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Title: Learning Approaches for the Early Detection of Kickback in Chainsaws

Abstract approved:

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John P. Parmigiani

Among the many safety hazards facing chainsaw operators, the phenomenon known as kickback is the most dangerous. Kickback occurs when the chain at the tip of the chainsaw is caused to stop abruptly, and transfers the energy of the cutting chain to motion of the saw. The saw will rotate backward toward the operator rapidly. The limited amount of published research on the topic of chainsaw kickback was conducted to develop standardized testing for consumer chainsaws. Modern chainsaws are equipped with safety measures such as low-kickback cutting chains and hand-guard braking mechanisms. These mechanisms have greatly improved the safety of chainsaws, but their inherent mechanical simplicity leaves room for improvement.

The current work presents the research that analyzed the possible methods for detecting kickback electronically. Phase 1 of this work utilized a set of two accelerometers and a single gyroscope to determine if it is possible to distinguish a kickback event from normal cutting operations. A method for applying weighting coefficients to the three sensor readings, then summing the three signal values was optimized to obtain the greatest margin between kickback and normal cutting. The result of this study was that kickback is most easily identified by using only a gyroscope and setting a threshold. Phase 2 focused on detecting kickback as early as possible. Three methods were attempted: Signal Differentiation, a

Simplified Bag of Words method, and applying a Support Vector Machine with selective undersampling and a stack of classifier vectors. Signal differentiation, while detecting the kickback events earlier, also suffered from many false positives. The Bag of Words method was unsuccessful in creating results different than the threshold method from Phase 1. The Support Vector Machine classification was able to detect kickback an average of 19.4 ms before the simple threshold method with no occurrence of either false positives or false negatives. This method is the most reliable and provides the greatest likelihood of detecting kickback early.

Learning Approaches for the Early Detection of Kickback in Chainsaws

by
Drew D. Arnold

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Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Drew D Arnold, Author

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Learning Approaches for the Early Detection of Kickback in Chainsaws

1 Introduction

1.1 The Problem of Chainsaw Kickback

Chainsaw kickback is the most dangerous phenomena facing chainsaw operators. It is not the most prevalent chainsaw related injury, but it has the highest likelihood of causing a life threatening injury [1]. Chainsaw kickback has been a concern to chainsaw opertors and manufacturers since they first gained popularty among average consumers in the 1970s. Kickback is most dangerous to novice users who are unaware of the potential danger.

Kickback occurs when the chain, as it travels around the tip of the chainsaw, is seized, causing the kinetic energy of the chain and drive system to transfer to rotational acceleration of the saw itself. This transfer of energy causes the tip of the saw to accelerate, which rotates the saw back toward the operator at high speed. The acceleration is so great, and the event happens so suddenly that an operator may not have time to react before the saw can make contact with him or her.

In the 1970s there was a surge of chainsaw use by inexperienced operators. The saws were made available to the general public and more consumers were purchasing them as a result of the energy crisis in this period of time. As a result the number of chainsaw accidents doubled from 1976 to 1979 [2].

In the 1980s, safety systems were incorporated on all consumer level chainsaws, as mandated by the United State Consumer Product Safety Commission. Chainsaw brakes were among the changes incorporated to modern chainsaws. The brakes consist of a mechanical lever that is forced forward at the onset of kickback. The mechanical lever is attached to a braking mechanism that stops the chain before it can cause damage to the operator.

The mandated safety systems on chainsaws were effective but still leave room for improvement. There are still thousands of injuries a year that may be attributed to chainsaw kickback [3]. The brakes are difficult to design and often become less effective over time. The design of these brakes has not changed significantly in 30 years.

Even with current safety measures, many chainsaw related injuries still occur each year. An estimated 31,000 chainsaw related injuries occurred in 2010 [3], of which an estimated 64 percent could be attributed to kickback [4]. Chainsaw injuries are typically more severe than other cutting accidents. A wide swath of flesh is removed if contact is made with a moving chain, leaving behind a wound filled with dirt oil and wood debris [5,6,1].

The safety equipment with which modern chainsaws are required to be equipped has improved the safety of chainsaws for average consumers. There are still many ways that the safety of these powerful tools can be increased.

Research has been conducted to better understand the causes of kickback and to help quantify the its dangers. The following sectin details to bodies of research that have attempted to better understand and quantify kickback. This is followed by an introduction to the current work which details the methods and analysis performed to effectively detect kickback as early as possible.

1.2 Prior Work

In the 1980s when consumer chainsaw use became so prevalent, and the US Consumer Product Safety Commission made the decision to require certain safety features be added to chainsaws, several different organizations set-out to quantify the kinematics of a chainsaw during kickback. Most of the research took place from a regulatory standpoint to quantify the kickback energy for different saws equipped with different bars and chain. These values were then used to develop the standards that govern the design of chainsaws, today. The works discussed in this section are relevant in that they attempt to better understand that kinematic signature of kickback. Two works are discussed that analyze the kinematics of kickback. First, the research used to develop the American National Standards Institute's (ANSI) chainsaw kickback regulations is discussed.

Secondly, a research paper that attempted to obtain a method for testing human reactions to chainsaw kickback by using a bio-mimetic robot is discussed.

1.2.1 ANSI B175.1-2000 Gasoline Powered Chainsaws-Safety Requirements

This standard details the methods for testing safety compliance of gasoline powered chainsaws. The research conducted in developing the testing device used to determine the kickback level for a chainsaw is relevant to this research. Section 5.11 of ANSI B175.1-2000 details the acceptance requirements for kickback and section 8 outlines the testing procedures [7].

The kickback test machine is used to gather data about the energy of a kickback. The saw is mounted at the handles with a center of rotation about it's center of mass. The saw's throttle is adjusted to bring the engine to either 8000 RPM or 10000 RPM. A coupon of Medium Density Fibreboard (MDF) is mounted on a horizontal slider, and a weighted pully system is pushed into the nose of the chainsaw. The angle of the coupon with respect to the chainsaw bar is adjusted until the highest energy kickback is obtained. The kickback energy is measured using a system of weights suspended pulleys. When a kickback is recorded, the saw rotates about it's center of gravity and the coupon with a similar weighted pulley slides forward, away from the chainsaw. The linear energy in the horizontal direction, and rotational energy are measured from these values and input into a computer simulation.

The computer simulation is designed to simulate an average person's reaction to kickback and model the reaction forces theoperators apply to the saw to arrest kickback. The result of this simulation is the Calculated Kickback Angle (CKA) which is used in the safety regulations as a way of quantifying the kickback severity, and thedanger of a given chainsaw.

The research performed to develop the computer simulation utilized various operators intentionally causing kickbacks. The kickbacks were recorded using a video camera, then the motion data for the saw was tracked on the video screen. The position values were fit to a curve then differentiated to get velocity and acceleration. Using the acceleration profile of the saw during multiple tests, the reaction forces through the two handles were extrated using several assumptions to reduce the complexity of the problem. One major assumption made was that the reaction forces that were applied to the saw were applied equally by both hands, as otherwise there would be too many unkown forces to solve for. These reaction forces were then applied to the computer simulation as a function of time after the kickback event. The computer simulation applies a reaction force to the handle at each time increment until the energy obtained from the test is reached. The model considers the polar moment of inertia of the saw, and the position of the handles with respect to the saw's center of gravity. These inputs are used to calculate the CKA for each saw [8] [9].

This research observed many interesting phenomena of chainsaw kickback and generated remarkably accurate results given the technology available. The goal of this research was to quantify the magnitude of kickback for the purposes of developing standards to reduce the dangers that average consumers would face when purchasing a chainsaw.

1.2.2 Construction and Evaluation of a Chainsaw Kickback Simulator

In this work a human-mimetic device was developed that was designed to match the anthropomorphic properties of the average (50th percentile) adult male's upper body [10]. Kickback was simulated by driving a flywheel into the nose of a chainsaw equipped with a bar that had no chain. The flywheel had a similar inertia and speed to a typical small to medium sized chainsaw. The goal of this research was to develop a robotic mechanism that could mimic the passive human response to a kickback to obtain more detailed reaction information than the ANSI kickback test machine without putting a human operator in harm's way.

The kickback fixture was modeled after a human chainsaw operator from the waste up. A series of ball joints were placed at the shoulder, and elbow joints. Actuators were attached to each appendage and programmed to respond at response rates similar to a human.

Five human subjects were equipped with electromyography sensors placed over the key muscle groups that would resist kickback. This data allowed the researchers to identify the reaction times of the operators to the kickback events. Subjects were also equipped with white markers that were analyzed to trace the path of key joints of the operator. Several different tests were performed with a small chainsaw and a medium chainsaw. The results from the five test subjects were compared to the simulator and analyzed for statistical significance. For the smaller saw it was determined that the simulator was similar to the humans at the 95% confidence level, but the larger saw was not statistically similar.

The poor performance with a heavier saw was believed to be the result of a rigid grip and lack of a wrist joint on the simulator. This type of simulator has promise for analyzing dangerous situations without endangering human operators but would need further refinement to reach a necessary level of reliability. The results from this type of simulation are more qualitative then quantitative so they are good for comparative analyses between multiple products but are less adequate for quantifying the kickback energies involved in a kickback event.

1.3

1.4 Current Work

Developing a safer chainsaw will help both consumers and manufacturers of chainsaws. The continual cost reduction of semiconductors like sensors and microprocessors allows for more advanced technologies to be incorporated into chainsaws without dramatically increasing the price. In order to utilize the reduced cost of sensors, research must be conducted to better understand their capabilities and determine the best method for detecting the occurrence of kickback. Once a method for detecting kickback reliably is established, a method for braking the saw could be designed.

An empirical approach was chosen to develop a detection algorithm over some sort of computational modeling. Computational models would be difficult to create with any accuracy. A computational model would rely on several probabilistic models with the following factors: the physical dimensions of the operator, the physical build of the operator, the position of the saw in relation to the operator at the onset of kickback, the position of the saw in relation to object causing kickback, the size and power of the chainsaw, the speed of the saw during a kickback event and the point of initial contact on the chain. Each factor is known to drastically affect the outcome of a kickback event.

An empirical approach was chosen to help account for the variability between operators, and kickback scenarios. A series of tests were performed that could be classified as normal cutting that were then compared to kickback events. Every test was performed with several operators, and on many different sizes and types of logs. The chainsaw arrangement was constant for each phase of testing as a detection system would be developed for a specific chainsaw.

This paper presents a new safety system that will use a system of electronics to detect kickback. First, a background of chainsaws will present an outline of standard chainsaw anatomy, explain how and why kickback occurs, define some typical chainsaw cutting scenarios, discuss the history of chainsaw safety, and examine the current chainsaw brake mechanism. Then, the setup and methods for the two phases of data collection will be discussed. The first phase attempted to determine if kickback could be detected and the third phase looked into detecting kickback as early as possible. The next chapter details the analysis methods used for each phase of data collection, followed by a discussion of the results and conclusions.

2 Background

2.1 Chainsaw Anatomy

While all chainsaws are different, they all contain at least the following common elements: a power head, a drive sprocket, a guide bar, and a cutting chain, as are depicted in Figure 1. The power head provides rotational energy to propel the cutting chain. It is typically either a two-stroke gasoline engine, or an electric motor powered by either standard AC power, or a DC battery. Energy from the power head turns the drive sprocket, which moves the cutting chain about the guide bar. The chain travels around the guide bar, giving the cutting surface its shape. A U-shaped channel in the guide bar prevents the cutters from leaning over. Veins that run through the inside of the guide bar supply lubrication to the chain to increase cutting performance and reduce wear.

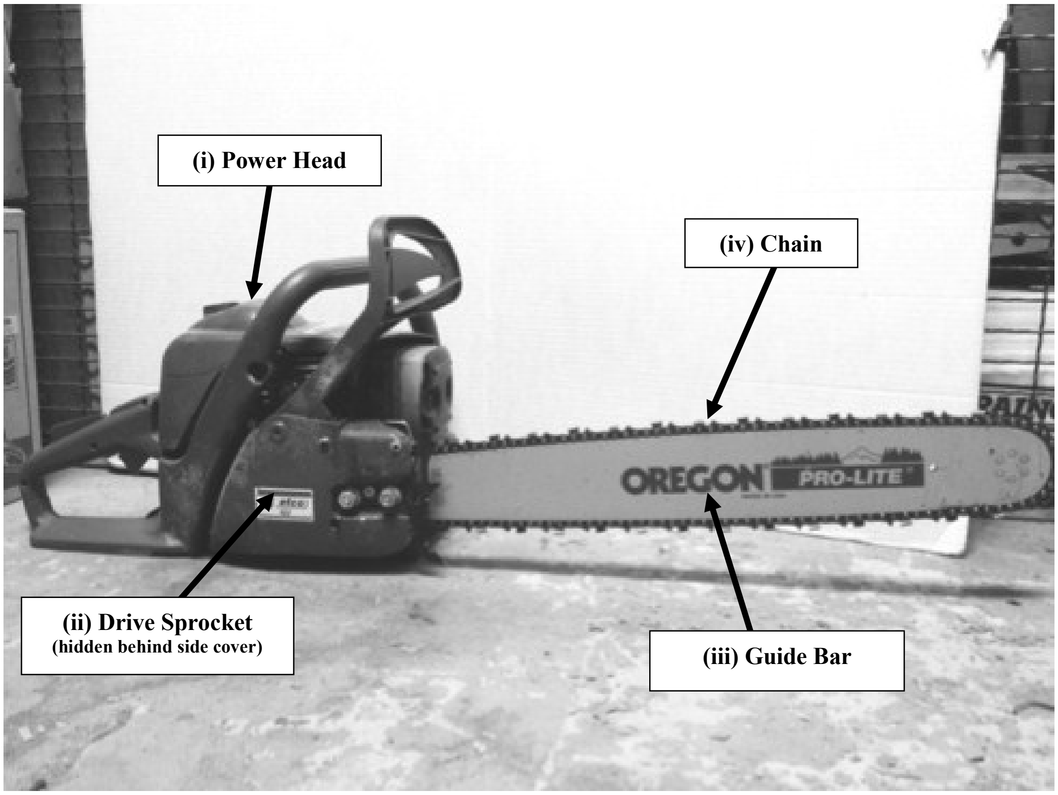

Figure 1: Efco model 152 Chainsaw showing the position of the (i) Power Head, (ii) Drive Sprocket, (iii) Guide Bar, and (iv) chain.

Most chainsaws have a two-handle configuration. The rear handle holds the throttle-trigger and interlock that controls the saw's engine while the top handle is used to help support and guide the saw. For a typical right-handed operator, the right hand holds the rear-handle and operates the throttle, while the left hand is placed on the top handle. The top handle carries the weight of the saw, as it is typically placed above the saw's center of gravity and the hand guard is placed directly in front of this handle. There are other configurations of chainsaw handles, but they are less common and are typically only for professional saws.

Figure 2 shows a typical arrangement for hand guard, handle, throttle trigger, and interlock placement.

While chainsaws have changed the logging industry, replacing many handheld, labor-intensive tools, there are many dangers associated with their use. Compared to other cutting tools like circular saws and band saws, chainsaws have a much larger exposed cutting surface and typically do not have safety guards that protect the operators from accidental contact with the cutting surface. Chainsaws are also unique in that both the top and bottom of the cutting surface are exposed.

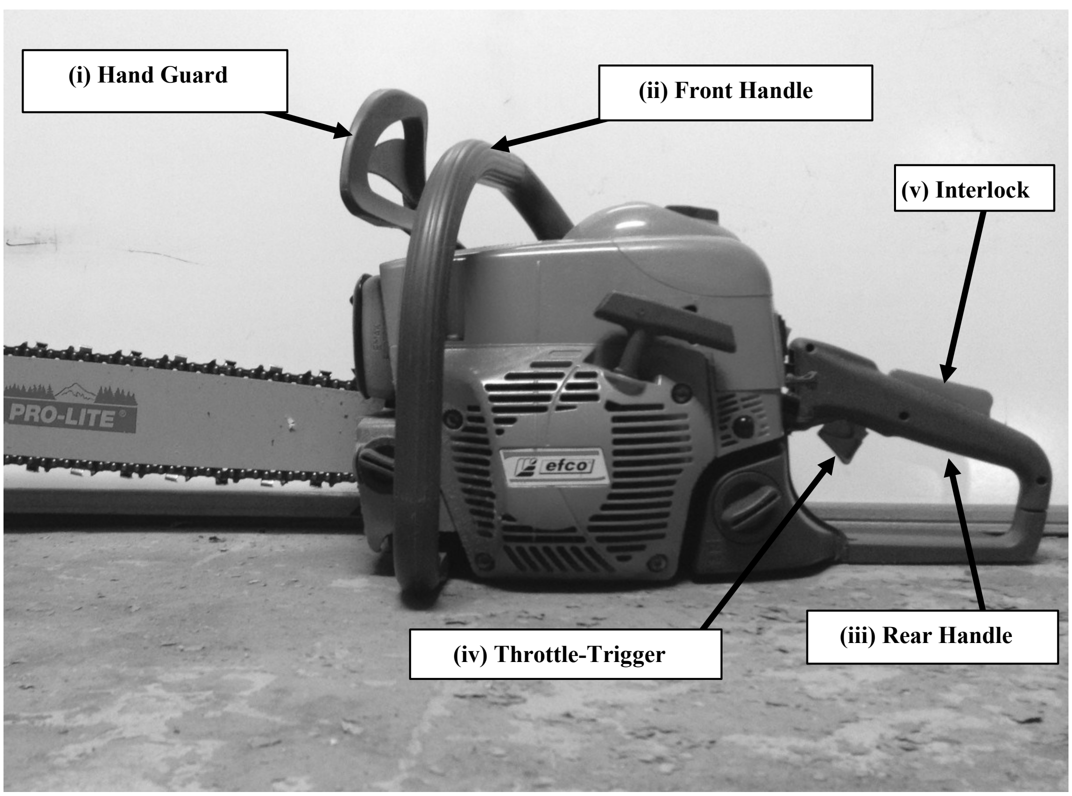

Figure 2: Image of a typical chainsaw indicating position of the (i) Handguard, (ii) Front Handle, (iii) Rear Handle, (iv) Throttle Control, and (v) Throttle Interlock.

The cutting portion of a most chainsaws is a type of roller or leaf chain. Drive links that mesh with the drive sprocket are sandwiched by two plates, called tie-straps. A cutter replaces a tie strap every second link (for larger chainsaws, the cutters are spaced further apart). Each cutter has two parts, the chisel and the depth gage. The cutter uses a chisel type cutting mechanism that removes a small wood chip with each pass. The depth gage is a small lobe that is placed just before the cutter that sets the depth of each cut. Figure 3 shows a typical section of chain showing the placement of the different links.

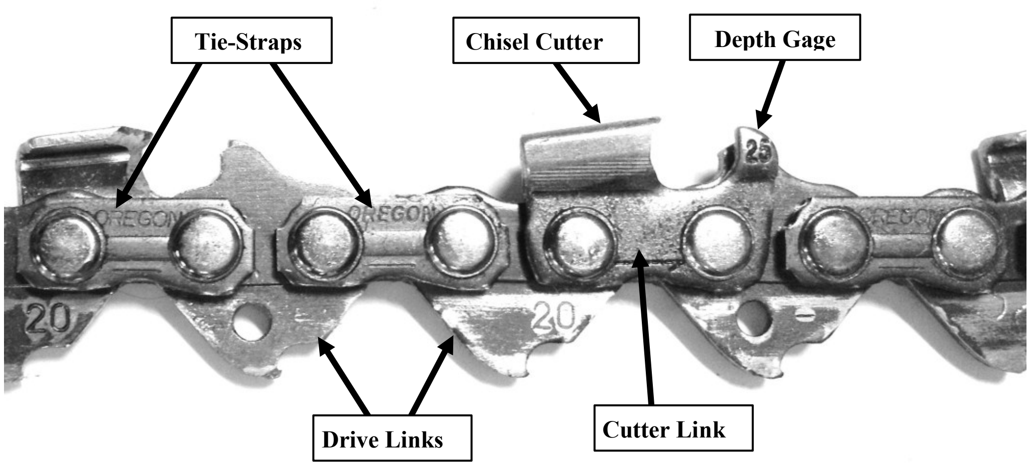

Figure 3: Segment of chainsaw chain indicating the different components

2.2 Chainsaw Kickback

On a typical chainsaw, the chain travels away from the operator on the top of the bar and back towards the operator on the bottom. When kickback occurs, the motion of the chain is suddenly transferred to a motion of the chainsaw body. The saw body rotates rapidly toward the operator. Figure 4 shows a typical chainsaw with arrows indicating the forces and rotation of the saw during kickback. The kickback event is so abrupt that the operator has little time to react. Figure 5 shows a four-frame sequence of an operator experiencing kickback that was shot with a high-speed video camera. The first frame shows the saw when the initial contact was made. The second frame shows the saw penetrating the log a small amount before kickback occurs. The third frame shows the saw as the brake begins to actuate. Most chainsaws are equipped with a brake attached to the hand-guard that actuates when the hand-guard is forced forward. In the instance detailed in Figure 5, the inertial mass of the hand-guard forces it forward without contacting the operator. The final frame shows the position of the saw at the point where the operator was able to bring its motion to a stop, 60° from the point of first contact. This was an intentional kickback performed by a skilled operator. If a similar kickback were to occur unintentionally to an unprepared operator, the consequences could be devastating.

