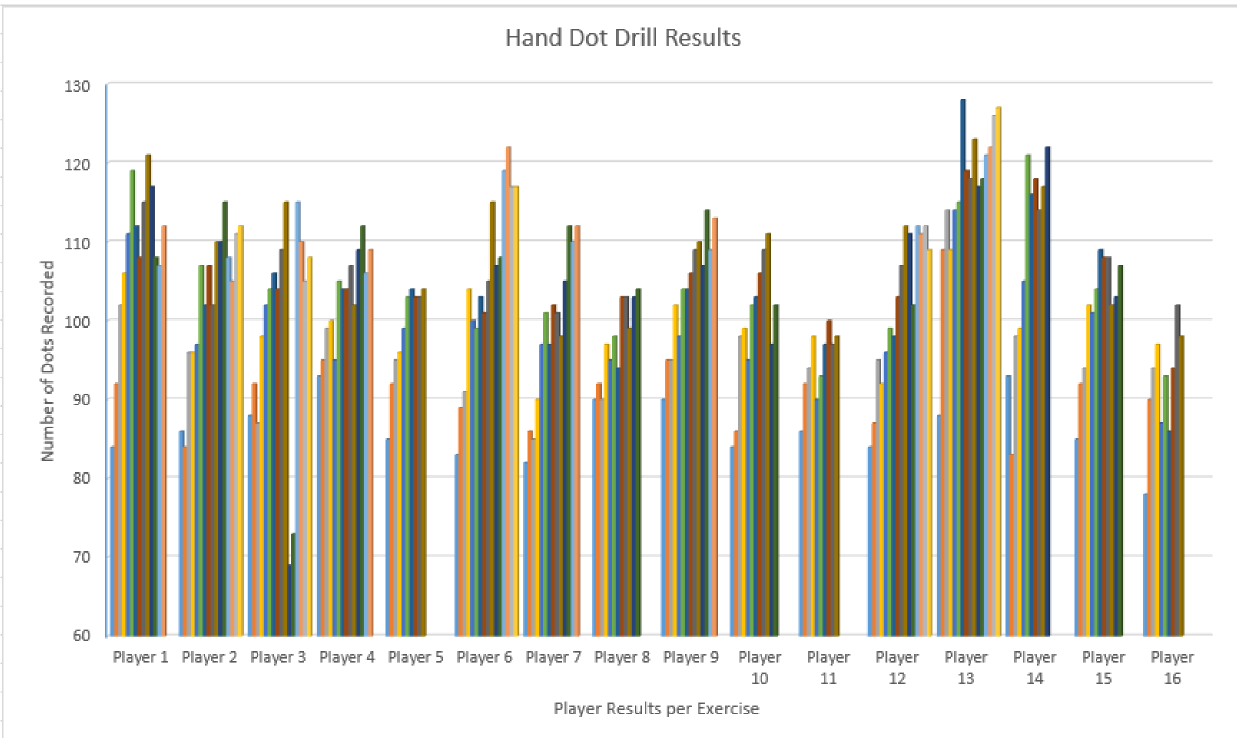


Figure 6.10: Hand dot exercise results grouped by individual player attempts

Table 6.9: Number of successful dots touched within one Minute by players

Tries	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	84	86	88	93	85	83	82	90	90	84	86	84	88	93	85	78
2	92	84	92	95	92	89	86	92	95	86	92	87	109	83	92	90
3	102	96	87	99	95	91	85	90	95	98	94	95	114	98	94	94
4	106	96	98	100	96	104	90	97	102	99	98	92	109	99	102	97
5	111	97	102	95	99	100	97	95	98	95	90	96	114	105	101	87
6	119	107	104	105	103	99	101	98	104	102	93	99	115	121	104	93
7	112	102	106	104	104	103	97	94	104	103	97	98	128	116	109	86
8	108	107	104	104	103	101	102	103	106	106	100	103	119	118	108	94
9	115	102	109	107	103	105	101	103	109	109	97	107	118	114	108	102
10	121	110	115	102	104	115	98	99	110	111	98	112	123	117	102	98
11	117	110	69	109		107	105	103	107	97		111	117	122	103	
12	108	115	73	112		108	112	104	114	102		102	118		107	
13	107	108	115	106		119	110		109			112	121			
14	112	105	110	109		122	112		113			111	122			
15		111	105			117						112	126			
16		112	108			117						109	127			
Avg	108.1	103.0	99.1	102.9	98.4	105.0	98.4	97.3	104.0	99.3	94.5	101.9	116.8	107.8	101.3	91.9

Table 6.10: Total miss percentage for all athletes on the number flash exercise

Test	Attempts	Total Miss	Percent Miss
500 MS	171	14	8.19%
250 MS	387	54	13.95%
100 MS	720	80	11.11%
50 MS	324	36	11.11%
Total	1602	184	11.49%

their first attempt and the last row is their last. Each player block is divided into two columns. The left column is the time, in milliseconds, that the number was displayed on the screen. There were four possible configurations used for this exercise: 500, 250, 100, and 50 milliseconds. The right columns display how many numbers the athlete got incorrect for the given exercise. An incorrect number being defined as any part of the 5 digit number being omitted or incorrectly recited.

Table 6.10 calculates several cumulative statistics from all the results. Overall there were 1602 attempts on numbers with the majority being at the 100 MS level. It is important to note that each individual exercise contains 9 attempts. Figure 6.11 is a graphical representation of this table. From the graph, it can be seen that percentage of misses rises when the length of time for which the number is displayed is decreased from 500 milliseconds to 250 milliseconds. This can be expected since the exercise has theoretically become twice as difficult. Likewise, stepping from 250 to 100 milliseconds, shows that the percentage missed decreases. Hence, despite the more difficult task, the athletes were able to improve their performance. For the most difficult task, the miss percentage remained the same, which was a desired result. By remaining constant on the most difficult exercise, their performance was considered to increase.

6.4.3 Foot Pedals

The results for the foot pedal exercise were divided based on the difficulty level. Results for the initial exercise, considered to be the easiest, are shown in 6.11. For this exercise, athletes had one full second to touch the correct foot sensor after the LED light directing them became visible. Each player's scores are aligned in columns by attempt number. The top 10% of scores for this exercise level are highlighted in the red cells. At this level, there were a total of 122 results with each player averaging 14.58 attempts. The scores ranged from 6 to 72 with the average being 47.6. A graphic representation of this data is displayed in figure 6.12.

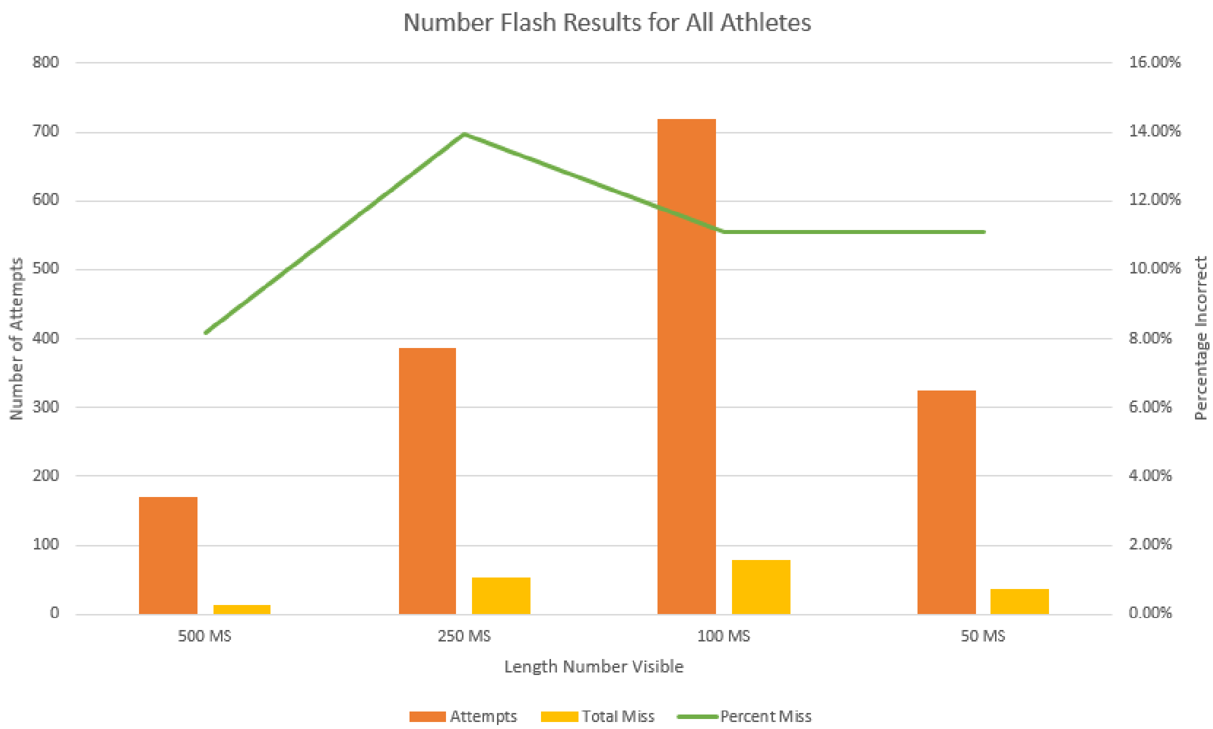


Figure 6.11: Total results for the number flash exercise

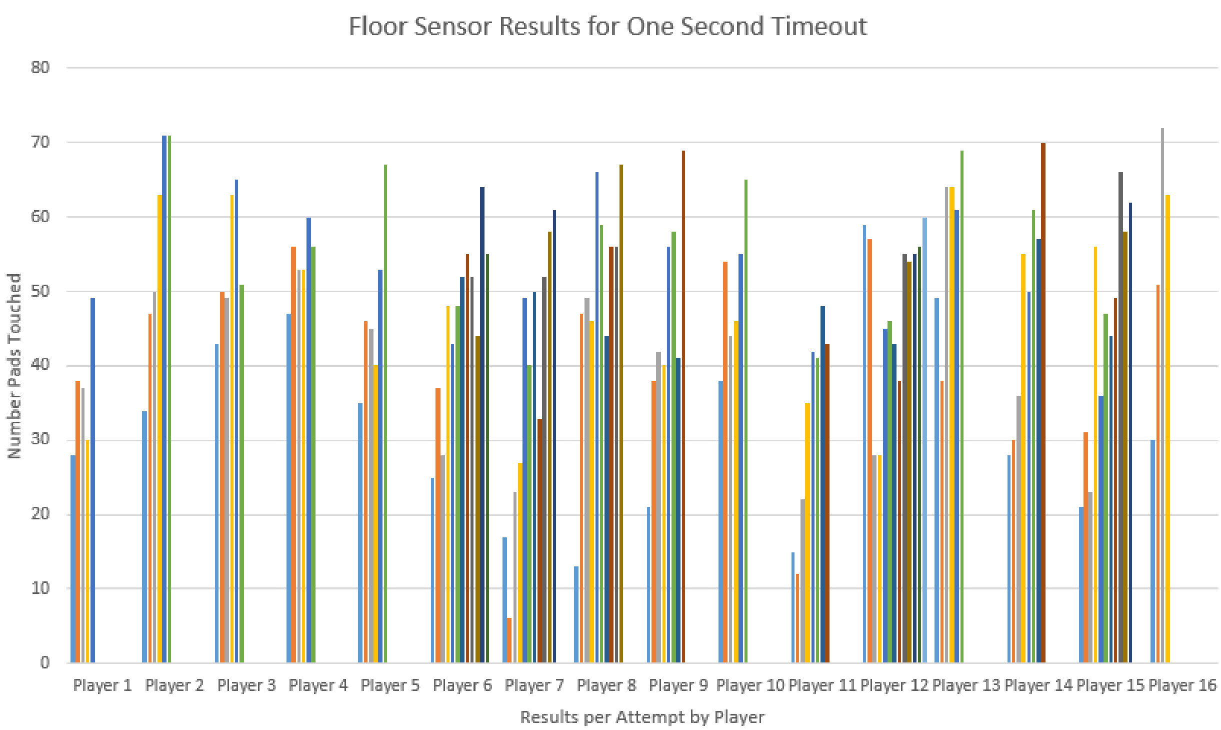


Figure 6.12: Graph of Floor Pedal Exercise results for one second timeout

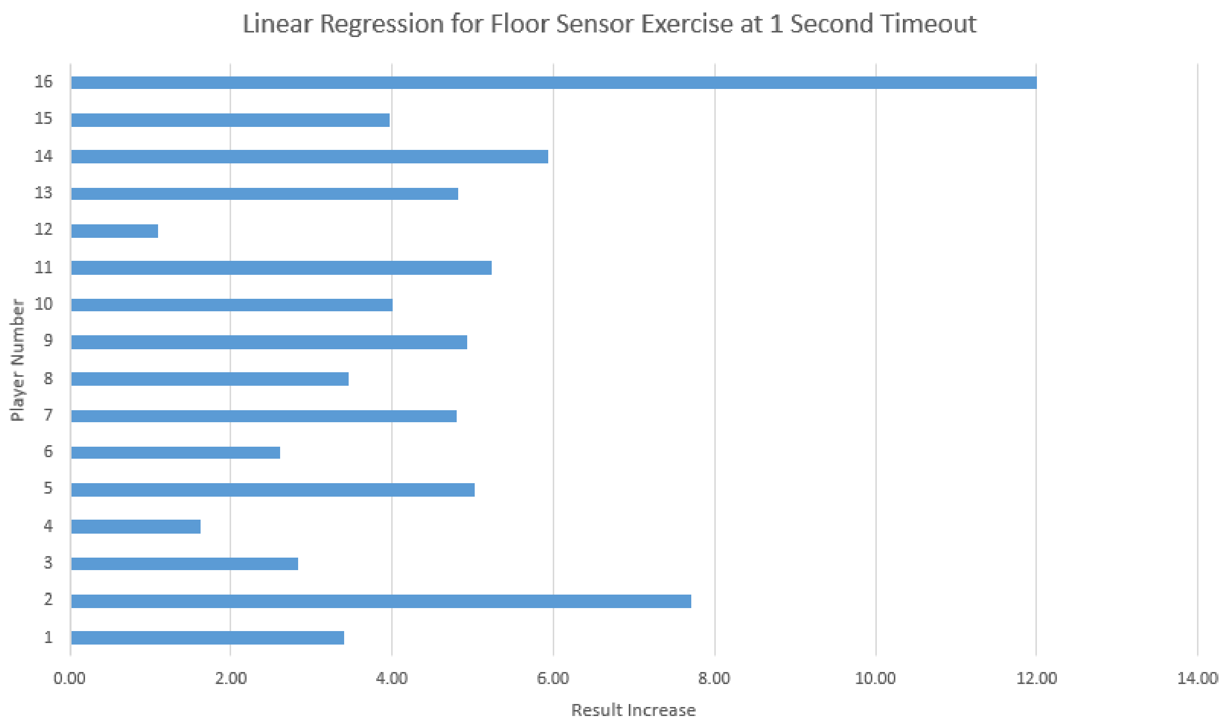


Figure 6.13: Linear regressions for Floor Pedal Exercise at one second timeout

Table 6.11: Results for Foot Pedal Exercise with a one second timeout

Attempt	Player 1	Player 2	Player 3	Player 4	Player 5	Player 6	Player 7	Player 8	Player 9	Player 10	Player 11	Player 12	Player 13	Player 14	Player 15	Player 16
1	28	34	43	47	35	25	17	13	21	38	15	59	49	28	21	30
2	38	47	50	56	46	37	6	47	38	54	12	57	38	30	31	51
3	37	50	49	53	45	28	23	49	42	44	22	28	64	36	23	72
4	30	63	63	53	40	48	27	46	40	46	35	28	64	55	56	63
5	49	71	65	60	53	43	49	66	56	55	42	45	61	50	36	
6		71	51	56	67	48	40	59	58	65	41	46	69	61	47	
7						52	50	44	41		48	43		57	44	
8						55	33	56	69		43	38		70	49	
9						52	52	56				55			66	
10						44	58	67				54			58	
11						64	61					55			62	
12						55						56				
13												60				
Avg	**36.40**	**56.00**	**53.50**	**54.17**	**47.67**	**45.92**	**37.82**	**50.30**	**45.63**	**50.33**	**32.25**	**48.00**	**57.50**	**48.38**	**44.82**	**54.00**
L. Reg	3.40	7.71	2.83	1.63	5.03	2.60	4.80	3.46	4.94	4.00	5.24	1.09	4.83	5.94	3.96	12.00

Table 6.12: Results for Foot Pedal Exercise with a 9/10 second timeout

Attempt	Player 1	Player 2	Player 3	Player 4	Player 5	Player 6	Player 7	Player 8	Player 9	Player 10	Player 11	Player 12	Player 13	Player 14	Player 15	Player 16
1	58	74	47	66	64	46		34	54	60		48	68			50
2	60	68	54	65	73	43		53	46	69		56	74			60
3	59		69	64					48	51		54				79
4			73	62					62	56		54				65
Avg	**59**	**71**	**60.75**	**64.25**	**68.5**	**44.5**		**43.5**	**52.5**	**59**		**53**	**71**			**63.5**