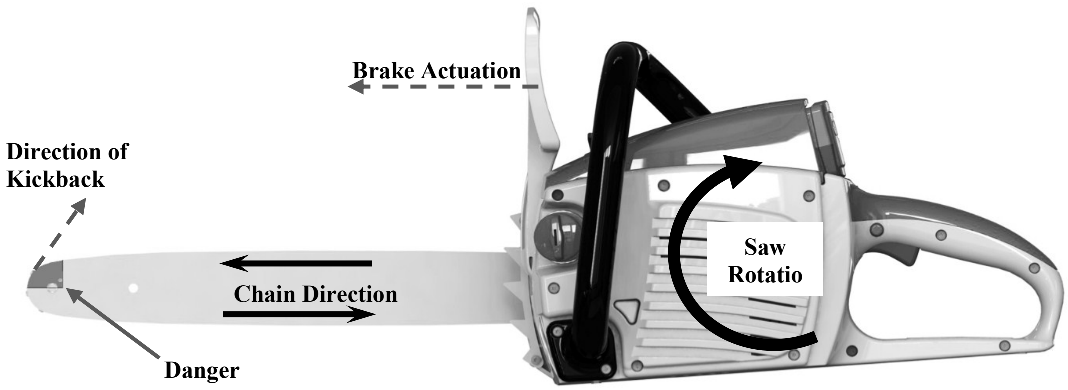

Figure 4: A typical illustration indicating the chain motion direction, and saw motions that occur during kickback.

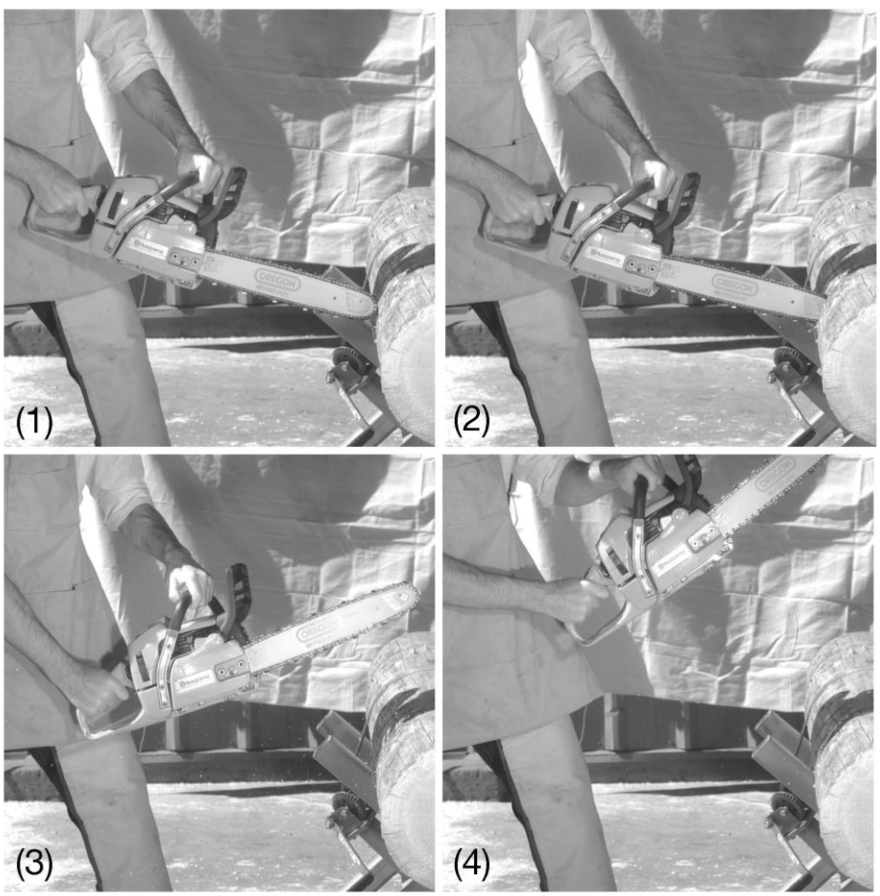

Figure 5: A sequence of images depicting a kickback event. (1) First contact was made with the log by the tip of the chainsaw bar. (2) The saw was able to cut into the log about ½ inch before the chain caught and kickback occurred. (3) The chain stops at this point. This kickback event was forceful enough to actuate the chain brake inertially. (4) The operator is able to stop the saw's motion because he was prepared for the recoil.

The first type of kickback is the result of the cutters on the top portion of the nose of the bar becoming lodged, rather than cutting. As the chain passes around the nose of the guide-bar, the orientation of the depth gage to the cutter changes, allowing the cutter to penetrate deeper into the wood. An illustration of the phenomena is shown in Figure 6. This change in cutting depth causes the cutter to get stuck. The kinetic energy of the chainsaw chain and motor is then transferred to the saw body. This method for initiating kickback is the most common, and the most easily initiated.

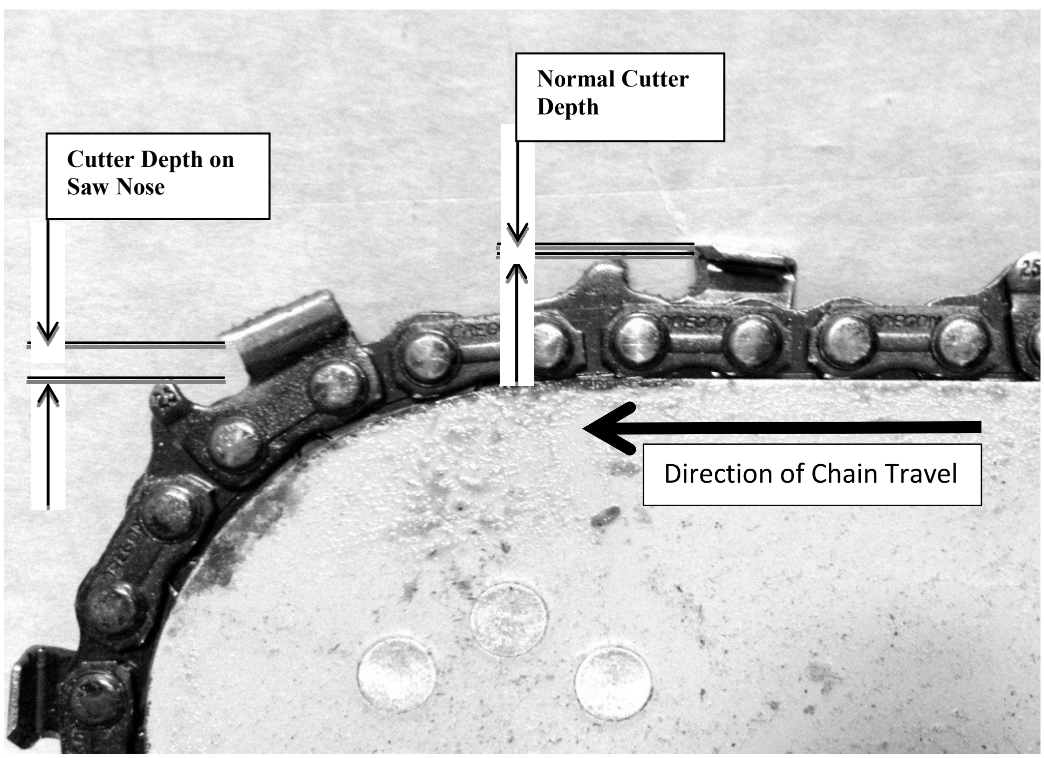

Figure 6: Typical Chainsaw bar equipped with high kickback chain illustrating the cutting depth change around the nose of the bar.

The second type of kickback occurs when the work-piece pinches the sides of the chain as the cut is made. Logs frequently shift as cuts are being made causing the chainsaw to bind, and stop its normal motion. If the chain is bound on the tip of the saw it can result in kickback. This mode of initiating kickback is much less common because typically this type of binding occurs when the saw has already progessed into a cut and binding the saw will cause the entire bar and chain to become lodged inside of a cut. Another phenomena that occurs from pinching the chain is known as linear kickback or pusback. This occurs when the top of the bar gets pushed and pushes the chainsaw out of the cut. This phenomena is not as dangerous because it does not cause a great deal of rotational energy, but it can still cause the operator to lose control of the saw.

2.3 Chainsaw Normal Cutting Operations

There are several types of cutting operations that a typical chainsaw will see. Each of these operations will have different motion and vibration characteristics that are important to characterize in order to establish a baseline of normal chainsaw use that must be distinguished from kickback by any type of detection system. The types of cuts performed during the three phases of data-collection were nose-clear vertical cuts, nose-clear horizontal cuts, boring cuts, bias cuts, and knot bumping.

Nose-clear vertical cutting is performed on logs or trees that are downed and lying parallel with the ground as is pictured in Figure 7. The bar of the chainsaw is long enough that the nose of the bar protrudes beyond the backside of the log.

This type of cutting is seen most commonly when cutting a log into smaller pieces for fire wood or brush clearing. With this type of cutting it is important to support the log such that the weight of the log pulls the cut apart. When cutting downward into a log, if it's supported in more than one place, the cut can try to close from the weight of the log. When cutting from beneath the log up, if the log is cantilevered it will have the same effect.

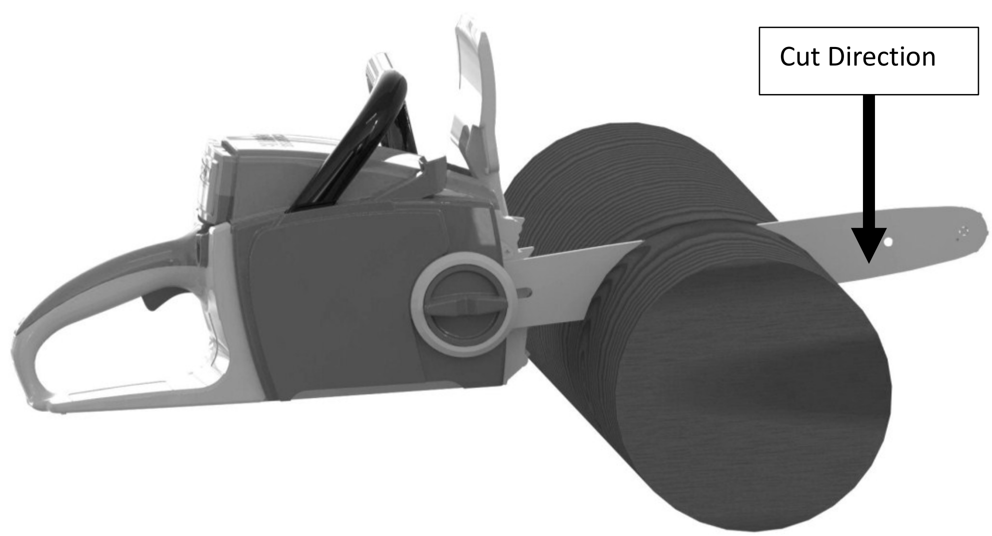

Figure 7: Illustration of nose-clear vertical cutting indicating the direction of the cut

Nose-clear horizontal cuts are performed during the tree-felling process. For this type of cutting, the saw is held on its side with the bar of the chainsaw parallel to the ground, and a cut is made in a vertical tree or log. A depiction of the orientation of the saw to the tree is shown in Figure 8. Felling trees is a fairly technical operation and requires the use of wedges to keep the weight of the tree from pinching the log into the cut.

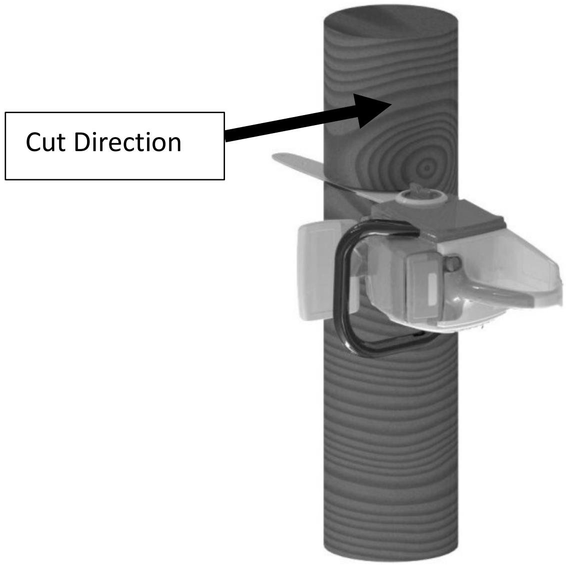

Figure 8: Illustration of a horizontal cut made into a vertically oriented log, showing the direction of cut.

Boring-cuts are made by pushing the nose of the chainsaw straight into the center of a log. A picture of an operator performing a boring cut can be seen in Figure 9. These types of cuts are performed to relieve in cuts in larger logs. The problems with the saw binding that can occur during nose-clear vertical cutting can be aleviated by beginning the cut in the center of the log. This type of cut is very susceptible to kickback as it utilizes the nose of the chainsaw. In order to safely bore into a log, the bottom portion of the nose is used to initiate the cut until a small knotch is created, then the rest of the bar can be plunged into the log. The initial kickback tests were performed by creating a notch in a downed log and performing the kickbacks inside this notch to prevent the operator from seeing as high a level of risk.

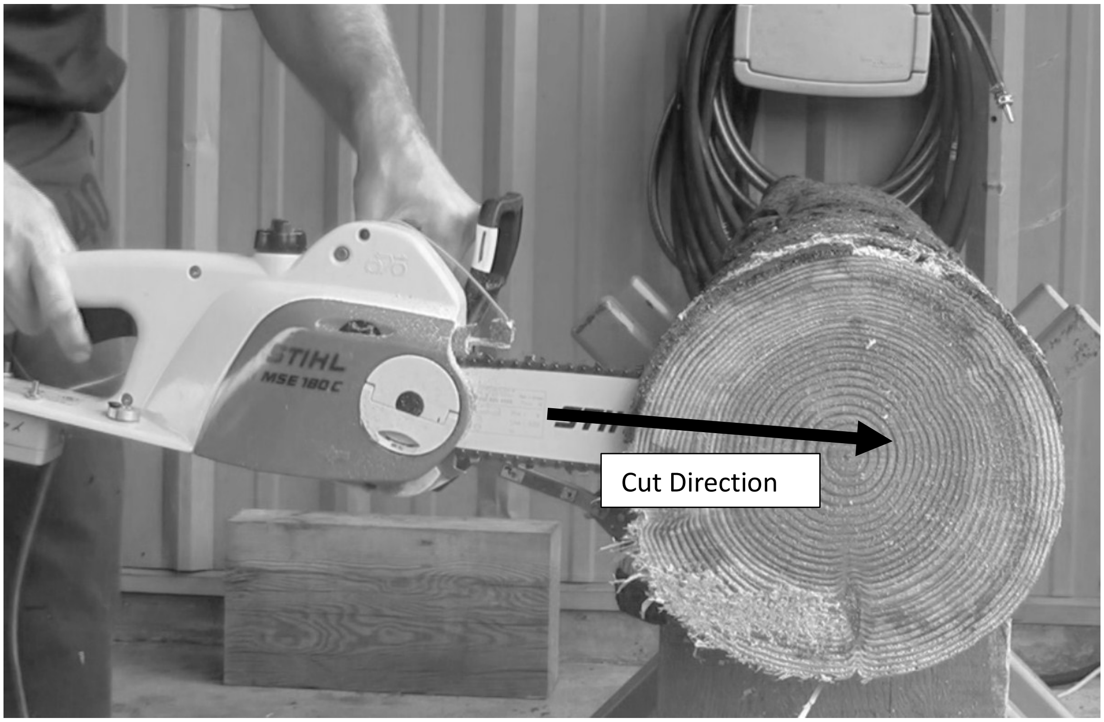

Figure 9: Image of a boring cut indicating the cut direction.

Bias cuts are used during the tree-felling process and during some of the limbing processes. A cut is made at approximately a 45° angle to the centerline of the log or tree. Figure 10 shows an illustration of a bias cut being made into a vertical log. These cuts are used to relieve the pressure that can be put on the bar during . Limbing often uses bias cuts because branches come out of the tree at an angle, rather than perpendicular, and the cut is usually made vertically with respect to the tree.

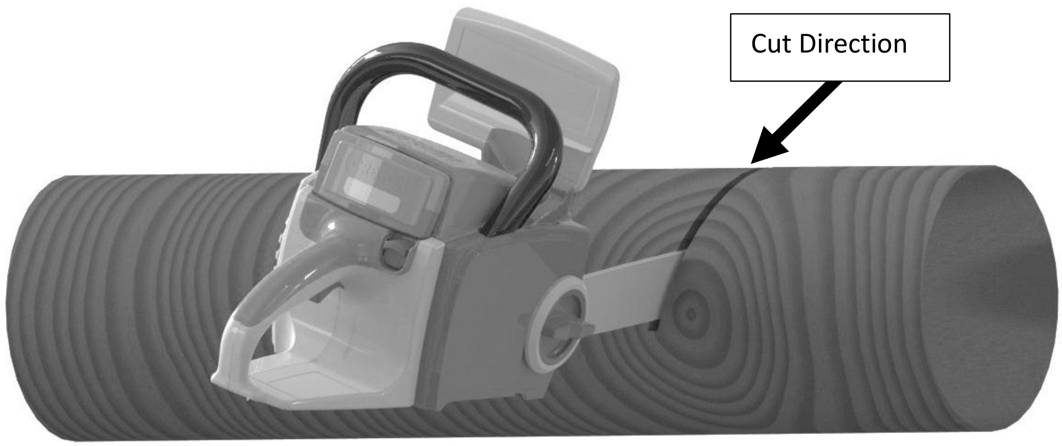

Figure 10: Illustration of a bias cut made into a horizontally oriented log, showing the direction of cut.

Knot-bumping is a process used sometimes to remove knots, or limbs from logs. This method requires that the operator swing the chainsaw like an axe or a hammer at the base of the knot. Figure 11 shows an illustration of knot bumping, indicating the direction of saw motion.This operation is a fairly technical operation and is not commonly performed by the average consumer. The saw can be swung upward or downard at the knot to remove it—that is to say that either the top of the chainsaw bar or the bottom can be used during knot bumping. The direction of knot bumping depends on the positions of the operator, log and knot to be removed with respect to oneanother.

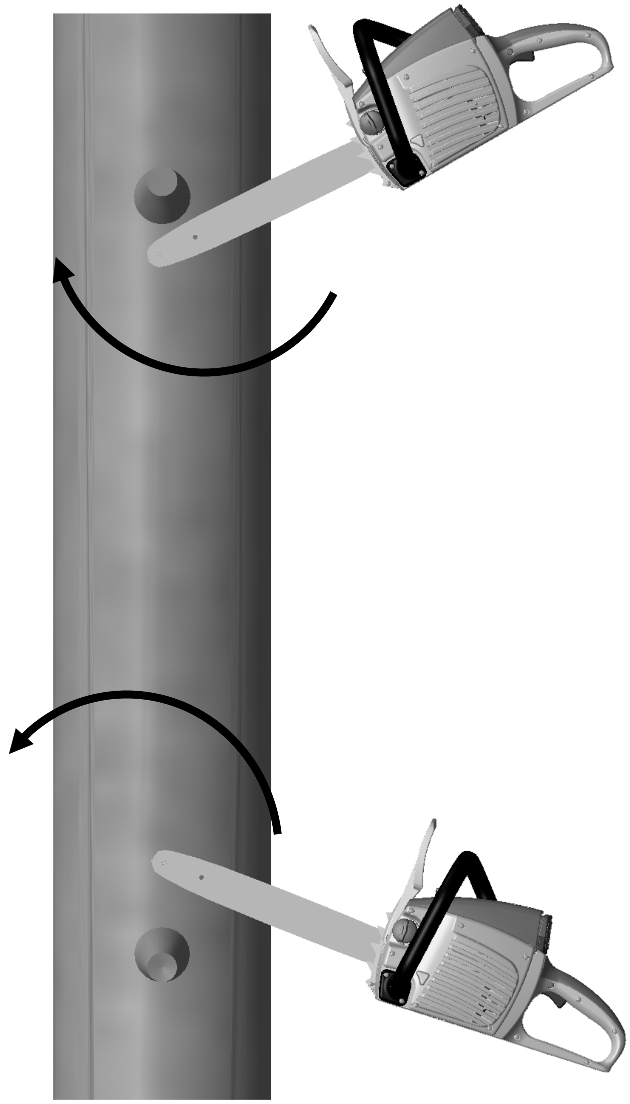

Figure 11: Illustration of knot-bumping from above and below with arrows indicating the direction of motion.

2.4 Chainsaw Safety History

Modern versions of chainsaws came into use after advancements in manufacturing techniques during World War II. Chainsaws became a common tool for lumberjacks around this time. It was during the energy crisis of the 1970s that a growing number of average consumers began using chainsaws to help with the high costs of heating by harvesting trees for firewood [11]. This increase in novice chainsaw use was correlated with an increase in chainsaw-related injuries [2,6].