This graph again shows that after several attempts all athletes performed better. A linear regression was derived and results are at the bottom of table 6.11 and graphed in figure 6.13. For this difficulty level, no athlete had a negative linear regression. This linear regression shows how much the athlete improved their score by reattempting the exercise. Overall, the average linear regression on this level was 4.59. The top 10% of scores for this level appears more evenly distributed than the results of the previous hand dot drill. This is because once a player reached a sufficient score, of roughly 70 or greater completed marks per attempt, they were moved up to the next level so their results did not constantly overshadow the others. Several athletes saw their peak on the fifth or sixth attempt indicating that may be an important threshold. The threshold could show that it takes 5 or 6 time of attempting an exercise for a normal athlete to become comfortable and start to see early peak performances.

The next difficulty level decreased the timeout by one millisecond. Results for this 9/10 second timeout are recorded in table 6.12. Unlike the previous level, not all athletes achieved this level of success. There were several players that were not able to move up by the end of their training sessions. Unfortunately, none of these players were able to complete the full, recommended number of attempts. If these players had continued with training their linear regressions suggested they would have shown gains and eventually moved forward. It is not predicted these players would have reached a plateau before achieving the next level: however, this is only an assumption due to the limited sample size. A graph of these results is figure 6.14. From these readings, 66.6% of the athletes performed better on their second attempt at this level.

The next level of this exercise had a timeout of 800 milliseconds, 8/10 second, and is recorded in table 6.13. Once again, another increase in difficulty filtered out several athletes leaving an overall 23 total attempts on this exercise. Figure 6.15 is graph of this table. It was on this level that many of the athletes that saw early success at the initial level started to reach their plateau. Player 2 in particular started to have trouble keeping pace with the exercise as evident from his greatly varying scores.