In 1980, the US Consumer Product and Safety Commission (USCPSC) issued a mandate to increase the availability of safety systems on consumer level chainsaws [2]. As a result, all consumer level chainsaws were required to be equipped with safety mechanisms to help reduce the danger of kickback. These safety measures, along with more ergonomic chainsaw shapes, have provided a dramatic reduction in the occurrence of chainsaw-related injuries [12].

The USCPSC issued a docket that describes the types of safety measures with which chainsaws must be equipped [13]. All chainsaws were required to be equipped with at least two of the following three mechanisms: a certified low-kickback chain, a chain brake, or a nose guard.

Low-kickback chains add an additional link in front of the cutter link that helps to reduce the change in cutter depth around the nose of the bar. These types of chain, while reducing the forces seen during kickback, also tend to reduce the performance of the chain by reducing the depth of each cut and preventing chips from being cleared from the cut as easily. Figure 12 shows one type of low-kickback chainsaw chain from Oregon®. This type of chain replaces a tie strap with a bumper that helps to reduce the change in cut angle that is shown in Figure 6.

Chainsaw brakes are designed to actuate when the saw rotates back toward the operator. The hand guard in front of the top handle on the saw is attached to a braking mechanism. As the saw rotates toward the operator during a kickback, either the operators wrist, or the inertia of the brake presses it forward which actuates a brake. The brake is effective in reducing the occurrence of injury in the event of a kickback. It does nothing to reduce the reaction force of the kickback event or deter the kickback event from occurring.

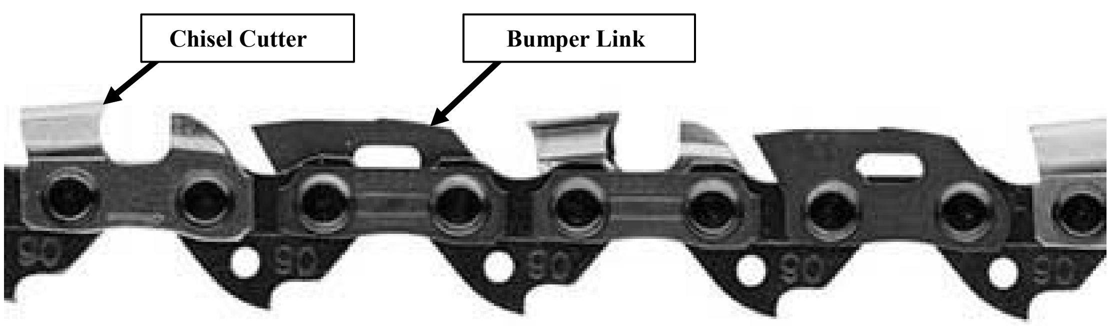

Figure 12: Oregon® R-Series(90SG) Saw Chain, a type of low-kickback chain[13]

Nose guards cover the nose of the guide-bar with a piece of plastic or metal, preventing the nose of the chainsaw from contacting the work piece. This system almost eliminates the occurrence of kickback, but limits the functionality of the chainsaw and may cause the saw to be more dangerous than without guard [12]. Any type of action that utilizes the tip of the chainsaw like felling trees, or removing limbs will be difficult or impossible to perform. Many operators commented on the precarious stances that must be used in order to perform certain tasks with a nose-guarded chain. They also commented on the increased likelihood of the chainsaw getting stuck during a cut. These guards are easy to remove and commonly are removed. Nose guards are typically only found on pole chainsaws and very small chainsaws (saws that have a bar that is 10-inches long or less) or on pole saws that have the cutting bar attached to the end of a long pole to trim tall trees from the ground. Mostly these saws do not have a brake mechanism because it would be too heavy, too complicated or too expensive for the product.

Most chainsaws are equipped with a low-kickback chain and chainsaw brakes as they have the least impact on saw performance while still significantly improving the saw’s safety. Chainsaw brakes are an integrated part of the saw, and are typically not tampered with [12]. Nose guards while actually providing the greatest protection from kickback, are rarely put on chainsaws. Nose guards inhibit the functionality of the chainsaw, as they prohibit certain cuts that use the nose of the saw from being made. The nose guard must be removed to change the chain, so they are not typically permanently fixed to the bar. Because they are easy to remove, chainsaw operators tend to simply remove them [12].

2.5 Current Braking Systems

Modern chainsaws are almost universally equipped with some sort of braking mechanism. The brake is the only system on chainsaws that protects the operator after kickback has occurred. The brakes are designed to actuate when the saw experiences a rapid rotation toward the operator. The hand-guard just in front of the top-handle is connected to a band brake that stops the motion of the cutting chain before contacting the operator.

A weighted hand-guard is used to detect the occurrence of kickback. During a kickback, the hand guard is either forced forward by its own inertia, or the operator's hand or wrist contacts the guard and pushes it forward if the saw rotates a large enough distance. The brake system is designed to actuate when rotational acceleration (α) of the saw exceeds a given threshold. The hand-guard's lever arm extends out from the center of rotation of the saw such that the mass at the end of the wrist-guard sees a tangential force (F_t) due to the rotational acceleration. Figure 13 shows the relative forces on the hand guard and the direction of saw rotation during a kickback.

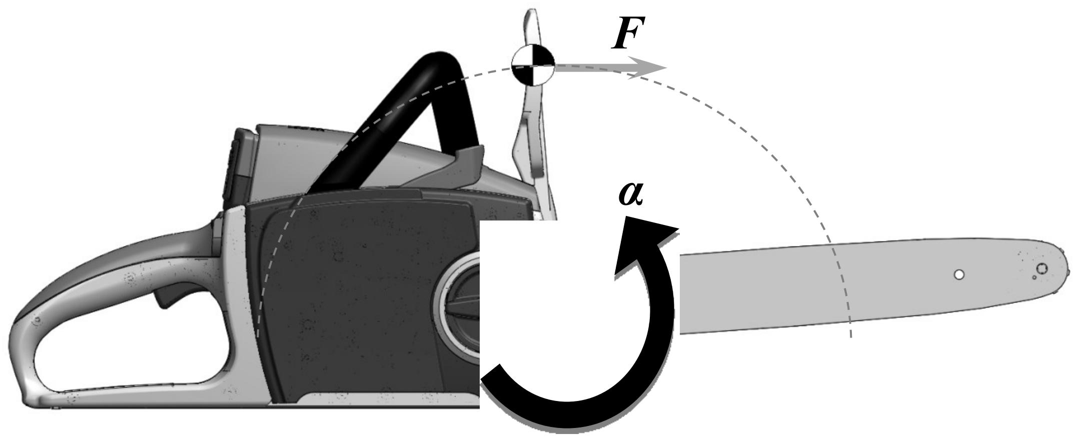

Figure 13: A typical chainsaw showing the rotational acceleration (α) of the saw during kickback and the reaction force (F_t) on the hand guard.

The brake mechanism is typically a band-brake that tightens around the saw's centrifugal clutch drum. The band brake is applied by spring tension and is held back by an over-center linkage. As the hand-guard is forced forward, the over center linkage is pushed under-center stops resisting the tensions spring as is depicted in Figure 14. Once the band brake is engaged, it must bring the drive sprocket to a stop in less than 150ms [7], [14], [15]. The motor transmits power to the drive sprocket through a centrifugal clutch. Once braking is applied the clutch slips to prevent the motor from stalling.

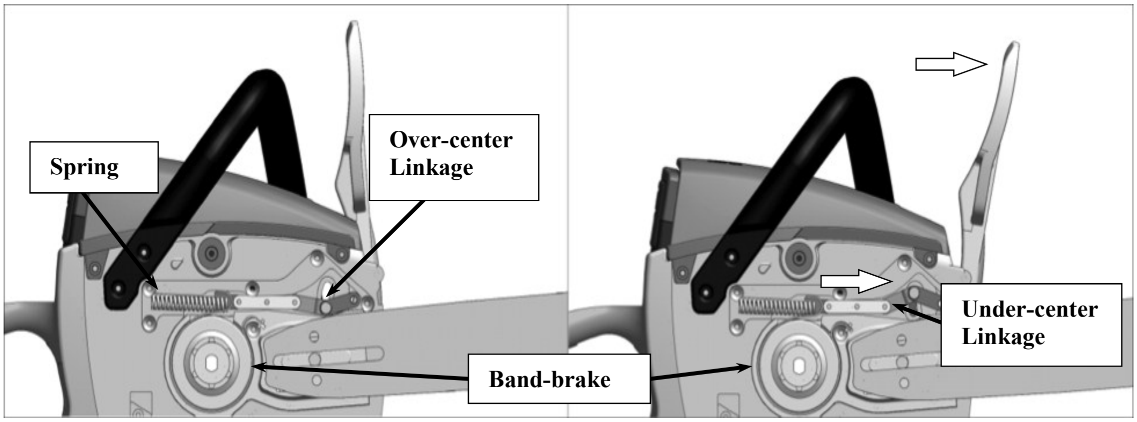

Figure 14:Chainsaw showing over-center linkage, band brake, and hand-guard position before actuation (left) and after brake actuation (right)

Using a purely mechanical braking system has several advantages. The mechanism is simple and robust. If the brake is not actuated inertially, it will likely be actuated by the operator's hand. The weighted system can be tuned by selecting the appropriate spring stiffness and hand-guard mass to provide the right cut-off acceleration, given a kickback event. The band brake that is typically used is a very simple and robust braking method that does not wear quickly and provides adequate stopping force. The system is so simple and reliable that it is has hardly changed in more than 20 years.

The system can be thought of as two separate subsystems: kickback detection and saw braking. Kickback detection is achieved by the weighted hand-guard that experiences a reaction force from the rapid rotational acceleration. The kickback detection system must be able to reliably detect the rapid acceleration of the saw while avoiding accidental actuation due to the high-frequency, high-magnitude vibrations of the saw. The kickback acceleration magnitude is essentially determined by the spring stiffness on the over-center linkage. To damp out the high-frequency noise of the saw's normal use, the hand-guard is designed so it must travel through a certain rotation before tripping the over-center linkage. Damping out this high-frequency noise means that the saw must travel a larger distance before the brake is actuated.

The braking mechanism is usually a band-brake. The band-brake is used because it is compact, simple, and it does not wear out quickly. It is also easily adapted to the use of a centrifugal clutch which transmits torque through the inside of a metal drum. The band brake wraps around the outside of the centrifugal clutch and is tightened around it with a spring. Centrifugal clutches use centrifugal forces to apply force to abrasive pads that transmit torque. This allows the motor to idle without rotating chain. The brake mechanism must be able to stop the chain when it is running at its maximum speed. This means that the band brake must slow the inertia of the saw and torque of the motor until the clutch begins to slip.

The danger of a purely mechanical system is not necessarily in the most violent kickback events, but in the less forceful events. If the brake mechanism is not actuated inertially it must rely on contact with the operator to brake the chain. This means the saw must travel even further before stopping. If the operator's hand is not in the correct position, there is nothing to stop the saw but the operator.

3 Exploritory Data Collection and Analysis

An exploritory study was conducted initially to provide information for appropriate sensor selection and data collection methods. The goal of this study was to determine the appropriate sensor bandwidth, the dynamic range of the sensors to be used, and an adequate sampling rate. The results of this study will be used to design the data collection setup and methods that will be used for Phase 1 and Phase 2 data collection and analysis. Phase 1 uses a battery powered chainsaw and Micro-Electro-Mechanical Systems (MEMS) sensors to determine if it is possible to detect kickback. Phase 2 uses a more cost effective set of MEMS sensors on a gasoline powered chainsaw to determine how early kickback can be detected.

3.1 Exploratory Data Collection

Exploritory Data Collection Setup

Exploritory data collection testing was performed with the components listed in

Table 1. The saw was a high-end, consumer AC-electric chainsaw and the sensors used were from existing lab equipment.

Table 1: Exploratory Data Collection Equipment

Component	Description
Stihl MSE 180 C	120VAC 11 amp electric Chainsaw

PCB Piezotronics T356A66	3-axis 4 kHz ±500 g piezo-electric accelerometer
Analog Devices ADXL335	3-axis 1.6 kHz ±3 g MEMS accelerometer
ST LISY300AL	1-axis 88 Hz ±300°/s MEMS gyroscope
National Instruments CompactDAQ	NI 9234 accelerometer DAQ, NI 9201 voltage DAQ, and NI cDAQ-9138 chassis

The sensors were mounted to the saw as depicted in Figure 15. The two MEMS sensors were mounted just beneath the handle in a sealed box and the piezo-accelerometer was mounted on a small bracket just in front of the handguard. The data acquisition hardware was connected to a laptop and stored at a sampling rate of 10 kHz.

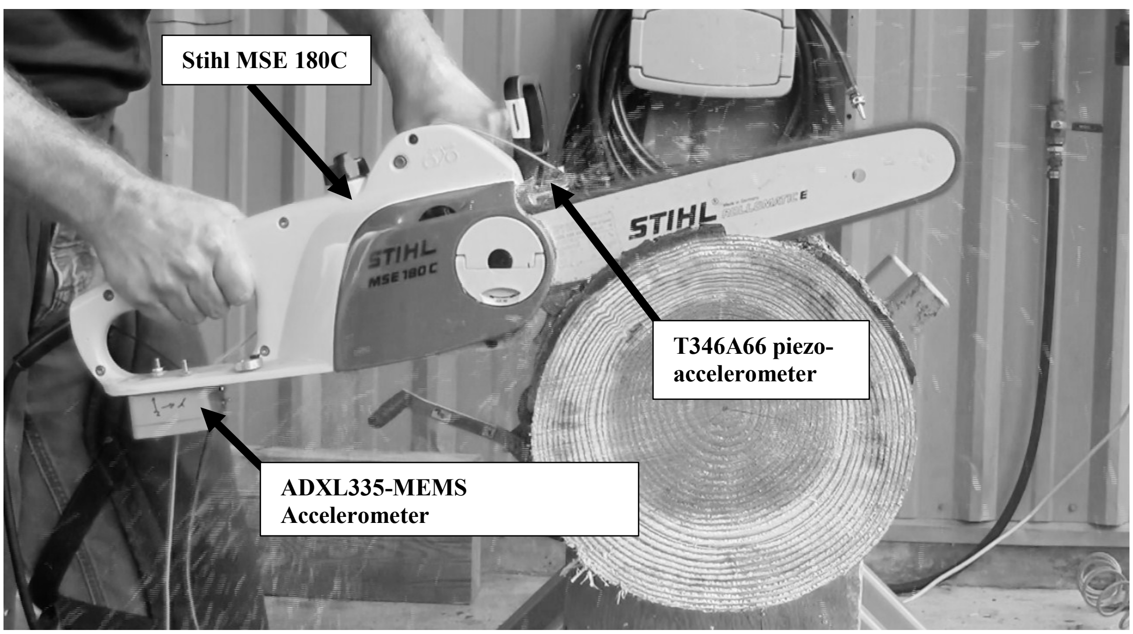

Figure 15: Image indicating the location of sensors mounted to the AC electric chainsaw during Exploratory Data Collection

Exploratory Data Collection Methods

Using the test setup described in baseline measurements were collected using the small Stihl electric chainsaw. The goal of this testing was to obtain baseline motion and vibration information for a typical chainsaw Table 2 lists the types of cutting operations performed on each of the several types of media.

Table 2: Exploratory Data Collection Normal Cutting Operations

Media	Cutting Operation
12-inch fir log	Nose-clear vertical cut
	Bore-cut
2-inch ash branch, cantilevered 3 feet	Nose-clear vertical cuts
	Vertical cuts at saw nose
	Simulated knot-bumping
6-inch fir log	Nose-clear vertical cut (bottom up)
	Bias cut
Dry 4x6 beam	Bias cut
	Nose-clear vertical cut
10-inch rain-soaked oak log	Nose-clear vertical cut
	Bore-cut

The method for simulating kickback that was commonly used for demonstration purposes was to bore part way into a log, and push the nose of the bar into the back side of the cut. This causes the saw to kickback but it contacts the top of the bored cut before it can accelearte toward the operator. The simulated kickback operations performed are listed in Table 3. The first two kickback simulations listed in Table 3 utilized the standard simulation method. The third simulation used a second log, rather than the inside of the bored-cut to attempt to better match reality. The last simulation was attempted on the outside of the log with no guarding.

Table 3: Exploratory Data Collection Kickback Simulations

Media	Cutting Operation	No. of Trials
12-inch fir log	Kickback simulations within bore-cut	8
10-inch rain-soaked oak log	Kickback simulations within bore-cut	11
	Simulated kickback by extending saw through notch to kickback on log hidden behind	13
	Kickback on outside of log	4

After initially reviewing the collected data a question was raised over the practice for safely simulating kickback. Because the nose of the saw stays within a knotch that is concave, it is difficult to determine what part of the kickback event is caused by the initial contact, and what part is caused by the saw contacting the top of the knotch. As a result, all future kickbacks were conducted on the outside of logs with some sort of guarding in place to protect the operator.

3.2 Exploritory Data Analysis

To better understand the noise characteristics of a chainsaw a spectral measurement tool was used to determine the dominant vibrational frequencies present during use. A Fast Fourier transform was chosen to characterize the vibrational noise of the chainsaw during normal use, as can be seen in Figure 16. A Fast Fourier transform (FFT) is an optimized method for determining the discrete Fourier transform (DFT). A DFT transforms a function in the time domain into components of different frequencies. The Cooley-Tukey method that was used [16] to obtain the FFT is the most widely used FFT and is very efficient at converting time series data into the frequency domain [17]. Using this tool a picture of the dominant frequencies present in a dataset was obtained to assist in future sensor selection, signal filtering, and samplng rate selection.

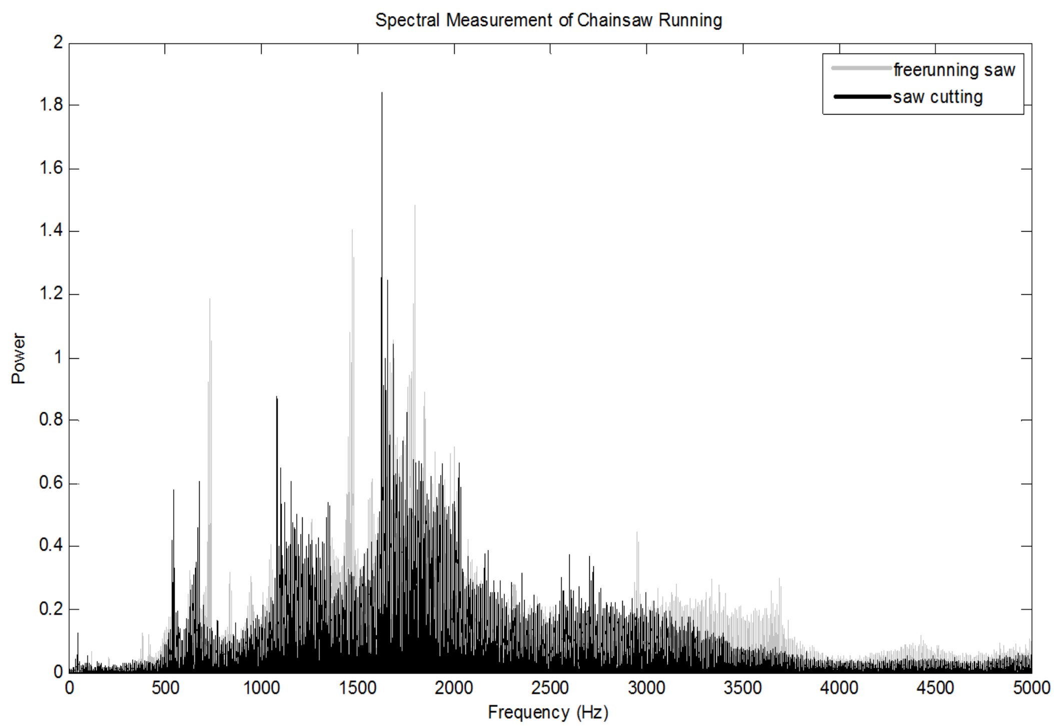

Figure 16: Spectral analysis of a saw during free running (black) and nose clear cutting (grey).

In addition to obtaining the FFT, the time series of each test was plotted to identify the maxima for both normal cutting and kickback scenarios. This information was used to select appropriate sensors and to better understand the differences between normal cutting and kickback motions.

The results of the spectral analysis seen in Figure 16 shows that the dominant frequencies for both a free-running saw, and a saw during a standard nose-clear cut, have similar vibrational noise characteristics. The sprocket on the chainsaw was rotating at approximately 2200 RPM, which translates to about 37 rotations per second. The most prominent frequencies occur between between 500Hz and 2200 Hz. A sampling rate was chosen that would capture these frequencies so that appropriate filtering could analyzed and selected later during post-processing. For subsequent testing a sampling rate of no less than 5000 samples per second was used. Many of the shorter tests were sampled at 10,000 samples per second, and for longer tests where the size of the data became an issue, a sampling rate of 5000 samples per second was used. The matlab code used to perform these analyses can be found in Appendix A.1.

Examining the maxima of each dataset, the dynamic ranges of sensors were chosen. The desired range of accelerometers was $\pm$100 g and the gyroscopes were chosen to be at least 300 degrees per second.

4 Phase 1: Detecting Kickback Reliably

The goal of Phase 1 of the project was to determine if kickback could reasonably be detected and distinguished from normal cutting activities. A low-powered battery powered chainsaw was used that would create the lowest energy kickbacks. The difference between normal cutting and kickback with will be the smallest with such a low-powered chainsaw, which allows the detection methods to be developed at the lower bound of possible detection levels. A series of cutting operations and intentionally inititated kickbacks would be performed and an empirical approach would be taken to determine the feasibility of detecting a kickback. Two types of MEMS accelerometers would be used to monitor the chainsaw along two axes, and two types of gyroscopes would be used to monitor rotation about the third axis. A method of combining the signals from three sensor axes was used that weighted the values from each sensor differently. An optimization scheme was used to find the combination of sensors that provided the largest margin between normal cutting and kickback.

4.1 Phase 1 Data Collection Setup

The first phase of testing was conducted with components selected specifically for this application. The components used are listed in table 2. For this phase of testing MEMS sensors were chosen as these are more likely to be used on a production saw because of their small footprint, ease of integration, and low cost. Sensors were mounted under the handle, as far forward as possible because this is close to the same location that a control board would be located. The dynamic range was selected to be over 50 g with a target above 100g, and a bandwidth over 1.5kHz with a target over 2 kHz. These values were chosen after examination of the testing results from the exploratory data collection to capture as much of the necessary information as possible.

Table 4: Phase 1 Data Collection Equipment

Component	Description
Oregon PowerNow 40V Max	40V Battery-powered prototype chainsaw
Analog Devices ADXL001-250	1-Axis 22 kHz ±250 g MEMS accelerometer
Analog Devices AD22281	1-axis 24 kHz ±70 g MEMS accelerometer
Analog Devices ADXRS620	1-axis 2.5 kHz ±300°/s MEMS gyroscope
Analog Devices ADXRS652	1-axis 2.5 kHz ±300°/s MEMS gyroscope
National Instruments USB-6211	NI multifunction DAQ module
Kickback Safety Shield	Plexiglas shield to protect operators during testing

For Phase 1, testing all of the sensors were mounted in a single box that was placed on the underside of the saw, just below the saw's throttle trigger as is shown in Figure 17. The sensors were mounted inside a single box that was connected to the USB DAQ module. The plexiglas shield was designed and built to provide some protection for the operators in the event of a kickback, though it proved to be somewhat unnecessary for the low-power of the battery powered saw. Figure 18 shows an operator performing kickbacks with the Plexiglas shield in place. Data was acquired at a rate of 5,000 samples per second as it was determined during exploratory data collection that this would be a more than adequate rate.

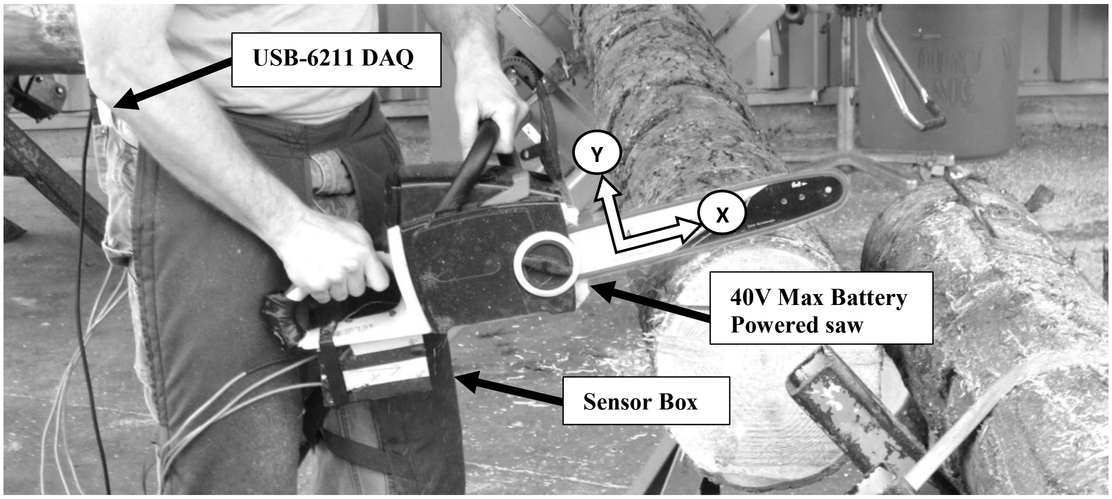

Figure 17: Image indicating the location of sensors mounted to the battery-powered chainsaw during Phase 1 testing. The orientation of the measurement axes are indicated by the x and y with the z-axis extending out of the picture perpendicular to the flat plane of the bar.

Figure 18: Figure depicting Dr. John Parmigiani performing intentional kickback simulations with the Plexiglas shield in place for protection

4.2 Phase 1 Data Collection Methods

The first phase of data collection was conducted with a well-defined testing plan and sensors chosen as a result of the exploratory data collection. The testing methods focused on normal cutting operations that would be most likely to give a false positive for a kickback event and attempted to provide more realistic kickback scenarios. In addition, several operators were used so that differences between operators could be accounted for.

The normal cutting scenarios chosen were nose-clear vertical cuts, bias cuts, boring cuts and knot bumping. Table 5 shows the list of normal cutting scenarios performed. These scenarios were chosen based on the results of the exploratory data collection because they were either the most representative of normal cutting situations or they were at the extremes for vibration or gross accelerations.

Table 5: Phase 1 Data Collection Normal Cutting Scenarios

Media	Cutting Operation	No. of Trials
12-inch fir log	Nose-clear vertical cut	35
	Bias cut	16
	Boring cut	10
8-inch vertical fir post	Nose-clear horizontal cut	9
2-inch ash branch, cantilevered 3 feet	Vertical cuts at saw nose and branch tip	15
	Simulated knot-bumping	30

Several new methods for simulating kickback were attempted because the kickback data obtained during the exploratory data collection was confounded by inadequate kickback initiation techniques. The experimental test methods used were designed to simulate the following two characteristics of realworld kickback accidents: kickback typically occurs unexpectedly and kickback typically occurs during some sort of cutting operation. Kickback is typically unexpected because it occurs more frequently with inexperienced operators who are unaware of its dangers. Kickback frequently occurs during a cut or just prior to beginning a cut because the chainsaw will not kickback while the saw is idling with the chain not moving.

The first method for initiating unexpected kickback consisted of inserting one-inch dowels two feet into the end of a log then boring into the log such that the tip of the saw would contact the dowel and kickback out of the log. This type of kickback is similar to the first type of kickback discussed in Section 2.2. The dowels used were made of high-density polyethylene and aluminum. Figure 19 shows a picture of this test with the aluminum dowel imbedded in the end of the

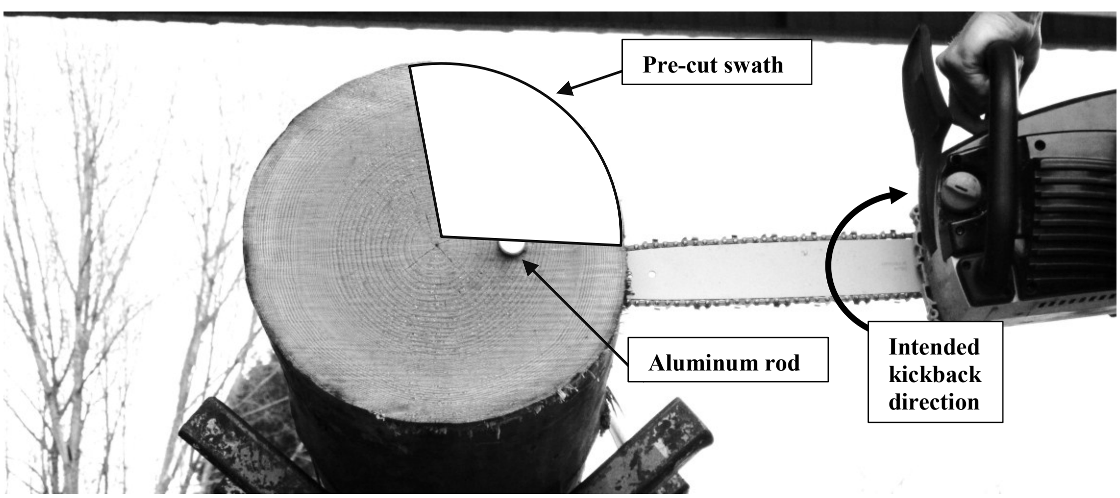

Figure 19: A log with an imbedded aluminum rod designed to cause the saw to kickback unexpectedly during a cut. The pre-cut swatch allows for the saw to kickback out of the cut once the saw contacts the aluminum dowel.

log with the approximate pre-cut swath location. The operator cut down from the top to clear a path for the saw to kickback, then bored in from the side until contact was made with the aluminum dowel.

The second method consisted of performing a standard nose clear vertical cut on a 12-inch log with a second log behind and slightly below the first log. Figure 20 shows the arrangement used for this simulation. This is a common real-world scenario for initiating kickback. Typically the chainsaw operator is unaware that there is a second log behind the first and kickback occurs when the nose of the saw contacts the second, hidden log. This method is also similar to the first type of kickback discussed in Section 2.2.

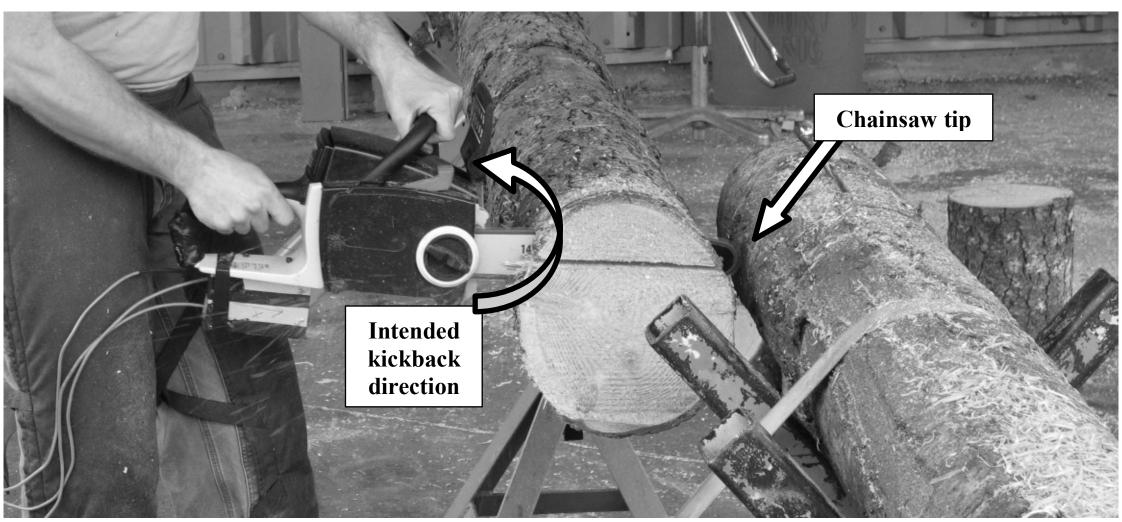

Figure 20: Nose-clear vertical cut with a second log behind that will contact the danger-zone of the nose of the chainsaw causing a kickback in the direction indicated.

These two methods for testing kickback were unsuccessful in generating the results desired. Using the first method, the aluminum and HDPE dowels did not catch on the saw as intended. The second method was fairly difficult to get the saw to kickback without simply cutting into the second log. During both tests the saw, when it did kickback, the saw did not exit the pre-cut swath as the saw tended to bind on the sides of the cuts.

Another kickback method was attempted to reproduce linear kickback. Linear kickback commonly occurs when making a nose-clear vertical cut in the middle of a log that is supported at either end of the log. The cut closes behind the saw as it progresses, and pinches the chain. Figure 21 shows the attempt made during testing to initiate linear kickback. This type of cut was attempted but a linear kickback was unsuccessful because the saw was not powerful enough to overcome the increased friction on the bar.

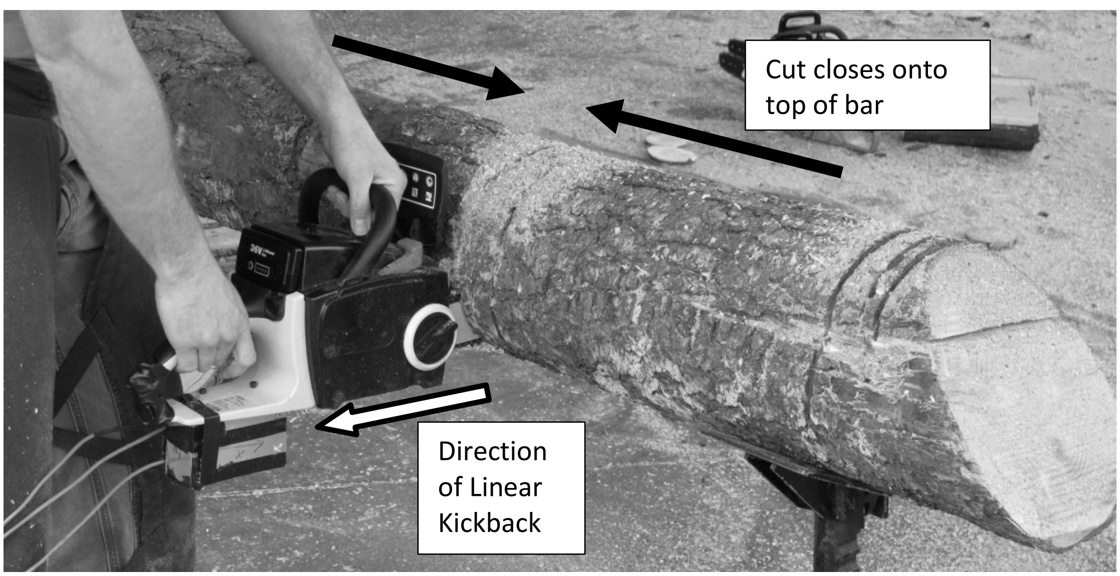

Figure 21: Test of linear kickback. The top of the cut closes onto the top of the saw bar, pinching the chain which pushes the saw backward out of the cut toward the operator. Attempts to replicate this phenomenon were unsuccessful.

The most successful method for initiating kickback required the several operators to press the top of the nose of the saw into the outside of a log. The log was held in a fixture that oriented the log so it's center axis was parallel with the ground. Kickbacks were initiated with the saw in two orientations. For the first orientation, the operator held the saw with the flat plane of the bar perpendicular to the ground, and the second orientationg the saw was held such that the flat plane of the bar was parallel with the ground. This second orientation proved to generate higher energy kickbacks because the saw nose can stay in contact with the log for a longer period of time as the saw is moving along the straight axis of the log, rather than the small contact patch of the rounded log. In addtion the fibers of the wood that run vertically in a tree are much more difficult to cut, so they tend to get caught in the cutters and cause higher energy kickbacks.

Given that causing kickback manually on the outside of the log was the only successful method, it was the method used numerous times to collect data with four different operators. Table 6 lists the number and type of simulated kickbacks that each operator performed.

Table 6: Phase 1 testing kickback simulations performed

Operator	Kickback type	No. of trials
Operator 1	Vertical	5
Operator 2	Vertical	15

	Horizontal	11
Operator 3	Vertical	31
	Horizontal	26
Operator 4	Vertical	12
	Horizontal	9

4.3 Phase 1 Analysis

The first phase of testing focused on the ability to detect a kickback and effectively distinguish it from normal cutting operations. Initial analysis methods consisted of filtering the data, then examining the differences between the maxima of normal cutting and the maxima of the each kickback. The next set of analyses looked at an optimized method of combining the sensor readings from multiple sensors in a way that increases the sensor's ability to detect kickback, but decreases the likelihood of a false detection.

4.3.1 Phase 1 Optimization Method

Filtering methods

The sensors that were used for this testing have built-in analog filters that keep the measurements within their respective design limits, however additional digital filter was performed with the stored readings. The analog filters are taylored to each MEMS circuit. Gyroscopic sensors operate by monitoring the frequency of small vibrating arms. The corealis effect of rotation of the sensor causes a change in frequency of the vibrating arms with corresponds to a change in rotational velocity. Because these sensors are looking for changes in vibration, they typically have a lowerbandwidth than accelerometers.

The data was filtered using a Butterworth, third order low-pass filter. There are many types of digital filters. A Butterworth filter utilizes a set of algorithms that attenuates frequencies in the stop-band —in this case high frequencies. The Butterworth filter was used because it can be used as a digital approximation of a fairly simple analog circuit that uses two inductors, a capacitor, and a resistor. The pass-band is flat, with no rippling, and drops off at a rate dependant on the order of the filter. Implementing a detection system would require replacing the digital filter with an equivalent analog circuit to reduce the required computing power.

Optimization Method

To increase the reliability of this detection system, an optimization scheme was used to combine and weight the three sensors in such a way as to hopefully attenuate the normal cutting signals while amplifying the kickback signal. A combination of multiple signals was first proposed after examining the last set of kickbacks during exploratory data collection.

It was obvious during the inspection of the data during the kickback events that a kickback was occurring, but when compared with the data taken during normal cutting, the difference between the magnitudes of the two signals were not substantial. Two samples of the data taken during exploratory data collection can be seen in Figure 22. A brief portion of the normal cutting data shows some large-magnitude vibrations that approach the intensity of the kickback data. The kickback had a peak value that was approximately 30% higher than the maximum value found during normal cutting. Because this margin was detected with a limited amount of data, it was believed that a false positive (a kickback detection when no kickback occurred) was possible. A margin of at least an order of magnitude more than this was desired so methods for improving this margin were pursued.

It was observed that during normal cutting operations, the accelerations along the X-axis tended to have a similar sign and phase to accelerations along the Y-axis. In contrast, the accelerations along the X and Y axes tended to be opposite in magnitude while remaining in phase. Based on this observation a simple function was implemented that leveraged this difference between the two scenarios. The signal from acceleration along the X-axis was subtracted from the acceleration along the Y-axis. This combination caused the difference between sensors during kickback to double, and the difference during normal cutting to be attenuated. This simple formula is shown in Equation (1).

$$\varphi_0 = a_y - a_x \qquad (1)$$

In this equation φ_0 is the combined signal, and a_y and a_x are the accelerations in the x and y directions, respectively (measured in multiples of the acceleration of gravity, *g*). The results of this simple combination of the two signals are seen in Figure 23.

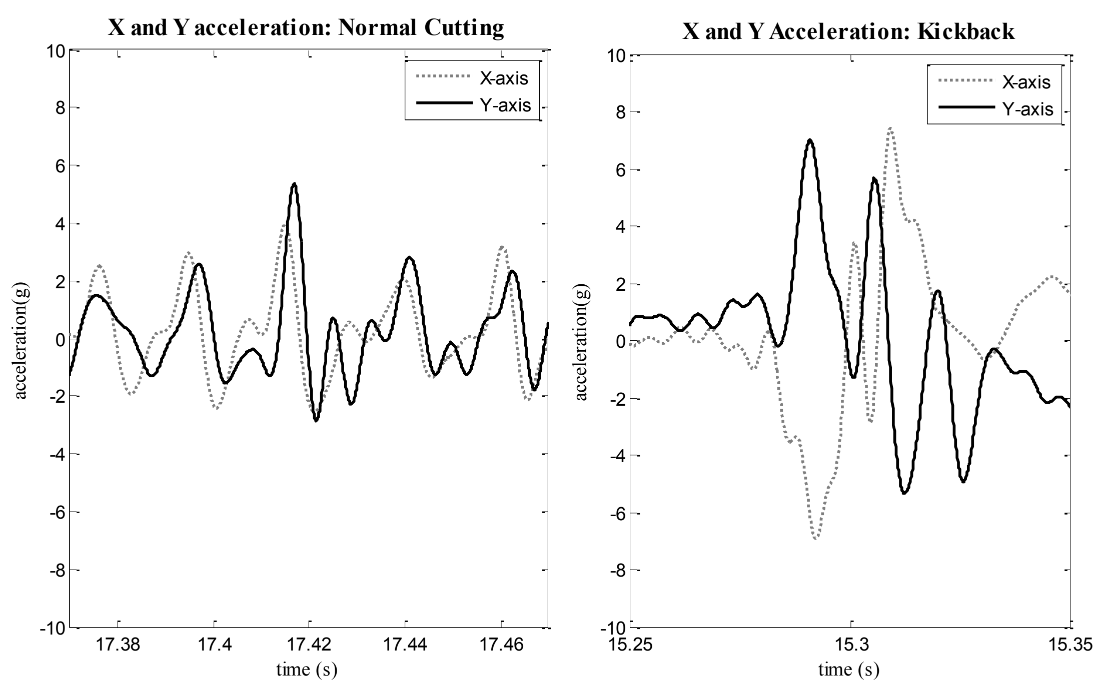

Figure 22: Samples of normal cutting data (left) and kickback data (right) taken during exploratory data collection. Note the marginal difference in magnitudes between maxima of both cutting scenarios.