Only two athletes, player 3 and player 14, attempted the next level at 700 millisecond timeout. Each athlete attempted this exercise twice scoring 19 and 38 for player 3, and 53 and 71 for player 14. This indicates that player 14 was able to read and respond at the highest level. This may

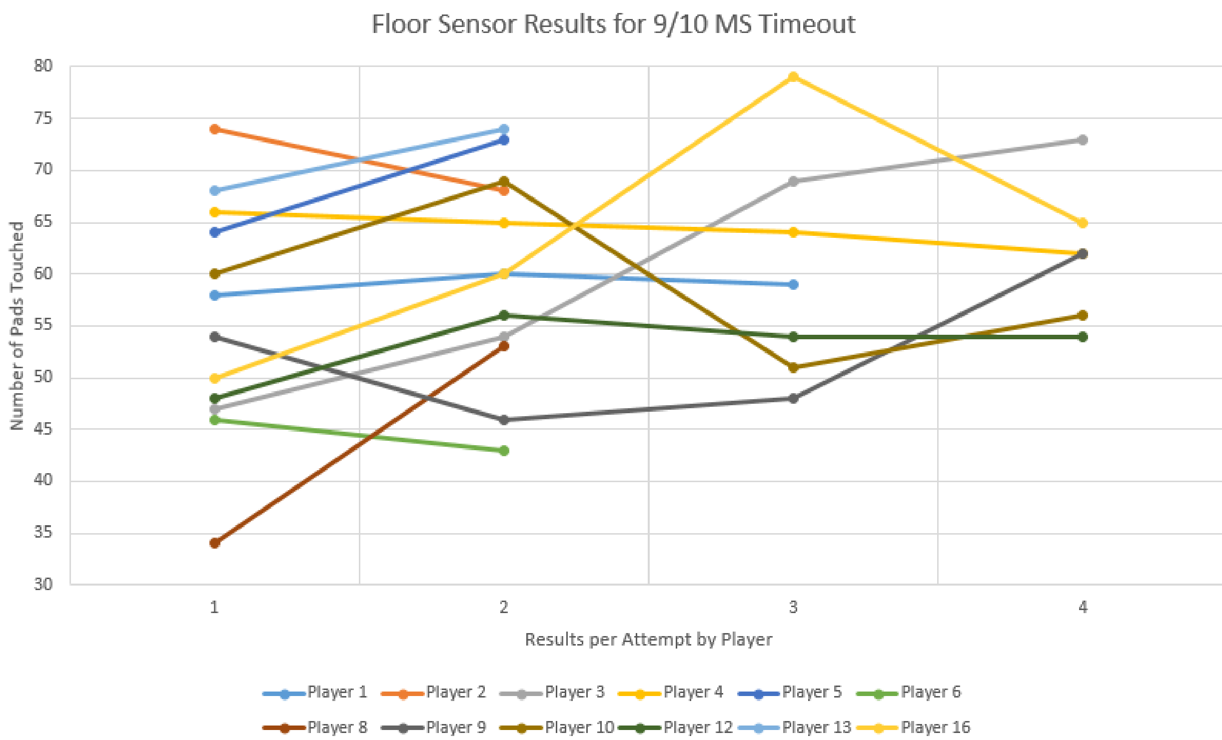


Figure 6.14: Graph of 9/10 second timeout results for the Floor Pedal Exercise

Table 6.13: Results for the subset of athletes that attempted the 8/10 second timeout level for the Floor Pedal Exercise

Attempt	Player 1	Player 2	Player 3	Player 4	Player 13	Player 14	Player 16
1	21	57	57	41	51	71	65
2	48	75	75	40	65	56	80
3	48	33			64		
4	57	80			64		
5		55			64		
6		67					
Avg	**43.5**	**61.17**	**66**	**40.5**	**61.6**	**63.5**	**72.5**
Attempts	4	6	2	2	5	2	2

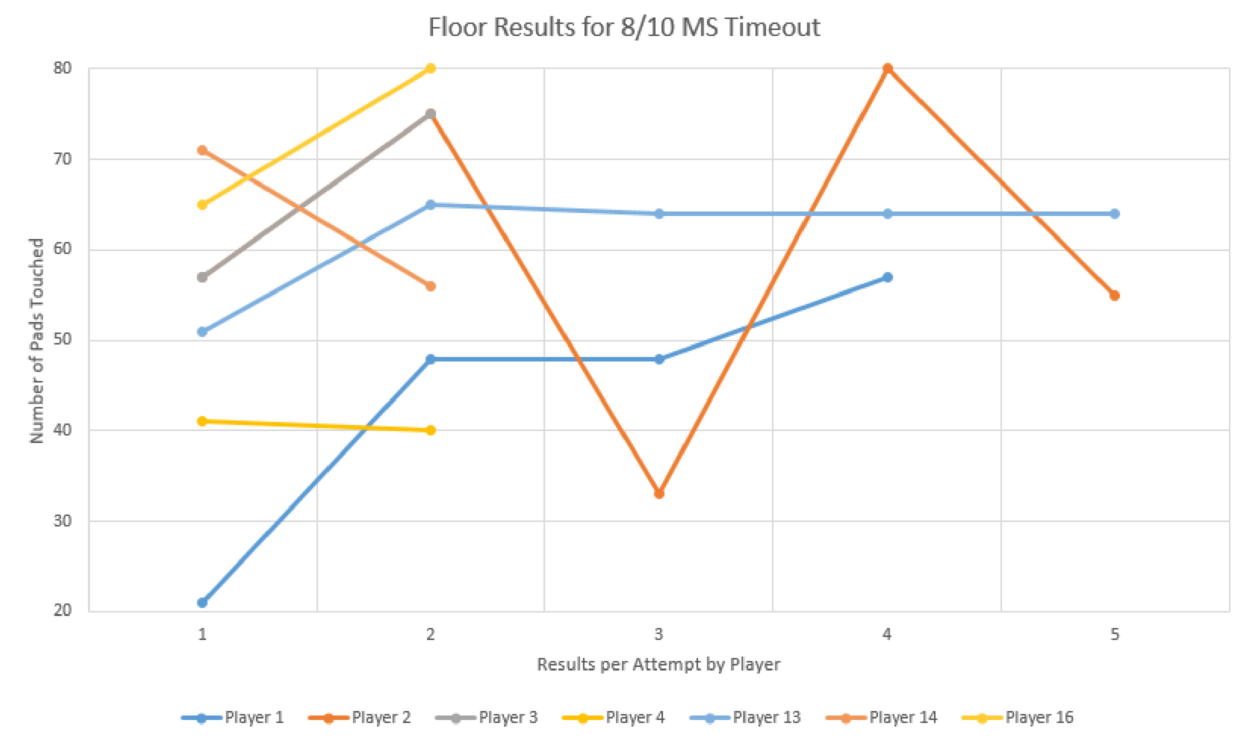
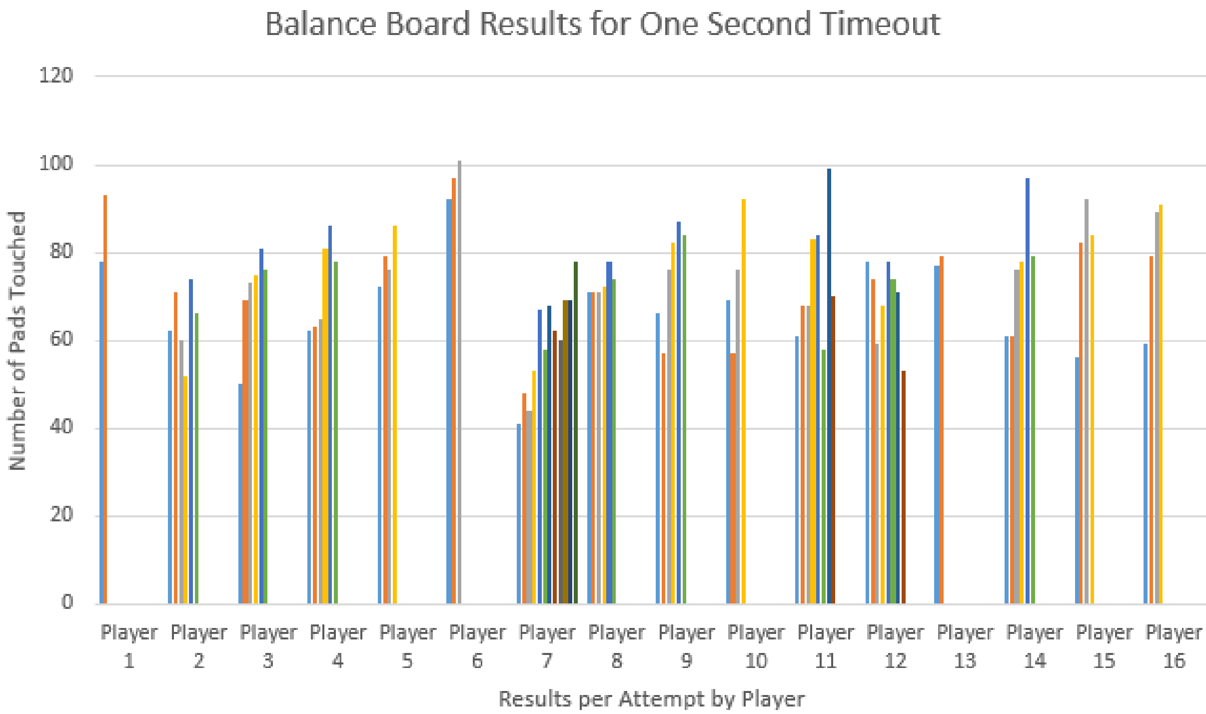


Figure 6.15: Graph of Floor Pedal Exercise results for the 8/10 second timeout

Figure 6.16: Graph of results for Balance Board Exercise at one second timeout



be misleading since not all players advanced on the same intervals. In all levels, this exercise was attempted a total of 190 times and was the most physically demanding task in the training program.

6.4.4 Balance Board

The balance board exercises were ran in a very similar fashion to the foot pedal exercises. Table 6.14 shows the results for athletes at the initial timeout level of 1 second. The top 10% of scores on this level are highlighted in red. Overall there were a total of 87 attempts at this level with the average score being 75.2. The table is also graphed in 6.16. Unlike the foot pedal exercise which saw lower, first attempt scores, initial performance for player 6 clearly stood out. In addition, the next two attempts at this level were also among the top scores. This is good evidence that the balance of player 6 was stronger than the fields prior to training.

Table 6.14: Results for Balance Board Exercise at one second timeout

Attempt	Player 1	Player 2	Player 3	Player 4	Player 5	Player 6	Player 7	Player 8	Player 9	Player 10	Player 11	Player 12	Player 13	Player 14	Player 15	Player 16
1	78	62	50	62	72	92	41	71	66	69	61	78	77	61	56	59
2	93	71	69	63	79	97	48	71	57	57	68	74	79	61	82	79
3		60	73	65	76	101	44	71	76	76	68	59		76	92	89
4		52	75	81	86		53	72	82	92	83	68		78	84	91
5		74	81	86			67	78	87		84	78		97		
6		66	76	78			58	74	84		58	74		79		
7							68				99	71				
8							62				70	53				
9							60									
10							69									
11							69									
12							78									
Avg	**85.50**	**64.17**	**70.67**	**72.50**	**78.25**	**96.67**	**59.75**	**72.83**	**75.33**	**73.50**	**73.88**	**69.38**	**78.00**	**75.33**	**78.50**	**79.50**
Regression	15.00	0.60	4.80	4.71	3.90	4.50	2.80	1.06	5.31	8.80	2.25	-1.61	2.00	5.71	9.40	10.60

Table 6.15: Results for Balance Board Exercise at 9/10 second timeout

Attempt	Player 1	Player 2	Player 3	Player 4	Player 5	Player 6	Player 8	Player 9	Player 10	Player 12	Player 13	Player 14	Player 15	Player 16
1	98	67	66	86	63	113	86	90	79	56	91	76	72	77
2	82	79	91	88	85		61	82	91	58	95	73	77	80
3	88				94		79		90	58				
4	87						61		97	54				
Avg	**88.75**	**73**	**78.5**	**87**	**80.67**	**113**	**71.75**	**86**	**89.25**	**56.5**	**93**	**74.5**	**74.5**	**78.5**

Table 6.16: Results for Balance Board Exercise at 8/10 second timeout

Attempt	Player 1	Player 2	Player 3	Player 4	Player 6	Player 8	Player 9	Player 10	Player 12	Player 13	Player 14	Player 15	Player 16
1	107	72	64	92	86	72	83	90	79	112	74	88	80
2		85	66	96	109	71	79	71	66	94	82	75	80