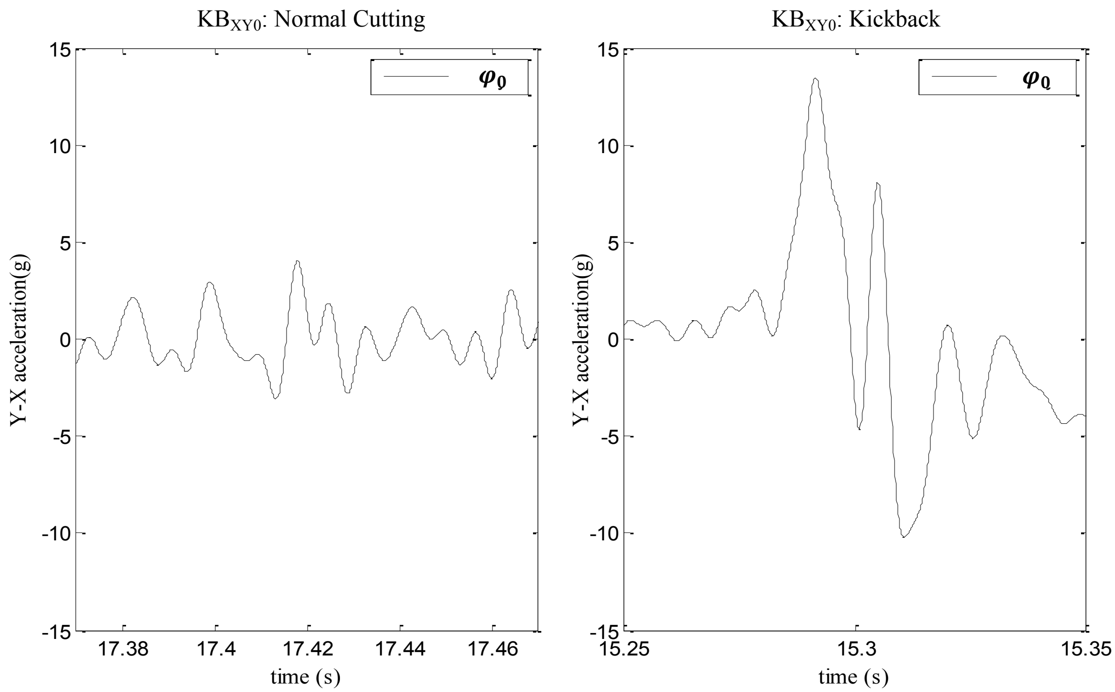

Figure 23: The same portions of data from Figure 22 plotted using the KB_{XY0} function. The signal for normal cutting (left) is attenuated while the signal for kickback (right) is amplified.

Based on the promising results of the combination of the two signals from Exploratory testing, a method for optimizing the combination of these signals was developed. This method included a third signal from the gyroscope measuring rotation about the Z-axis. The goal was to find a combination of the three signals that would multiply each signal by a weighting coeficient then sum the values to give the greatest difference between normal cutting and kickback. (**2**) shows the combination of signals that was optimized to get the greatest difference between normal cutting and kickback.

$$\varphi = \alpha a_y - \beta a_x + \gamma \omega_z \qquad (2)$$

Here, φ is the optimized equation used to detect kickback, ω_z is the rotational velocity of the saw about Z-axis in °/second, and α, β, and γ are scaling factors for each sensor.

The optimization was performed by adjusting two of the three scaling factors above and below zero. The values for acceleration were varied from between -2 g and +2 g and the values for the rotational velocity were held constant at .1 °/s. During typical operation the rotational velocity of the saw tended to be on the order of ten times greater than the data obtained from the accelerometers. Because of this, the gyroscope was scaled down an order of magnitude so the two sensors would be considered relatively equally in the optimization scheme.

The optimization was performed by chosing a set of scaling factors, and applying them to the sensors to obtain the output of φ with respect to time. All of the data taken during normal cutting operations were combined into a single dataset, while each kickback event was placed in it's own dataset. For each set of the applied weighting factor values, the maximum value of normal cutting φ_N and the maximum value for each individual kickback event φ_{KB} were collected and a normalized difference Δ_φ was calculated. Equation 3 shows the method used for calculating the normalized difference of each combination of scaling factors.

$$\Delta_\varphi(\alpha,\beta) = \frac{\varphi_{KB}(\alpha,\beta) - \varphi_N(\alpha,\beta)}{\varphi_N(\alpha,\beta)} \qquad (3)$$

For each kickback, the maximum value of Δ_φ was found, and the corresponding values for α, β, and γ were collected and plotted on a histogram to see which combinations were the most prominent. The most prominent values for α, β, and γ were collected then applied individually to the data. The average differences for all kickback events were then analyzed for accuracy and rates of error. This method of optimization was published in [18].

4.3.2 Phase 1 Optimization Results

The optimization technique was performed on the data in four separate configurations. The first configuration contained all three sensor readings from the 2 accelerometers and the one gyroscope. The other three configurations examined the three possible combinations of two sensors. If a combination of two sensors would perform well, it could potentially reduce the cost of the necessary sensors.

The optimization provided the most successful scaling factors for each kickback event. These results can be seen in Figure 24 where the magnitude of the histograms correspond to the number of kickback events that had the given scaling factors. The most prominent scaling factors were than reapplied to the data sets and their accuracies were measured which can be seen in Table 7. The table shows the statistics for the margin between the maximum value of normal cutting and kickback for each given scaling factor, indicated by the $\Delta_\varphi(kickback)/\Delta_\varphi(\max normal\ cutting)$. There is also a statistic for the percentage of kickback events that were greater than the maximum normal cutting value (Δ_{φ}>0).

The results of this optimization shown in Table 7 showed that the data from the gyroscope was the best at detecting a kickback event. The gyroscope readings had the highest difference between kickback and normal cutting operations. The knot bumping scenarios were analyzed separately because they tended to be the closest to kickback but it is a less commonly used operation. From the combination of the three sensors, it was shown that the two accelerometers tended toward a weighting of close to zero, and the gyroscope tended towards it's maximum rating. The next closest sensor combination used the Y-axis accelerometer and the gyroscope readings. The y-axis acceleration was minimized here was well. The matlab code for this analysis can be found in Appendix A.2.

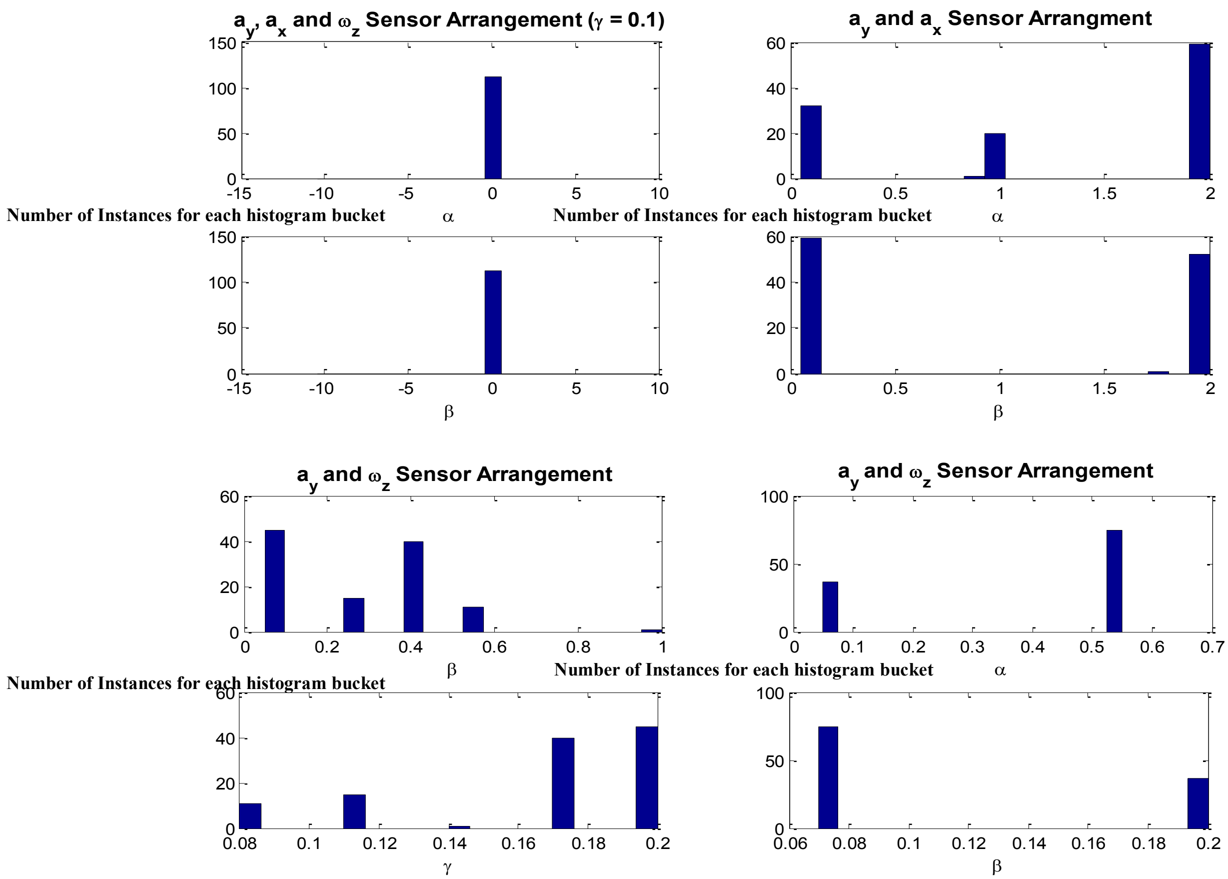

Figure 24: A histogram presenting the most successful scaling factors for each kickback event with the following four sensor configurations: all three sensors with the gyroscope value held constant (top left), the two accelerometers (top right) , acceleration along the y-axis and rotational velocity along the z-axis (bottom left), and acceleration along the x-axis and rotational velocity along the z-axis (bottom right).

Table 7: The weighting factors that generated the greatest margin between normal cutting and kickback from figure 24 were applied to the entire data set, and the results are noted in this table.

Vertical, Horizontal & Bias Cutting							
Sensors	Weighting Factors			Δ_φ			$\Delta_\varphi > 0$
	α	β	γ	Mean	Max	Min	
X,Y,&Z	0.1	0.1	1	3.92	6.12	0.63	100%
Y&Z	0.05	0	0.2	**11**	14.87	2.81	100%
X&Z	0	0.4	0.18	4.06	6.54	0.65	100%
X&Y	2	0.1	0	-0.2	1.16	-0.98	22%
Z	0	0	1	**11.2**	14.99	2.89	100%
Knot bumping							
Sensors	Weighting Factors			Δ_φ			$\Delta_\varphi > 0$
	α	β	γ	Mean	Max	Min	
X,Y,&Z	0.1	0.1	1	2.39	6.12	0.63	100%
Y&Z	0.05	0	0.2	**2.37**	14.87	2.81	100%
X&Z	0	0.4	0.18	2.43	6.54	0.65	100%
X&Y	2	0.1	0	0.15	1.16	-0.98	45%
Z	0	0	1	**2.36**	14.99	2.89	100%

5 Phase 2: Detecting Kickback Early in the Event

The goal of Phase 2 of the project was to find the method that would allow kickback to be detected as early as possible. A higher-powered gasoline chainsaw was used that would create much more energetic, and therfore much faster, kickbacks. Because a gasoline saw has much more power, a much more powerful kickback event may occur that will accelerate the chainsaw much more quickly. Detecting a faster kickback early will be more challenging than it would be for a lower powered battery saw, putting this scenario at the upper bound. A new set of sensors that were more cost effective were chosen. Two gyroscopes were used, and a single 3-axis accelerometer was used to monitor acceleration. Three analysis methods were applied to the data set to try to detect kickback as early as possible while holding the rate of false positives to a minimum. The three analysis methods used to classify the kickback data were signal differentiation, a Simplified Bag of Words (Naïve Bayes Model), and a Support Vector Machine with Selective Under Sampling and a Classifier Vector Stacking.

5.1 Phase 2 Data Collection Setup

Several changes in the data collection setup were implemented after Phase 1. Most notably, the chainsaw was switched to a gasoline powered chainsaw. The gasoline chainsaw is more powerful and produces more energetic kickback events. These saws are inherently more dangerous, so there is more latitude to increase their safety. In addition, having a high-energy kickback event places an early detection at the upper-bound of a kickback speed. If an early kickback detection is possible with a gasoline saw, it is definitely possible with an electric chainsaw.

Phase 2 testing utilized a different set of MEMS sensors that were more cost appropriate for this application. The gyroscopes had a much larger dynamic range, and the accelerometer used was a 3-axis, digital accelerometer. The setup used for the data collection is shown in Table 8.

Table 8: Components used during Phase 2 testing

Component	**Description**
Efco 152	3.4 hp 52cc gasoline powered chainsaw
STMicroelectronics LY3100ALH	1-axis 140 Hz ±1000°/s MEMS gyroscope
InvenSense ISZ-500	1-axis 140 Hz ±500°/s MEMS gyroscope
STMicroelectronics LIS331HH	3-axis 1 kHz ±24 g MEMS digital accelerometer
National Instruments USB-6211	NI multifunction DAQ module
Kickback Safety Shield	Plexiglas shield to protect operators during testing

The sensors were mounted to the saw beneath the powerhead in a single box as can be seen in Figure 25. The two gryoscopic sensors output simple anaolg voltage outputs that were measured and recorded by the data acquisition setup. The LIS331HH digital accelerometer was mounted to an evaluation board with it's own data acquistion software. The two programs recorded data simultaneously, but were not synchronized. Data was sampled at 5000 samples per second for the gyroscopes and the digital accelerometers were sampled at around1000 times per second. An issue with the data acquisition software that came with the digital accelerometer caused the sampling rate to vary for each sample.

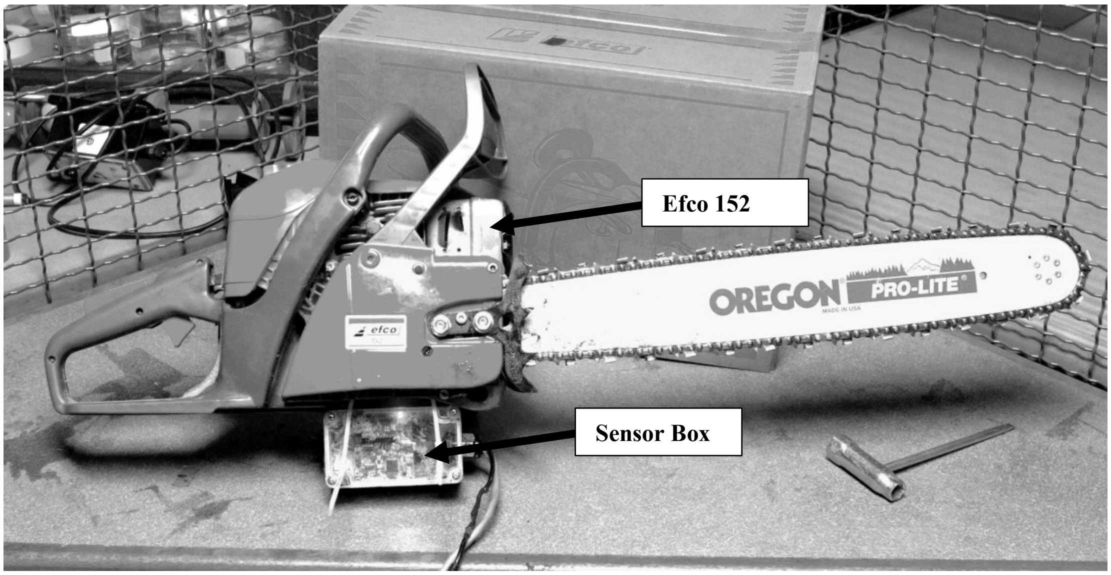

Figure 25: Image of Efco chainsaw equipped with sensor box used during Phase 2 testing.

Phase 2 Data Collection Methods

The testing procedures for the second phase were simplified and focused on the tests that were shown to be the most effective from Phase 1 testing. Because the differences between the multiple operators were not significant, a reduced number of operators were used. Normal cutting experiments were limited to nose-clear vertical cuts, bias cuts, and knot bumping to reduce in setup time, and increase the number of cuts recorded. Kickback scenarios were limited to purely vertical kickbacks on the outside of logs that were described in Section 4.1 Phase 1 Data Collection Methods.

This round of testing focused on obtaining a large number of samples of kickback and longer duration normal cutting experiments. This round of testing used the more powerful and more dangerous gas powered chainsaw, so it was more difficult to collect a large number of kickback readings. The operator became fatigued from the more forceful kickbacks and, as a result, took more frequent breaks.

The tests took place over two sessions with similar experiments. The second session was necessary because there was an error with the data-acquistion of the accelerometers in the first session. Table lists the type and number of tests performed during the two sessions. The kickback activities performed we all vertical kickbacks.

Table 9: Phase 2 testing scenarios

Session	Cutting/ kickback operation	No. of trials
Session 1	Nose-clear vertical cut	21
	Bias cut	16
	Knot-bumping	27*
	Vertical kickback	32
Session 2	Nose-clear vertical cut	35

	Bias cut	42
	Knot-bumping	20
	Vertical kickback	109

5.2 Phase 2 Analysis

The focus of the data analysis in Phase 2 is different than it was for Phase 1. During Phase 1 testing, it was important to accurately and reliably identify when a kickback occurred. After examining the results from this phase of testing, it was decided that detecting kickback was easily achievable, but now it was important to detect the occurrence of kickback as early as possible.

When a kickback occurs, the energy of the chain and motor rotating is transferred to gross motions of the saw itself. This transfer of energy occurs during the brief instant when the chainsaw is still in contact with the object. In order to reduce the intensity of a kickback, the energy present in the chainsaw must be reduced in the brief moment that it is in contact with the log.

The only practical methods for reducing the energy in the chainsaw are to begin braking the saw, to decouple the chainsaw engine from the drive sprocket, or both before the saw loses contact with the interfering object. When examining the gyroscopic signal it is easy to identify the point at which the saw has lost contact with the log, as this is the point where the slope of the rotational velocity becomes negative.

Figure 24 shows gyroscope readings of a typical kickback event. The time from the beginning to the peak of the kickback can vary significantly. There are several factors that effect the magnitude and duration of a kickback event, so many kickbacks will tend to be longer in duration. It is difficult to determine the exact start point of a kickback event. Typically the saw will cut into the log for a brief moment before the chain catches on the nose. This amount of time varies greatly

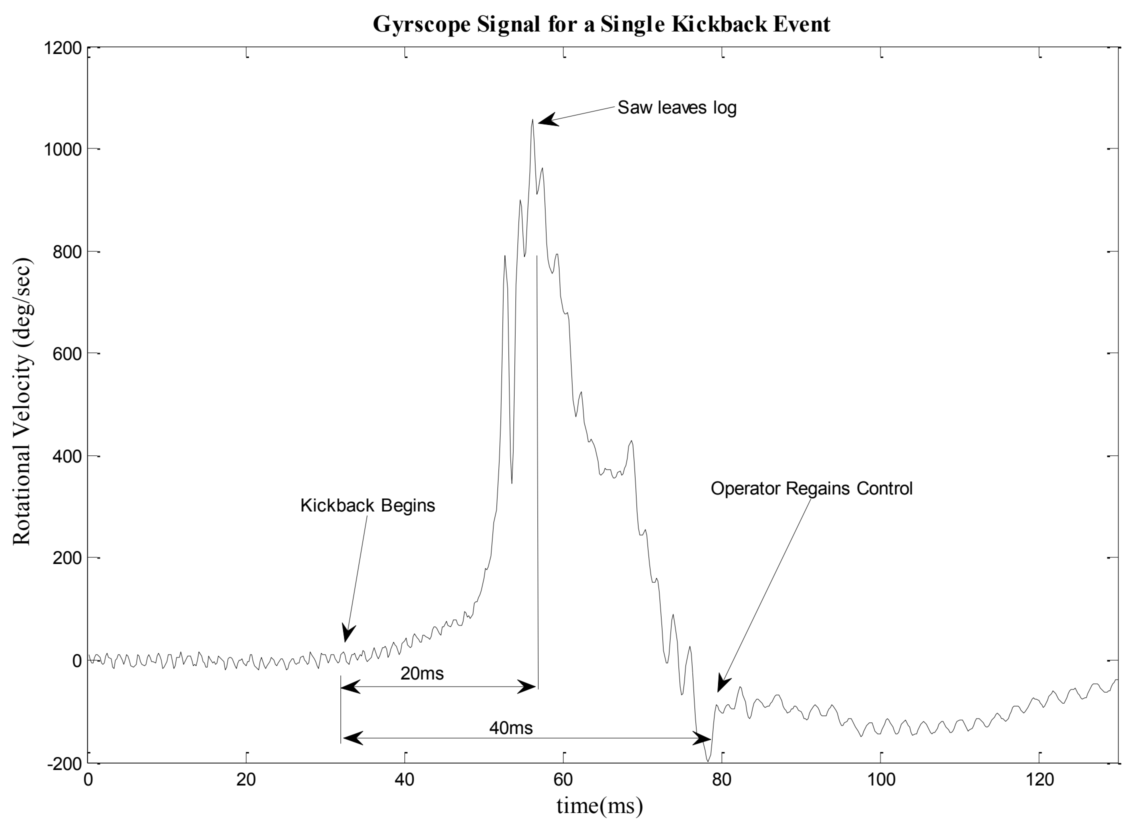

Figure 26: A typical gyroscope signal from a gasoline powered chainsaw. Note the length of time for the entire event (40 ms), and the length of time the saw is in contact with the log (20 ms).

depending on the operator, the type of log, the type of chainsaw, and the bar and chain being used. It is important to normalize the data for kickbacks at a certain time point. This allows the kickback signals to be aligned and analysis operation can be performed on specific time points.