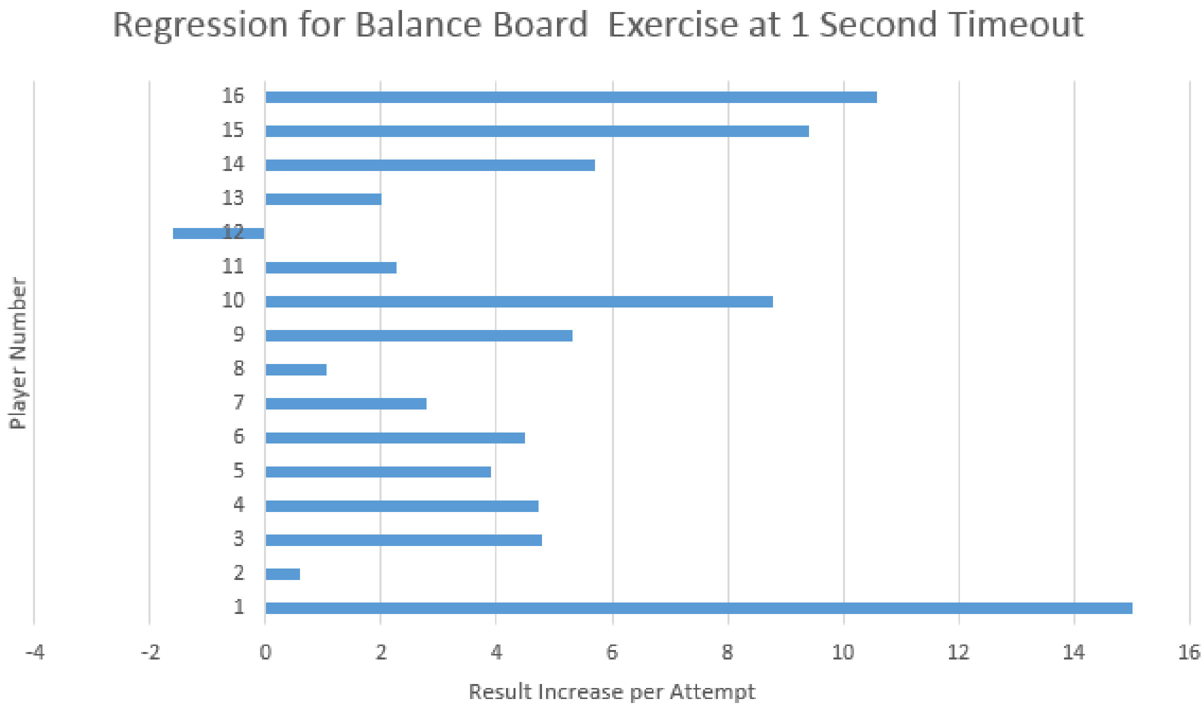


Figure 6.17: Linear Regression for Balance Board Exercise at one second timeout

A graph of the linear regression for this level located on figure 6.17. All except one of the athletes showed a positive linear regression with the average being 4.99. A closer look at the player with the negative regression, player 12, shows that the initial score of 78 was higher than the majority of the other players and was the best score for player 12 at this level. By achieving the best score on the first attempt, it left a small margin for error resulting in a seemingly decreased performance. However, it could also be that the player was chasing the high score and felt the need to rush through the exercise. Feeling panicked on a balancing exercise could cause quick movements leading to slippage and ultimately a low score as observed during the study.

Results for the next level at a 9/10 second timeout are shown in table 6.15. This exercise was attempted 36 times by 14 out of the 16 athletes. players 7 and 11 did not make an attempt at this level. Player 16 continued to excel posting the overall highest score of any level with a 113. Figure 6.18 graphs all the players that made an attempt at this level more than one time. From this graph nine out of the thirteen recorded athletes, 69.2%, showed improvements when moved up

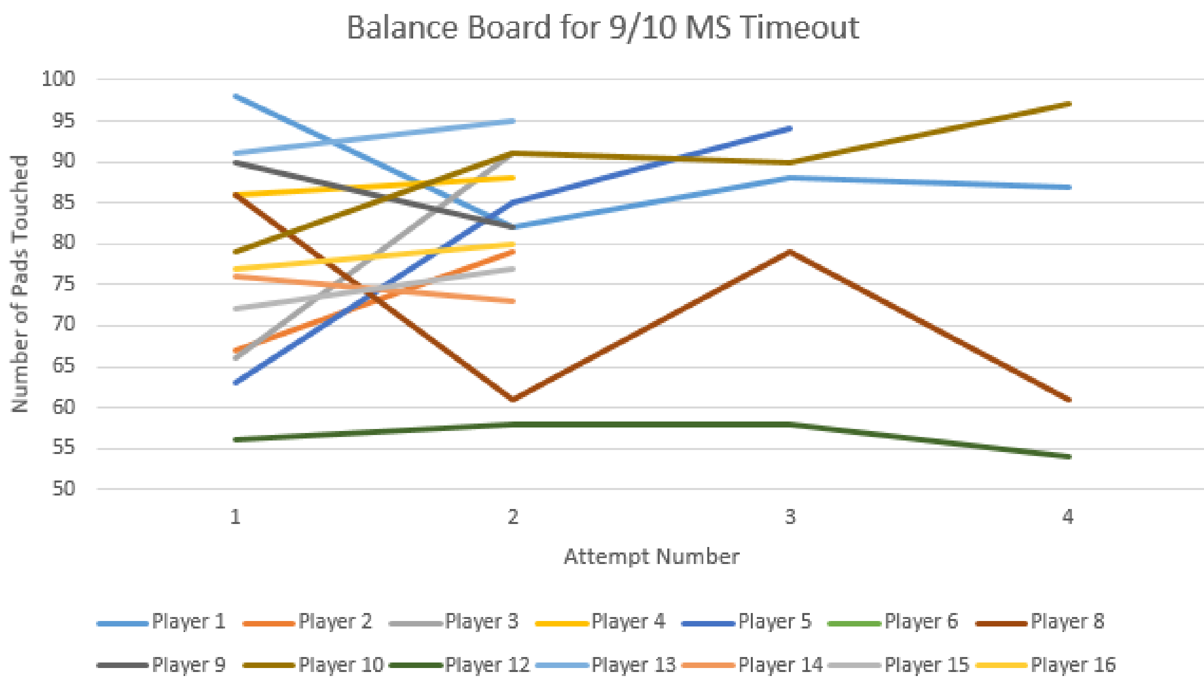


Figure 6.18: Graph of results for Balance Board Exercise at 9/10 second timeout

to the next level. player 12 appeared to struggle scoring the lowest average of 56.5 while player 8 had the greatest variance causing his regression to be -5.7.

The 8/10 second level timeout was attempted 25 times by all the same athletes that attempted the previous level. The results for this exercise level are shown in table 6.16. It was at this level that player 13, a previously mid scoring player, saw great improvement and scored higher than player 16. The second attempt by player 13 at this level fell 18 points, but still placed this player towards the top of the field. On the other hand, the initial attempt by player 6 at this level placed that player in the middle of the field, while the second attempt put player 6 at the top with a 23 point gain. The rest of the players saw relatively small variances suggesting that they may be starting to reach an upper threshold. This can be seen by the low variation in the graph of the results in figure 6.19.