Two methods were considered to allign the data. The first method identified kickback by the maximum rotational velocity for the each kickback event. The second method selected a threshold based on the maximum values experienced during normal cutting, then examined the kickback data for the first peak above this threshold. Ultimately the second method gave more consistant kickback shapes because of the variability of the kickback events. Using the first method often caused the kickbacks to be identified at many different time periods relative to the initiation of kickback, whereas the second methods tended to line the data up much more reliably. Some of the difficulty in using the first method was also the result of the signal saturating during many of the more intense kickback events. This caused the signal to be chopped off at the upper threshold of the sensor and the identification point (ID point) is selected almost arbitrarily based on which reading was marginally higher. This can be seen visualy in Figure 27. This first method shows a greater variability in the signal than the second method does. For the rest of the Phase 2 analysis, the kickback events were identified using this method. It is important to note that the kickback event itself can continue beyond the Method 2 ID point for some time, or it can end abruptly after the ID point depending on the type of interaction that caused the kickback to occur.

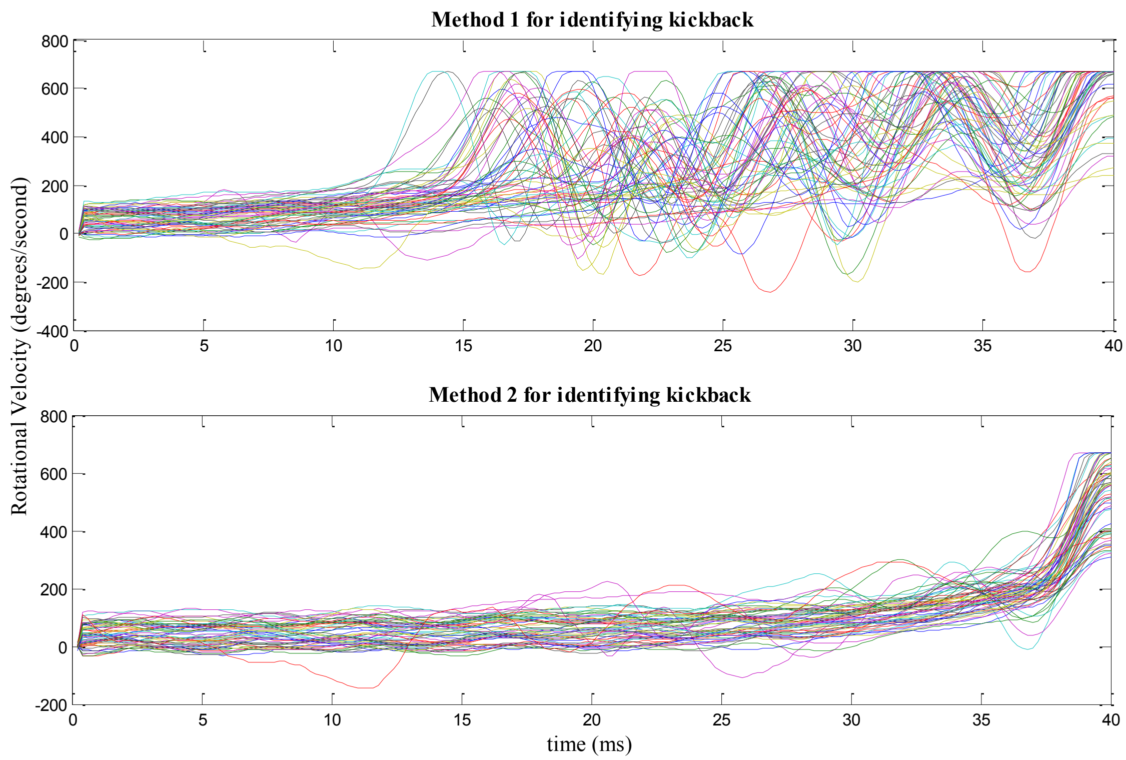

Figure 27: Plots of all of the kickback signals from their identification point and the previous 200 samples. Method 1 picked the highest point during the entire kickback event, and method 2 used the highest point of the first peak above a threshold of 300°/second.

This section covers several methods of detecting a kickback event as early as possible. The methods pursued were signal differentiation, a simplified Bag of Words method, and support vector machine learning.

5.2.1 Signal Differentiation

Signal Differentiation Methods

To perform the signal differentiation, the signals from the two accelerometers and the gyroscope were first filtered using the second-order Butterworth as before, then differentiated with respect to time. Differentiating the signal gives the change in acceleration(also known as jerk, in g/s), for the accelerometers on the X and Y axes, and the rotational acceleration ($°/s^2$) of the gyroscope. An optimization scheme was used to determine the best low-pass cutoff frequency. An optimization like the one described in section 0was also employed to determine the best combination of signals that allow kickback to be detected the earliest.

Signal Differentiation Results

The results of using a differentiation method for detecting kickback were less successful at detecting kickback. The detections that were successful were detected slightly earlier in the even but there were many occurrences of false dections and the margins between the normal cutting kickback event were much less than those found using the undifferentiated signal.

Figure 28 shows a typical kickback event with the undifferentiated, filtered signal in blue, and the differentiated signal in green. From this it is possible to see that the peak of the differentiated signal occurs 10 to 20 milliseconds earlier than the undifferentiated signal. The unfortunate side effect of using a differentiated signal is the amplification of any signal noise. Additional filtering can be used, but this will cause the peak of signal to shift later in time.

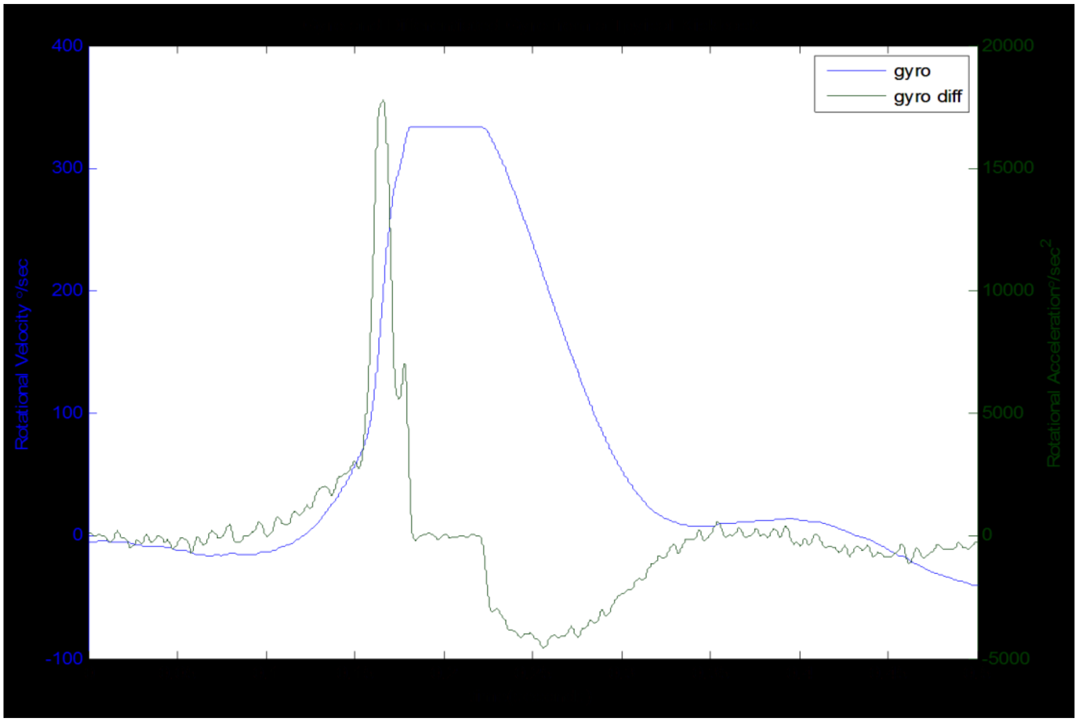

Figure 28: A typical kickback with the filtered signal in blue and the differentiated signal in green. The flat region was a result of the gyroscope reaching its dynamic range limit. Note that the differentiated signal peaks earlier than the undifferentiated gyroscope signal.

Figure 29 shows a comparison between a kickback event, a knot bumping even and a section of nose-clear vertical cutting. The axes along the y-axis for the three graphs are all the same scale, making it easy to tell that distinguishing normal cutting from kickback would be easy. When the kickback event is compared to the knot bumping event, it is apparent that the knot bumping event has a higher magnitude than kickback for the differentiated signal. Of the know bumping experiments, 31% were greater in magnitude than all of the kickback events. Things like starting the chainsaw, or letting it contact the log too aggressively could easily reach the rotational acceleration of kickbacks. Because of the poor results with this method of differentiation. The optimization scheme was ineffective. There was no combination of signals that would effectively reduce the high magnitudes seen during knot bumping. Were a differentiated signal to be used a much higher rate of false positives could be expected. The matlab code for this analysis can be found in Appendix A.3.1

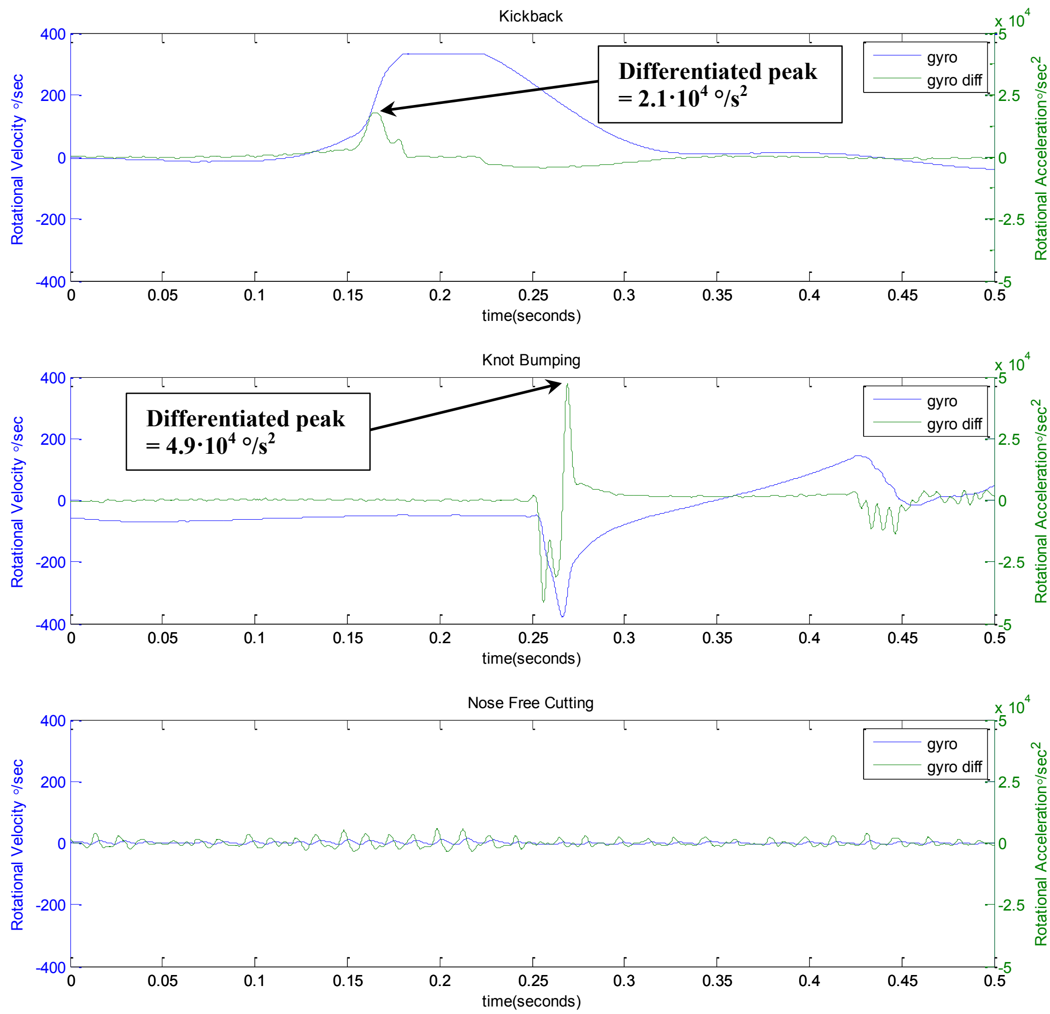

Figure 29: Figure showing the gyroscope data of undifferentiated (blue) and differentiated (green) of kickback (top), knot bumping (middle), and normal cutting (bottom) data. The peaks of the differentiated signal are labeled on the kickback and knot bumping plots to show the dramatic difference between magnitudes.

5.2.2 Simplified Bag of Words

Simplified Bag of Words Analysis Methods

The Bag of Words method is commonly used to classify different types of written documents for search queries or to detect email spam. The Bag of Words method is a type of naïve Bayes model for classification. Rather than classifying an entire document based on the presence of a single word or phrase, the Bag of Words method counts to occurrence of each word in the document, regardless of any grammar or order. The quantity of each word is stored and correlated with probabilities associated with different queries.

To use the Bag of Words method for this scenario, the sampling window of 50 data points is considered the “document”, and the “words” are different regions of data values. To classify the chainsaw data, a number of data samples above a certain threshold would indicate a kickback event. To optimize the method for detecting kickback, the threshold, was varied and the number of samples that were above the threshold were recorded. For the 200 data points of each kickback event, a 50 datapoint window was examined and the number of occurences above the given threshold were counted and stored. For all of the normal cutting data, a 50 data-point window was examined for ever point of the data and the number of instances above the given threshold were recorded. This method was repeated for several different threshold values. Once all of the data was classified, the maximum number of “word” counts during normal cutting was compared to the minimum number of word counts for a kickback at each point leading up to the identification point. The threshold value and number of word counts that could detect kickback the earliest without falsely detecting kickback in the normal cutting data would be selected as the classifier.

Simplified Bag of Words Results

The results from the Simplified Bag of Words analysis resulted in a poor quality classification method. There are two variables that can be adjusted to optimize this detection mechanism. The threshold, and the number of words for a classification. Because this method is similar to an averaging method which can be viewed as a type of filtering, only the gyroscope data was examined. Because of the results from the optimization method performed in Phase 1, the data set most likely to succeed would be the gyroscope data. If the analysis of the gyroscopic data proved successful, the study could be expanded to include accelerometer readings.

The normal cutting data was analyzed first. Using these results a minimum value for the threshold could be applied to the kickback data and the number of counts between the two sets could be analyzed. Figure 30 shows the results of the normal cutting analysis (top) and the kickback analysis (bottom). From the normal cutting data it can be seen that the first threshold level where less than 100% of a 50 data point window were counted occurs at a threshold of 215 degrees per second. This means that for the window size of 50 points, any threshold below 215 will result in the occurrence of at least one false positive.

The bottom of Figure 30 presents the location of the first point above the various thresholds for the kickback data. Each kickback event was analyzed by

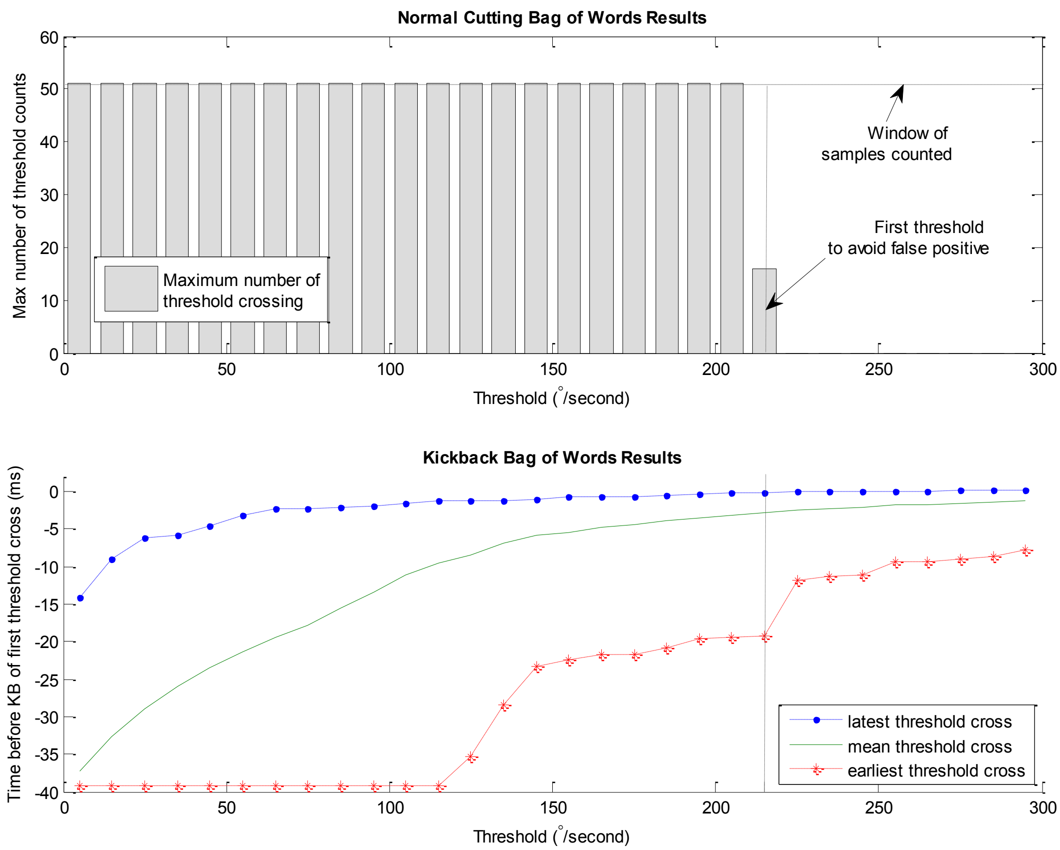

Figure 30: Results of the bag of words analysis. The top plot shows the maximum number of over-threshold counts for the normal cutting data. The bottom plot shows the distance away from the kickback ID point that the first threshold was detected.

counting the number of over-thresholds for each window of 50 data points leading up to the kickback identification point. The dashed vertical line represents the minumum threshold limit based on the normal cutting data. Even at these higher thresholds, there are points that do not first cross the threshold until 2 milliseconds before the kickback Identification point. This means that there would only be 10 over-threshold counts for the worst case kickback events. This is not much different than simply setting a threshold as in the optimization method from Phase 1.

If a threshold of 225 degrees per second were chosen, the average kickback event would be detected 3.5 millseconds before the identification point. If any number of threshold-counts greater than 1 were used, the average kickback detection would occur later in the kickback event. Because the result of this analysis were only marginally better than the results of simply using a threshold, further analysis of the accelerometer kickback data was not pursued. The matlab code for this analysis can be found in Appendix A.3.2.

5.2.3 Support Vector Machine Learning

Support vector machines (SVM) are a type of supervised artificial intelligence used for classification and regression analysis. This method is more efficient than many other methods because it uses only the most difficult data vectors to learn from rather than build a model with every point. A good illustration to help understand this concept would be a classifier built to differentiate between pictures of cats and pictures of dogs. The classifier would select the pictures that are the most difficult to differentiate and learn the difference between this smaller set. If the classifier can distinguish between the most difficult pictures, it should easily differentiate easier pictures.