The next three level are timeout at 700, 600, and 500 millisecond and are displayed in figures 6.20, 6.21, and 6.22 respectively. The top score from each level is highlighted in red. As with the previous steps between levels, there was a gradual filtering of athletes that attempted the higher

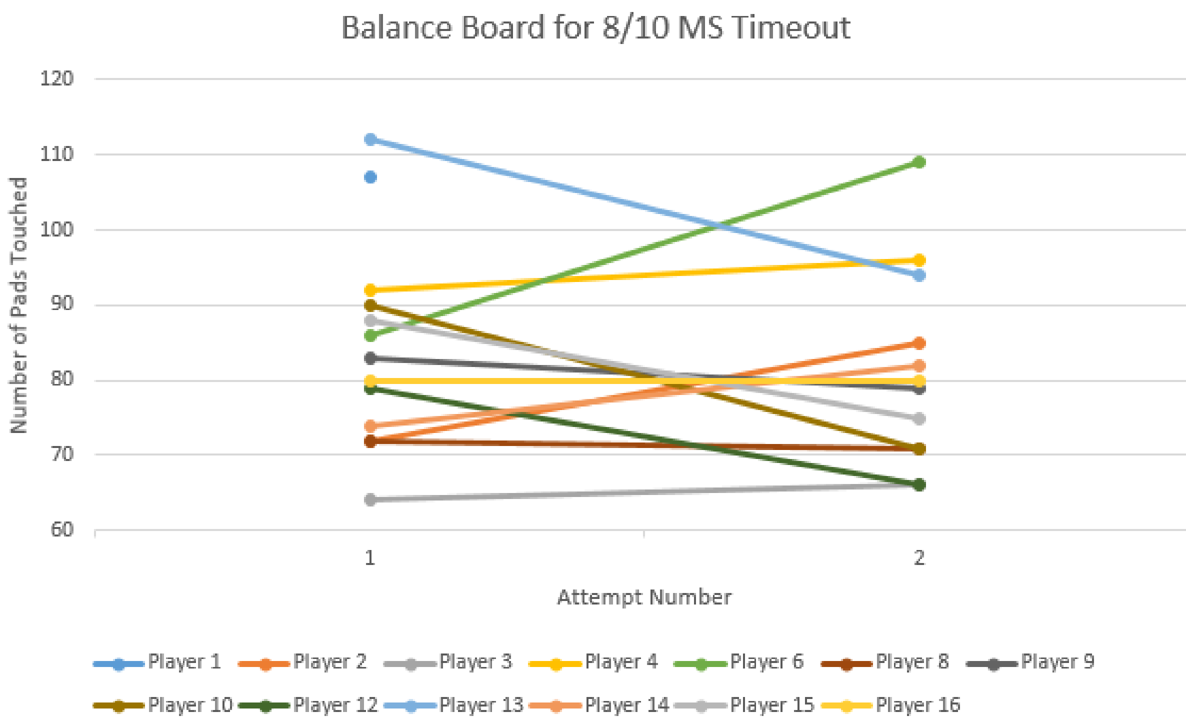


Figure 6.19: Graph of results for Balance Board Exercise at 8/10 second timeout

Attempt	Player 1	Player 2	Player 3	Player 6	Player 9	Player 12	Player 13	Player 14	Player 15	Player 16
1	72	69	69	100	80	70	92	82	69	79
2		75	74		81	57	79		83	99

Figure 6.20: Results for Balance Board Exercise at 7/10 second timeout

Attempt	Player 1	Player 2	Player 3	Player 4	Player 6	Player 13	Player 14
1	52	58	38	68	91	75	68
2	59	72	45	79	76	74	
3	75				78	81	
4	79				79	75	

Figure 6.21: Results for Balance Board Exercise at 6/10 second timeout

levels. However, it must be noted that not all athletes were able to make the same number of attempts on all exercises. Only player 6 and player 13 made attempts at the highest level, which consisted of a half second timeout. At this level, player 6 saw scores in the 90-100 range brought down into the 60-70 range. This shows that he was able to perform, however that performance decreased as the exercise became difficult. Conversely, player 13 saw similar scores at highest level as at the lowest level. This would be considered a desired result since is shows that player was able to maintain a certain level of success throughout the training exercises. Given the full history of player 13, the trend would dictate that after training at this level for several attempts performance would excel and allow achievement of a 70s score in the 4/10 timeout level.

Attempt	Player 6	Player 13
1	63	71
2	75	73

Figure 6.22: Results for Balance Board Exercise at 5/10 second timeout

CHAPTER 7

CONCLUSION

The totality of this work set forth to use commercially available sensors in order to monitor and to enhance the performance for a wide range of people. Much prior work was done outlining sensory applications for older adults that allowed them to perform independently while providing peace of mind to their loved ones. This was followed by the proposal of a system that deployed sensors in order to increase the performance of athletes at the highest level. The system exercised the user's visual and neurological circuitry to increase performance across several biological levels. This was accompanied with an introductory discussion of how the eye works and several ways to measure visual cognition.

This work also provided a major contribution of a unique algorithm to the field of computer science that calculates a fast reaction using an array of different sensors. This was achieved as outlined in the Sensor Fused Reaction Time Algorithm section. Reaction time was classified as an athletic movement in response to stimulus that was cognitively complex to evaluate. The algorithm combined both inertial and skeletal data in order to achieve a practical way to quickly determine reaction time on the millisecond scale.

Trials were also conducted in which athletes were placed in a training program specially designed to increase their visual and cognitive performance. This work outlined the designed program and exercises, documented the results for a small number of athletes, and discussed the findings. In addition, the visual evoked potentials of the athletes were recorded before and after training program in an effort to show enhanced performance on the neurological level.

Due to the limited number of data points no definitive conclusions could be drawn. However, many of the players showed minor gains in several of the exercises, and the VEP measures are indicative of greater success if training were to continue. As a whole, gains appeared be the greatest in the weaker systems of the peripheral vision and non-dominate eye.

APPENDIX A

IRB APPROVAL

This form was for the approval to use human subjects for the purposes of research. The form was awarded on March 26 of 2014 and expired on March 25 of 2015. All human subjects research reported in this dissertation was perform within the parameters set forth by the attached document. Personal information was redacted from the form.

The Florida State University
Office of the Vice President For Research
Human Subjects Committee
Tallahassee, Florida 32306-2742
(850) 644-8673, FAX (850) 644-4392

APPROVAL MEMORANDUM

Date: 3/26/2014

To: Frank Sposaro [*******@cs.fsu.edu]

Address: 253 Love Building
Dept.: COMPUTER SCIENCE

From: Thomas L. Jacobson, Chair

Re: Use of Human Subjects in Research
Vision Training for Athletes

The application that you submitted to this office in regard to the use of human subjects in the proposal referenced above have been reviewed by the Secretary, the Chair, and one member of the Human Subjects Committee. Your project is determined to be Expedited per 45 CFR Â§ 46.110(7) and has been approved by an expedited review process.

The Human Subjects Committee has not evaluated your proposal for scientific merit, except to weigh the risk to the human participants and the aspects of the proposal related to potential risk and benefit. This approval does not replace any departmental or other approvals, which may be required.

If you submitted a proposed consent form with your application, the approved stamped consent form is attached to this approval notice. Only the stamped version of the consent form may be used in recruiting research subjects.

If the project has not been completed by 3/25/2015 you must request a renewal of approval for continuation of the project. As a courtesy, a renewal notice will be sent to you prior to your expiration date; however, it is your responsibility as the Principal Investigator to timely request renewal of your approval from the Committee.

You are advised that any change in protocol for this project must be reviewed and approved by the Committee prior to implementation of the proposed change in the protocol. A protocol change/amendment form is required to be submitted for approval by the Committee. In addition, federal regulations require that the Principal Investigator promptly report, in writing any unanticipated problems or adverse events involving risks to research subjects or others.

By copy of this memorandum, the Chair of your department and/or your major professor is reminded that he/she is responsible for being informed concerning research projects involving human subjects in the department, and should review protocols as often as needed to insure that the project is being conducted in compliance with our institution and with DHHS regulations.

This institution has an Assurance on file with the Office for Human Research Protection. The Assurance Number is FWA00000168/IRB number IRB00000446.

Cc: Gary Tyson, Advisor
HSC No. 2014.12256

APPENDIX B

CONSENT FORM

This form was presented to the athletes used in this this study. The form was presented by an unaffiliated party whom informed both athletes and coaches of the goals, procedure, and commitments of this study. All athletes used in this study were volunteers and were free to terminate their participate at any time for any reason without fear of repercussion from the investigators, coaches, or university. Personal information was redacted from the form.

Informed Consent Form

Vision Training for Athletes

Dear Participant:

You are invited to be in a research study about vision. You were selected as a possible participant because of your experience with physical training at FSU. We ask that you read this form and ask any questions you may have before agreeing to be in this study.

The study is being conducted by Frank Sposaro (The Mobile Lab @ FSU. Department of Computer Science).

The purpose of this study is to develop a computer application that will exercise an athlete's visual system. The eye and visual system is a muscle that can be more efficient by repeated use, similar to a muscle becoming bigger due to strength training. By incorporating vision exercises into their daily routine an athlete can condition their vision system causing it to perform better in several ways.

If you choose to participate in the study we ask you incorporate vision training as part of your daily routine for four weeks and get a pre and post eye exam. All exams are performed by Dr. Orsillo's practice *free of charge*. Each exam will take about fifteen minutes and you will be able to view and discuss any results. We ask you schedule the exams before and after the four week training period in order to gauge your progression. Once again, all *exams are free* and there will be *no cost* to you.

The four week vision training program is conducted in the Albert J. Dunlap Athletic Training Facility at FSU. Each session is 30 minutes long and occurs twice a week. Therefor the entire length of training will be 8 sessions *totaling about 4 hours*. A session is comprised of several tests lasting about 1 minute a piece. Each test will ask you to perform various tasks based on certain conditions. As you progress the conditions will become increasingly more difficult. The tasks are minor physical activities such as pressing a button, stepping to a certain area, or making a short athletic movement.

The benefits of this study may strengthen your visual system by decreasing the amount of time it takes information to get from your eyes to your brain; in addition, it will widen your degree of peripheral vision. This may result in faster reaction times and increased range of vision. As our procedure is noninvasive, there are minimal risks associated with our study. However, you should physically conditioned enough to make short, quick movements and be able to view flashing lights for no more than 30 minutes at a time. A side effect of the movements may include minor muscle fatigue depending on your level of physical condition.

The records of this study will be kept private and confidential to the extent permitted by law. Recording may include the measurements from the test along with audio and/or video. To protect your privacy you will be assigned an id instead of using personal identifying information throughout the training process. Only the PI will have the link between your personal identifying information and subject id and it will be secured. You may also request that your video recording be obscured. In this case we will a different recording method to ensure you are unidentifiable.

Your participation in this study is voluntary and there is no penalty for nonparticipation. Your decision whether or not to participate will not affect your current or future relations with Florida State University. If you decide to participants, you are free to not answer any questions or withdraw at any time without affecting those relationships.

The researchers conducting this study are Frank Sposaro ([redacted]@cs.fsu.edu), John Nguyen ([redacted]@cs.fsu.edu), and Daniel Porrello ([redacted]@cs.fsu.edu). You may ask any questions you have at any point. You may contact them by email or visiting The Mobile Lab in 171 Love Building, FSU Campus. You may also contact Orsillo Vision Care & Optical at 1901 Miccosukee Road. Tallahassee, FL, 32308 or call at (850) 701-2540. You may also contact the faculty advisor Dr. Gary Tyson ([redacted]@cs.fsu.edu) (850) 644-[redacted]. Office [redacted].

If you have any questions about your rights as a research participant, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Committee, Institutional Review Board, through the Vice President for the Office of Research at (850) 644- 8633 or email humansubjects@magnet.fsu.edu.

Sincerely,

Frank Sposaro

PhD Student

[redacted]@cs.fsu.edu

The Mobile Lab @ FSU

Mobile.cs.fsu.edu

Please initial here that you read all (3) pages of this letter _________.

Please verify you understand the following and sign below:

- I wish to voluntary participate in the study and there is no penalty for nonparticipation
- I may withdraw my consent and discontinue my participation at any time without penalty
- All responses and recorded information will be kept in a locked office (The Mobile Lab @ FSU) with restricted access by only Frank Sposaro and his staff of graduate students trained for this project
- The benefits of visual training may result in faster reaction times and increased peripheral vision
- Visual training is non-evasive and risks are minimal
- I am physically fit enough to make short, athletic movements with minor muscle fatigue a possible side effect based on my level of conditioning
- This study will last 4 weeks, twice a week for 30 minutes totaling 4 hours
- Include 2 eye exams, about 15 minutes each, from Dr. Orsillo's practice at no cost to me
- Special measures will be taken to secure my personal identifying information and I may request to blur my likeness in recorded video.
- In signing this consent form, I am not waiving any legal claims, rights or remedies
- A copy of this consent form will be given to me

Name: ________________________________

Participant: ____________________________ Date: _________________________

Investigator: ____________________________ Date: _________________________

FSU Human Subjects Committee approved on 3/26/2014. Void after 3/25/2015. HSC # 2014.12256

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BIOGRAPHICAL SKETCH

In his short but brilliant career, Frank has found a unique path using his classroom education to blaze a trail in the real world. For starters, he created and found funding for his own android apps that help to monitor the elderly and infirm while providing rapid response care in case of emergency. Plus in his "spare" time as a student, he ran the FSU affiliate program for EA Sports and became responsible for marketing and promoting the Xbox platform including the Madden and Halo franchises using innovative techniques such as gaming parties, tailgates, and mixtape hosting; merging his loves of gaming and entertainment. Professionally, Frank has successfully climbed the ladder from student to intern to teacher and is now at the professional level, where he has earned so much computer cred, Microsoft and Google both competed for his services. When the dust settled and Microsoft won, Frank moved to Redmond, WA to work as Microsoft's Software Development Engineer to develop the Windows store application for upcoming release of Windows 10.

Biographical Sketch attributed to Keith Kennedy.