There are two inputs used to train the classifier: a training matrix, x, of input vectors, x_i, belonging to either of two classes, and a second vector, y, containing the classifications of each input vector. A training set, D, will take the following form.

$$D = \left\{ (x_i, y_i) \middle| x_i \in \mathbb{R}^n, y_i \in \{-1, 1\} \right\}_{i=1}^{p} \qquad \textbf{(4)}$$

Here, p, is the number of data sets in the training set that are n data points long. A positively classified vector is given a value of $+1$ and a negatively classified vector is given a value of -1. The matrix x of training data as it would appear in Matlab is made of p examples of vectors that are n data-points long. The matrix x takes the following form:

$$x = \begin{bmatrix} x_1(1) & x_2(1) & \cdots & x_p(1) \\ x_1(2) & x_2(2) & \cdots & x_p(2) \\ \vdots & \vdots & \ddots & \vdots \\ x_1(n) & x_2(n) & \cdots & x_p(n) \end{bmatrix} \qquad \textbf{(5)}$$

The row-vector y stores the classification of each vector x_p in the following form:

$$y = [\ y_1 \quad y_2 \quad \cdots \quad y_p\ ] \qquad \textbf{(6)}$$

Each data vector is mapped as an individual point in high-dimensional space—that is, a space with many more than 3 dimensions that can easily be visualized. The Maximal Margin Plane (MMP) is a plane that separates the two data classes with the maximum margin between the two classes. The MMP is defined by the normal vector $\boldsymbol{w}$. The support vector machine identifies the data-vectors that are closest to the maximal margin plane by setting up a margin on either side of the plane, called a soft margin. The vectors selected by the SVM to take part in learning the classification are called support vectors. Equation (7) is the decision function used to map the data into high-dimensional space.

$$D(x) = \sum_{i=1}^{N} \boldsymbol{w_i} \cdot x_i - b \tag{7}$$

Here, $\boldsymbol{w}$ defines the vector normal to the maximal margin plane, and b is the bias offset of the plane (note that here the dot represents the dot product of the two vectors). The maximal margin plane occurs when D(x) = 0. The soft margins occur when D(x) =1 for the positive classifier and when D(x) = -1 for the negative classifier. The support vector machine choses $\boldsymbol{w}$ and b such that the three criterion of the decision function are met. A two dimensional depiction of the mapping of points around the maximal margin plane is shown in Figure Figure 31 [19,20,21].

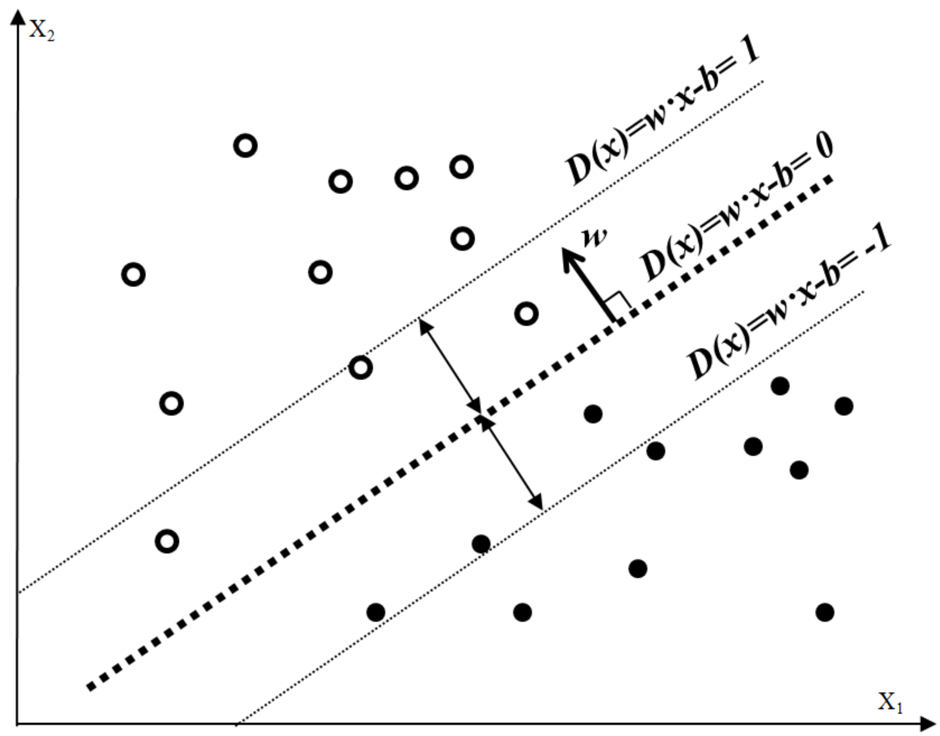

Figure 31: A two dimensional representation of the maximal margin plane, and the soft margin used to find the support vectors, and define the classifier vector, *K*.

The data sets that fall within the soft margin of the decision function are placed into a matrix of support vectors, φ. The distance each support vector is from the maximal margin plane is known as the Support Vector Coefficient, and are placed in vector μ. The classifier vector, K, is defined by equation 7.

$$K = \varphi \times \mu \qquad \textbf{(8)}$$

The classifier vector, K, is a vector the length of the original input data, x_i. Every piece of data that is to be classified, is simply multiplied by the transpose of, K. The result is a scalar value. If this multiplication is above a certain threshold, the data can be classified as a positive event, and if it is not above the threshold, it is classified as a negative event. The threshold is determined by applying each vector from the training data set to the classifier. The number of false positive and true positive detection helps to set the threshold. There may not be a threshold that is perfect at classifying every event, so, in these cases, a decision must be made as to what level of inaccuracy is acceptible. The threshold is raised to decrease the occurrence of false negatives and is decreased to avoid false negatives.

The support vector machine package that was used for this analysis was the LIBSVM package. This package provides tools to use several different SVM kernels with applications that can be run on many different programming platforms. This package also has several data repositories for testing different data sets.

5.2.3.1 Parameter Imbalance

Parameter Imbalance Analysis Methods

One potential pitfall with the use of SVM occurs when the training data set is imbalanced. This occurs when the ratio of positive to negative instances is far greater or less than one. In order to minimize the amount of error, the support vector machine tends to push maximal margin plane toward the minority dataset. This causes the classifier to fail to identify the minority class. In the case of this project, as is frequently true for SVM classification, the minority case is more unique and more critical to identify.

There are several standard methods for handling parameter imbalance. Typically they consist of either over-sampling the minority case, under-sampling the majority case, adjusting the error weighting to reflect the importance of the minority case [22], or synthesizing additional minority cases [23,24]. These methods each have their own inherent problems that often cause the data quality to be sacrificed in order to obtain the appropriate location of the maximal margin plane.

The method used to deal with the data imbalance in this case has been used in similar ways in several publications [25,26]. Rather than taylor the data sets so that they become balanced, this method attempts to find the samples from the majority dataset that are closest to the maximal margin plane, and uses only these cases as inputs into the SVM. This method is sometimes called active learning, but a good name for it is selective under-sampling. The input negative cases are

For this analysis, the amount of data obtained for normal cutting scenarios is several orders of magnitude larger than the amount of data obtained for the kickback events. The kickback event lasts approximately 40 milliseconds whereas there is close to an hour of normal cutting data. This level of parameter imbalance is actually under representative of what can be seen during real-world use. A normal chainsaw operator may never see a kickback event in the use of their chainsaw, or, if they do, it is only a few times over the span of many hours of operation. So it is important that the normal cutting data not accidentally trigger a deteciton.

To apply the selective undersampling to this data set, a random selection of data was chosen from the normal cutting data that had three times the number of data sets than the kickback data sets (this is an acceptible level of data imbalance). This data set was learned by the SVM, and the support vectors were noted and saved. The data from each test that were found to be within the margin were than analzed by placing the data into a histogram to determine which of the data was most commonly selected as a support vector. Any areas of the data that had a higher incidence of being close the maximal margin would than be used in the final analysis to decide the final support vector.

Parameter Imbalance Results

The method for handling parameter imbalance was used to select the most challenging normal cutting events. It could also be used to give an understanding of how easily the data can be classified. Examining the number of support vectors that are selected to perform the machine learning provides n excelent insite into how easily the two data classes can be distinguished.

The first parameter imbalance analysis that was performed examined the ability of each of the sensor readings individually. Portions of data were selected randomly from the normal cutting data and then applied to the SVM. The results of this simple analysis can be seen in Table 10. Based on these results it is apparent that the gyroscope has the most easily classified data. The decision was made to only classify the gyroscope data based on these results and the results from the Phase 1 analysis that similarly showed that gyroscope data was the most successful at classifying kickback.

Table 10: Results of the imbalanced parameter list showing the ability to classify the different sensor readings.

Sensor analyzed	Number of normal cutting data vectors	Average number of vectors selected to be support vectors	Number of random sample iterations
Z-axis Gyroscope	150	4.78	1607
X-axis Accelerometer	150	52.13	1503
Y-axis Accelerometer	150	43.6	1821

The imbalanced parameter analysis was performed using only the gyroscope data. The data for each kickback event was 150 data points long. Each kickback was split into 10 regions of 50 points that overlapped by 40 points. These ten regions were each analyzed for selective undersampling individually. The reason for dividing the data into regions is explained in the following section. For each kickback region of 142 kickback vectors, 150 vectors of normal cutting data were randomly selected from the normal cutting data set. The kickback data and normal cutting data was supplied to the SVM and the support vectors were noted and saved. This process was repeated 2,142 times with a different set of randomly selected normal cutting data each time. The locations of the selected support vectors were stored for each set of randomly selected normal cutting data, and a histogram was created to determine which regions of normal cutting data were more likely to be selected as support vectors. These histograms can be seen in Figure 32. Each kickback region was analyzed separately so there is a histogram that corresponds to each kickback region. The bin size for the historgram was 350 data points wide, and the 200 bins with the most data points were used to develop a selectively undersampled data set for each kickback region. The matlab code for this analysis and that of the following section are contained in Appendix A.3.3.

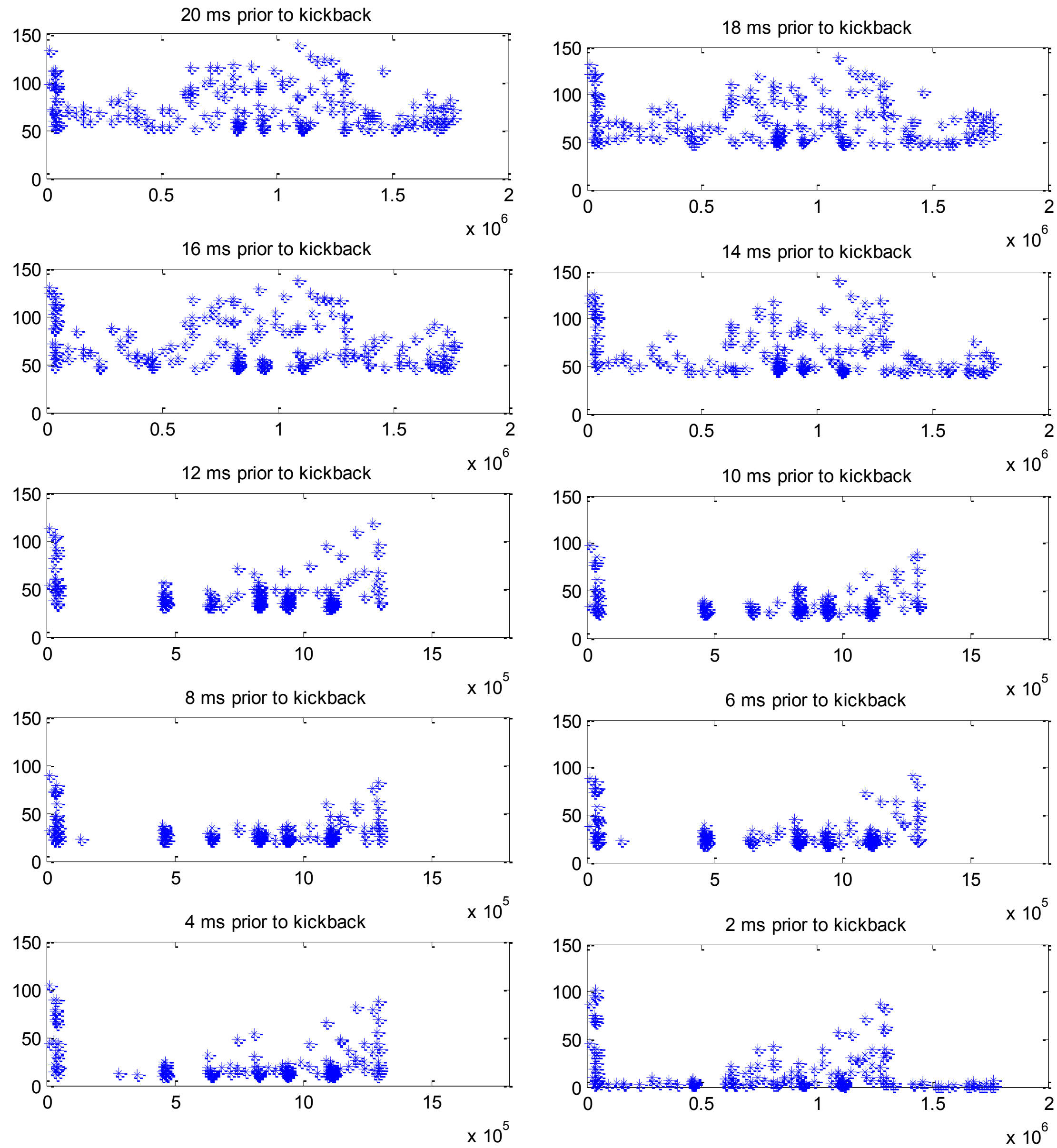

Figure 32: Histogram showing the most prominent normal cutting points for each region of the stacked classifier vector. The selective undersampling points would be inputs for the SVM to build a classifier for each region of kickback.

5.2.3.2 Classifier Vector Stacking

Classifier Vector Stacking Methods

In order to detect kickback as early as possible, it was decided to use several classifier vectors simultaneously. Because the kickback signal rapidly increases in magnitude it is apparent that kickback events will become easier to detect as they reach the end of the kickback. This means that the accuracy of detecting a kickback event will grow as the kickback progresses. This is not to say, though, that it is impossible to detect a kickback early, it just will have a higher susceptibility to error.

To attempt to detect as many kickbacks as early as possible a stack of classifier vectors will be used. The classifier vector, K, is found for specific time periods of the kickback that correspond to a length of time before the kickback's ID point. These regions are analyzed by the SVM separately and an idividual classifier vector, K, is generated for each time-frame prior to the kickback event. The earliest classifier that can be used is one that can successfully classify all the negative instances of normal cutting without false positives and can identify at least one of the kickback events. Figure 33 shows an illustration of the different regions that will be used to create the stack of classifiers. This figure uses the second type of kickback identification points.

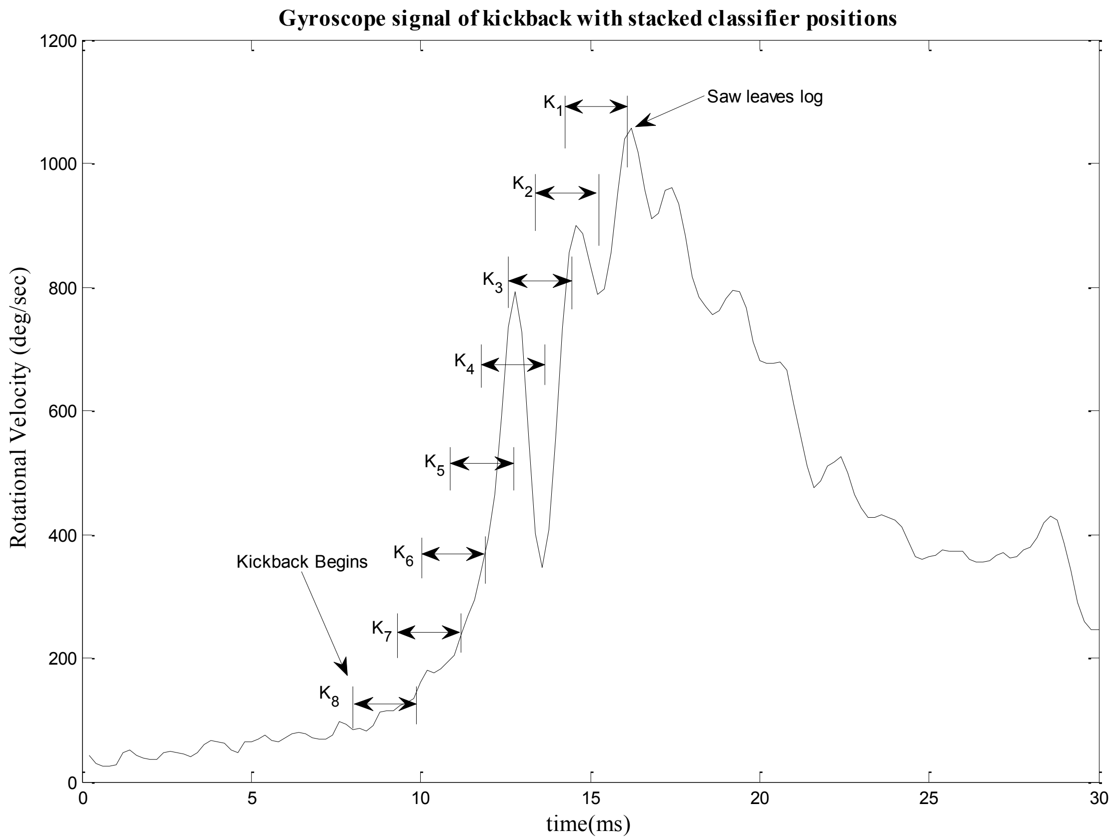

Figure 33: Signal of a kickback showing the potential classifier regions of a kickback event. (Note that the classifier regions are for illustration purposes and are not to scale.)

Classifier Vector Stacking Results

Using the selectively undersampled normal cutting data, a stack of classifier vectors was developed. Each classifier vector, K_i, was developed using the respective selectively undersampled data points from normalcutting and the data region corresponding to a given time prior to the kickback identification point. The resulting stacked classifier matrix was a ten by 50 matrix. Every 50 data points was multiplied by this matrix as follows.

$$[\omega_z(1) \quad \omega_z(2) \cdots \omega_z(50)] \times \begin{bmatrix} K_1(1) & \cdots & K_{10}(1) \\ \vdots & \ddots & \vdots \\ K_2(50) & \cdots & K_{10}(50) \end{bmatrix} = [T_1 \quad T_2 \quad \dots \quad T_{10}] \tag{9}$$

Here, T_i test value that must be compared to the threshold for each classifier θ_i. If any T_i is greater than its respective θ_i the data is given a positive classification, and a kickback is identified.

To determine the vector of ten values of θ the classification matrix, K was applied the entire normal cutting data set. The highest resulting values of T were then used as the threshold value of θ with an additional 10% safety margin.

The classifier was then applied to the kickback data. The classifier vector was applied to a given region of 50 data points for each kickback event. Then, the region was moved forward, by a single data point and repeated, until 150 regions prior to kickback were analyzed. The point at which kickback first was detected was stored and can be seen in Figure 34. From this figure it can be seen that the earliest detection point occurs at -29.4 ms prior to the kickback identification point, the latest detection occurred at -0.2 ms prior to the identification point and the average distance was 19.32 ms from the identification point. All of the kickback classifier vectors ended up being used at some point, though each detection vector did not always correspond to the detection algorithm that would have been appropriate for the given time region.

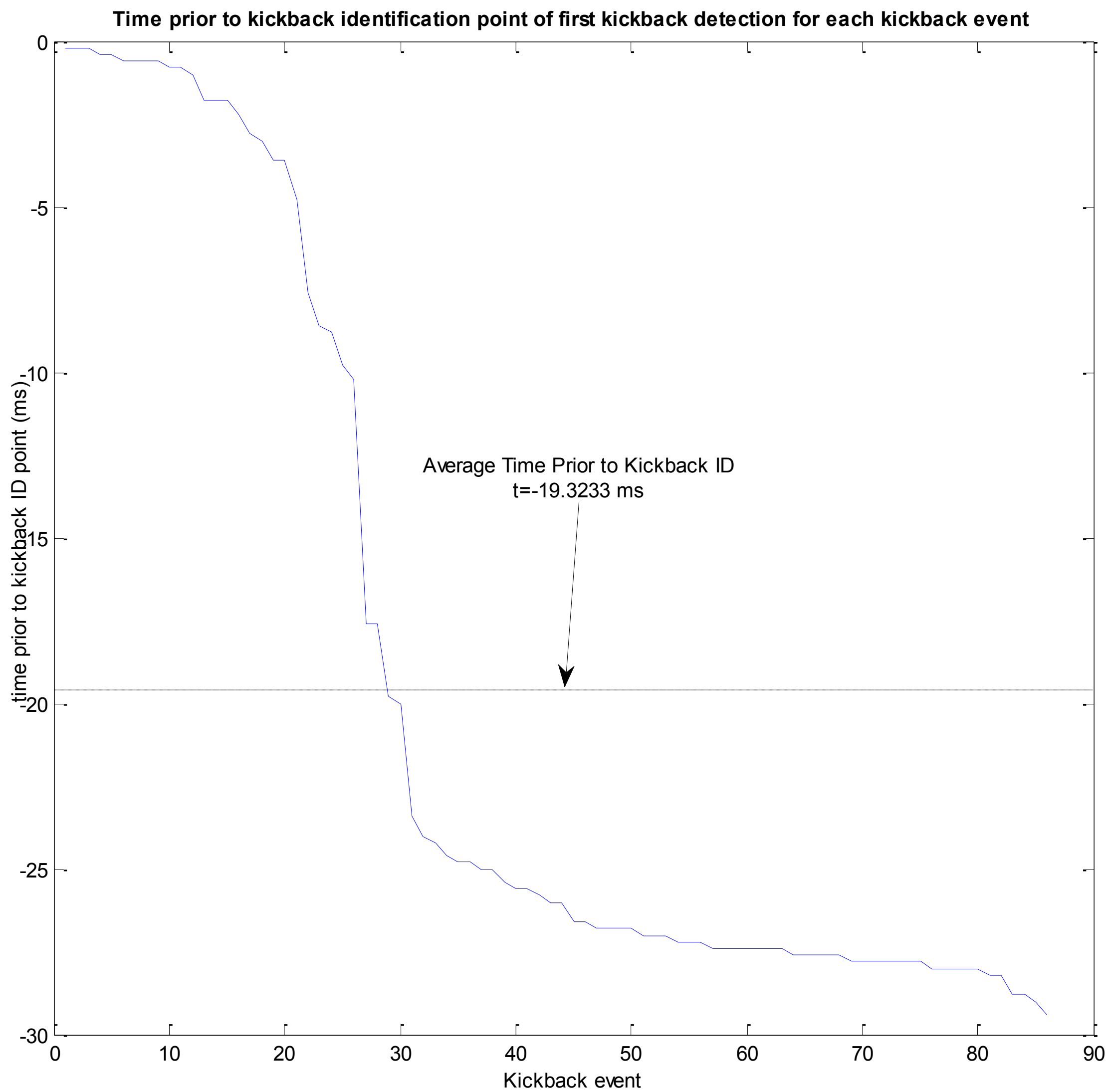

Figure 34: A graph of the earliest kickback detection prior to the kickback identification point. The events are presented in descending order for clarity. The average detection occurred 19.3233 ms prior to the identification point.

6 Discussion

This work has explored several methods for detecting kickback and attempting to detect it as early as possible. The different methods had varying degrees of success. Table 11 summarizes the the four methods used to detect the occurrence of kickback. The

Table 11: Summary of the four kickback detection methods

Detection method	Time prior to detection			Accuracy	Number of false positives
	Min	Max	Mean		
Optimization	0 ms	15 ms	5.2 ms	100%	**0**
Differentiation	5.2 ms	18.1 ms	7.8 ms	93%	**9**
Bag of Words	0.4 ms	15 ms	5.2 ms	100%	**0**
SVM Learning	0.2 ms	29.4 ms	19.3 ms	100%	**0**

The Optimization method revealed that gyroscopes provided the greatest difference between normal cutting and kickback events. The accelerometers were capable of detecting kickback a large portion of the time, but they never proved as useful as the gyroscopes, as was verified with each of the four methods of detecting kickback

The differentiation method was a useful method that could potentially be used if it is accepted that knot-bumping, which is a somewhat rare cutting method, will trigger a kickback event. This method is easy to implement compared to the other Phase 2 analyses.

The Bag of Words method was unable to provide any improvement over the optimization method which simply utilizes a threshold. Adjusting the threshold and number of word counts revealed sharp drop off for the level at which no false positives were detected. For this method to be successful, only one word could be counted at a higher threshold, which is the same as the optimization method.

As can be seen by the results, the detection method capable of detecting kickback the earliest with a 100% accuracy for the given data available for verification is the Stacked Support Vector Machine method that utilized Selective Undersampling for the training data. At worst, this method performed as well as a simple threshold, and on average, it is capable of detecting kickback 19.3 ms before the kickback event with a maximum of 29.4 ms before the kickback identification point which is, on average, three times earlier than the next best method while still maintaining 100% accuracy.

This method if capable of detecting kickback early and reliably in a way that could drastically improve the effectiveness of chainsaw brake mechanisms. Twenty milliseconds is enough time for a brake mechanism to actuate and begin braking a chainsaw. A safety system such as this could potentially prevent thousands of serious injuries and dozens of deaths a year if it were implemented on all chainsaws. Not only will this help save lives and money in medical expenses, but it could potentially make chainsaw more marketable to a wider range consumers that may have otherwise been intimidated by such a dangerous tool.

6.1 Source of Error

One of the main difficulties with developing these detection mechanisms was working with sensor technology that could be priced reasonably enough to be incorporated on a consumer level chainsaw. Finding sensors that had the necessary requirements of dynamic range and low cost proved to be difficult. Gyroscopes in the appropriate ranges tended to be easier to find than accelerometers. Many MEMS sensors are geared toward cellphones and other entertainment devices that do not experience such high vibrations or large accelerations. Phase 2 testing was affected by this a great deal because of a greater focus on finding lower cost senors. The sensors used for Phase 2 testing had much too low of a dynamic range. As time passes, the cost of sensors will drop and their quality will improve. An accelerometer in the appropriate dynamic range may prove to be provide helpful information when the technology becomes available.

6.2 Potential Future Work

One area for improving the detection methods would be to incorporate the use of a rotational velocity sensor on the chainsaw motor. It was observed that the speed of the motor slows substantially when the saw first makes contact with the kickback object. If the rotational speed could be measured with an encoder, or possible by monitoring the voltage on the ignition coil, it could be incorporated into the analysis. In the time that a kickback occurs(about 40 ms) the motor will only rotate ten times, so the motor position may need a fairly high resolution.

More work should be done to find better quality, low cost accelerometers. As technology continues to improve the cost of these sensors should come down. A better quality accelerometer could also be added back into the analysis.

7 Conclusion

Kickback is generally regarded as the greatest danger of chainsaw use. Thousands of people are still injured each year by chainsaws. The existing body of research has focused on understanding the causes and quantifying the dangers of kickback. There has not been any published research that examines the methods for detecting kickback, nor have there been any significant advances in the development of chainsaw braking mechanisms for the past twenty years. Developing a detection mechanism that is more reliable, easily controllable and can detect the occurrence of kickback early stands to significantly improve the safety of chainsaws. An empirical approach has been used to analyze over 250 kickback events and several hours of normal chainsaw use.

A mechanism for reliably detecting the occurrence of kickback in a small 36-Volt battery-powered chainsaw was first shown to be effective with the use of a gyroscope. This method will more reliably and controllably detect kickback than current methods. However, this method does not offer a substantial performance improvement over current braking methods, as kickback is not detected and therefore is not slowed before the log loses contact with the object causing kickback.

To improve the performance of a kickback safety system, the kickback event needed to be detected early enough that a brake mechanism could slow the chain quickly enough that it reduced the amount of energy transferred into saw motion. Three methods were pursued to try to detect kickback early than a simple threshold method. Differentiating the signal from the motion sensors proved to move the detection point forward in time,but introduced a higher level of noise. The Bag of Words method was unsuccessful at detecting kickback any earlier than the simple threshold used in the optimization scheme.

Using a Support Vector Machine, with a stack of classifier vectors and selective undersampling resulted in kickback detection an average of 19.2 ms before the kickback identification point. This method has the capability to help prevent or reduce the risks of many accidents that occur every year, if combined with a fast-acting brake.

8 Bibliography

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9 Appendices

9.1 Appendix A.1

```
%Code used during exploratory data analysis
close all
clear
clc

load testpa0.lvm
load testpaosu.lvm

osu=testpaosu(10000:length(testpaosu),3);
blnt=testpa0(10000:length(testpa0),3);
Fsosu = 10000;                  % Sampling frequency
Tosu = 1/Fsosu;
% Sample time
Losu = length(osu);                  % Length of signal
tosu = (0:Losu-1)*Tosu;              % Time vector
% Sum of a 50 Hz sinusoid and a 120 Hz sinusoid
xosu = 0.7*sin(2*pi*50*tosu) + sin(2*pi*120*tosu);
yosu = xosu + 2*randn(size(tosu));     % Sinusoids plus noise
NFFTosu = 2^nextpow2(Losu); % Next power of 2 from length of y
Yosu = fft(osu,NFFTosu)/Losu;
fosu = Fsosu/2*linspace(0,1,NFFTosu/2+1);

Fsblnt = 10000;                  % Sampling frequency
Tblnt = 1/Fsblnt;
% Sample time
Lblnt = length(osu);                  % Length of signal
tblnt = (0:Lblnt-1)*Tblnt;              % Time vector
% Sum of a 50 Hz sinusoid and a 120 Hz sinusoid
xblnt = 0.7*sin(2*pi*50*tblnt) + sin(2*pi*120*tblnt);
yblnt = xblnt;     % Sinusoids plus noise
NFFTblnt = 2^nextpow2(Lblnt); % Next power of 2 from length of y
Yblnt = fft(blnt,NFFTblnt)/Lblnt;
fblnt = Fsblnt/2*linspace(0,1,NFFTblnt/2+1);

% Plot single-sided amplitude spectrum.
plot(fosu,2*abs(Yosu(1:NFFTosu/2+1)),'r',fblnt,2*abs(Yblnt(1:NFFTblnt/2+1)),'b')
title('Spectral Measurement of Chainsaw Running')
xlabel('Frequency (Hz)')
ylabel('Power')
legend('freerunning saw','saw cutting')
load testpa0.lvm; load testpa1.lvm; load testpa2.lvm; load testpa3.lvm;
load testpa4.lvm; load testpa5.lvm; load testpa6.lvm; load testpa7.lvm;
load testpa8.lvm; load testpa9.lvm; load testpa10.lvm; load testpa11.lvm;
load testpa12.lvm; load testpa13.lvm; load testpa14.lvm; load testpa15.lvm;

Xnormal=[(testpa0(:,2)); (testpa1(:,2)); (testpa3(:,2));(testpa4(:,2)); (testpa7(:,2));(testpa8(:,2)); (testpa9(:,2));
(testpa10(:,2));(testpa12(:,2))];
Ynormal=[(testpa0(:,3)); (testpa1(:,3)); (testpa3(:,3));(testpa4(:,3)); (testpa7(:,3));(testpa8(:,3)); (testpa9(:,3));
(testpa10(:,3));(testpa12(:,3))];
Xknot=testpa5(:,2);
Yknot=testpa5(:,2);
```

```
Xkick=testpa15(:,2);
Ykick=testpa15(:,3);

aaa=.01:.01:2;
bbb=.01:.01:2;

dt=.0001;
lowpassP=[50,100,150,200];


tnormal=dt:dt:(length(Xnormal)*dt)
tknot=dt:dt:(length(Xknot)*dt)
tkick=dt:dt:(length(Xkick)*dt)

T0=dt:dt:length(Y0)*dt;
   fNorp0 = lowpassP/(10000/2);
   [b,a] = butter(10, fNorp0, 'low');
      xlp0=filtfilt(b,a,x0);
      ylp0=filtfilt(b,a,Y0);
      zlp0=filtfilt(b,a,Z0);
for L=1:length(lowpass)
for i=1:length(aaa)
   for j=1:length(bbb)
      xnorm=Xnormal*aaa(i);
      ynorm=Ynormal*bbb(j);
      NORM=xnorm-ynorm;
      xknot=Xknot*aaa(i);
      yknot=Yknot*bbb(j);
      KNOT=xknot-yknot;
      xkick=Xkick*aaa(i);
      ykick=Ykick*bbb(j);
      KICK=xkick-ykick;

      NormKick(i,j)=max(KICK)-max(NORM)
      Normknot(i,j)=max(KNOT)-max(NORM)
   end
end
end
   figure
   subplot(2,1,1)
   plot(T0,Y0,T0,Z0)
   title('Piezo-3 Axis Accelerometer Full Waveform Signal')
   legend('y-axis','z-axis')
   xlabel('time (s)')
   ylabel('acceleration(g)')

   subplot(2,1,2)
   plot(T0,ylp0,T0,zlp0)
   legend('y-axis','z-axis')
   title('Standard Cut:Piezo-3 Axis Accelerometer Full Waveform Signal Filtered at 100HZ')
   xlabel('time (s)')
   ylabel('acceleration(g)')

   figure
   plot(T0,d0)
   title('Standard Cut: Difference between Y and Z Axes')
   xlabel('time (s)')
   ylabel('Z-Y acceleration(g)')
```

9.2 Appendix A.2

```
%Code used during Phase 1 optimization data analysis
clear
clc
close all


% Optimization of Individual Kickback Events
% TTnormal uses only cutting events when the saw is running and there
% aren't large motions being detected by the saw.
   load('TKnBuNormal.mat','TKnBuNormal')
   TTnormal=TKnBuNormal;
   NY1=TTnormal(:,2);
   NX1=TTnormal(:,3);
   NG1=TTnormal(:,5);

   load('TKnBuNormal.mat','TKnBuNormal')
   TTnormal=TKnBuNormal;
   NY2=TTnormal(:,2);
   NX2=TTnormal(:,3);
   NG2=TTnormal(:,5);

%Scaling Factor Values
   a=.05:.05:3;
   b=.05:.05:3;
   c=.005:.005:.3;
for k=1:112
   close all
   DifXYZ1=sparse(length(a),length(b));
   DifXYZ2=sparse(length(a),length(b),length(c));
  %Load Kickback (k) data
   load(sprintf('TKB%d.mat',k),'Ttemp3')
   t=Ttemp3(:,1);
   Y1=Ttemp3(:,2);
   X1=Ttemp3(:,3);
   G1=Ttemp3(:,5);
  %Run kickback(k) and Normal cutting through algortihm

         XaYaZg=(Y1.*a(i)-X1.*b(j))+G1.*.1;
         NXYZ1=(NY1.*a(i)-NX1.*b(j))+NG1.*.1;
         DifXYZ1(i,j)=(max(XaYaZg)-max(NXYZ1))/max(NXYZ1);

         XaYaZg=(Y1.*a(i)-X1.*b(j))+G1.*.1;
         NXYZ2=(NY2.*a(i)-NX2.*b(j))+NG2;
         DifXYZ2(i,j)=(max(XaYaZg)-max(NXYZ1))/max(NXYZ1);


   % Save Contour Plot Values
    save(sprintf('Opt4Acc%d',k),'DifXYZ1')
    save(sprintf('Opt4Acc%d',k),'DifXYZ2')

  % Contour Plots


MaxA=max(max(DifXYZ1));
   indA=find(DifXYZ1==MaxA);
```

```
   [Ya,Xb] = ind2sub(size(DifXYZ1),indA);
   YA1=a(Ya(1));
   XB1=b(Xb(1));
   Astatxyz1(k,1)=MaxA;
   Astatxyz1(k,2)=YA1;
   Astatxyz1(k,3)=XB1;
   Astatxyz1(k,4)=k;

MaxB=max(max(DifXYZ2));
   indB=find(DifXYZ2==MaxB);
   [Ya,Xb] = ind2sub(size(DifXYZ2),indB);
   YA2=a(Ya(1));
   XB2=b(Xb(1));
   Astatxyz2(k,1)=MaxB;
   Astatxyz2(k,2)=YA2;
   Astatxyz2(k,3)=XB2;
   Astatxyz2(k,4)=k;
end

save('Astatxyz1','Astatxyz1')
save('Astatxyz2','Astatxyz2')

%% Histogram of Accelerometers
close all
% clc
figure %1

  subplot(3,1,1)
  plot(A5statxy(:,4),A5statxy(:,1),A5statxy(:,4),A5statxy(:,2),A5statxy(:,4),A5statxy(:,3))
  legend('max value','a','b')
   subplot(3,1,1)
  plot(A5statxy(:,4),A5statxy(:,1),A5statxy(:,4),A5statxy(:,2),A5statxy(:,4),A5statxy(:,3))
  legend('max value','a','b')
   subplot(3,1,1)
  plot(A5statxy(:,4),A5statxy(:,1),A5statxy(:,4),A5statxy(:,2),A5statxy(:,4),A5statxy(:,3))
  legend('max value','a','b')
   subplot(3,1,1)
  plot(A5statxy(:,4),A5statxy(:,1),A5statxy(:,4),A5statxy(:,2),A5statxy(:,4),A5statxy(:,3))
  legend('max value','a','b')


 figure %2
  subplot(3,1,2)
   hist(A5statabs(:,2),40);
    xlim([.05 2])
    xlabel('a values')
  subplot(3,1,1)
   hist(A5statabs(:,3),40);
    xlim([.05 2])
    xlabel('b values')
    subplot(3,1,3)
   plot(A5statabs(:,4),A5statabs(:,1),A5statabs(:,4),A5statabs(:,2),A5statabs(:,4),A5statabs(:,3))
   legend('max value','a','c')

 figure %3
  subplot(3,1,2)
   hist(G5statYY(:,2),40);
    xlim([.05 2])
    xlabel('a values')
```

```
  subplot(3,1,1)
    hist(G5statYY(:,3),40);
     xlim([.05 .2])
     xlabel('c values')
    subplot(3,1,3)
    plot(G5statYY(:,4),(G5statYY(:,1).*.1),G5statYY(:,4),G5statYY(:,2),G5statYY(:,4),G5statYY(:,3))
    legend('max value','a','c')

figure %4
  subplot(3,1,2)
    hist(G5statXX(:,2),40);
     xlim([.05 2])
     xlabel('a values')
  subplot(3,1,1)
    hist(G5statXX(:,3),40);
     xlim([.05 .2])
     xlabel('c values')
    subplot(3,1,3)
    plot(G5statXX(:,4),(G5statXX(:,1).*.1),G5statXX(:,4),G5statXX(:,2),G5statXX(:,4),G5statXX(:,3))
    legend('max value','a','c')
```

9.3 Appendix A.3.1

```
% Code used during Phase 2 differential analysis
clear
clc
close all

for k=1:112
  %Load Kickback (k) data
   load(sprintf('TKB%d.mat',k),'Ttemp3');
   t=Ttemp3(:,1);
   Y1=Ttemp3(:,2);
   X1=Ttemp3(:,3);
   G1=Ttemp3(:,5);
   yi=Y1(1);
   xi=X1(1);
   gi=G1(1);
   ti=t(1);

%     Xdif=sparse(length(X1)-1,1);
%     Ydif=sparse(length(Y1)-1,1);
%     Gdif=sparse(length(G1)-1,1);
   for i=2:(length(t)-1)
       clc
       k
       i
       Ydif(i)=(Y1(i)-yi)/(t(i)-ti);
       Xdif(i)=(X1(i)-xi)/(t(i)-ti);
       Gdif(i)=(G1(i)-gi)/(t(i)-ti);
       T(i)=t(i);
       xi=X1(i);
       yi=Y1(i);
       gi=G1(i);
   end
  % Dif=sparse(4,(length(T)-1));
   Dif=[T', Xdif', Ydif', Gdif'];
   save(sprintf('DIF%d',k),'Dif');
end

% %This program optimizes the kickback detection algorithm for a differential
% %of the kickback signals for X and Y accelerometers and Z Gyroscope. The
% %Normal cutting signal had to be spliced together again, taking the
% %differential before combining the signals as a large magnitude jump
% %occurred where two signals met.
% %*********************************************%
clear
close all
clc
a=-1.5:.05:1.5;
b=-1.5:.05:1.5;
%dNorm is the differentiated signal of normal cutting, and dKnB is the
%differentiated signal of Knot Bumping. dKnB was divided by the time step
%but dNorm was not, so dKnB is multiplied by the time step to bring it back
%into a similar range.
load('dNorm','dNorm')
load('dKnB','dKnB')
dKnB=dKnB/20000;
```

```
%OptNxyz15 and OptKNxyz15 are the optimized values of a and b wit rating.
OptNxyz15=zeros(112,4);
OptKNxyz15=zeros(112,4);
for k=1:112
   twe=20000;

   load(sprintf('DIF%d.mat',k),'Dif')
   Dif=Dif/20000;
   DKy=Dif(:,2); DKx=Dif(:,3); DKz=Dif(:,4);
   dXYZnorm=zeros(length(a),length(b));
   dXYZKnB=zeros(length(a),length(b));
   for i=1:length(a)
      for j=1:length(b)
         clc
         k
         i
         j
         KB=a(i).*DKy+b(j).*DKx+DKz;
         dN=a(i).*dNorm(:,2)+b(j).*dNorm(:,3)+dNorm(:,4);
         dKn=a(i).*dKnB(:,2)+b(j).*dKnB(:,3)+dKnB(:,4);
         dXYZnorm(i,j)=(max(KB)-max(dN))/(max(KB));
         dXYZKnB(i,j)=(max(KB)-max(dKn))/(max(KB)) ;
         clearvars KB dN dKn
      end
   end

      MxN=max(max(dXYZnorm));
      indA=find(dXYZnorm==MxN);
      [Ya,Xb] = ind2sub(size(dXYZnorm),indA);
      YA=a(Ya(1));
      XB=b(Xb(1));
   OptNxyz15(k,1)=MxN;
   OptNxyz15(k,2)=YA;
   OptNxyz15(k,3)=XB;
   OptNxyz15(k,4)=k;
      clearvars Ya Xb YA XB MxN

      MxKn=max(max(dXYZKnB));
      indA=find(dXYZKnB==MxKn);
      [Ya,Xb] = ind2sub(size(dXYZKnB),indA);
      YA=a(Ya(1));
      XB=b(Xb(1));
   OptKNxyz15(k,1)=MxKn;
   OptKNxyz15(k,2)=YA;
   OptKNxyz15(k,3)=XB;
   OptKNxyz15(k,4)=k;
      clearvars Ya Xb YA XB MxKn dXYZKnB dXYZnorm
end

save('OptNxyz15','OptNxyz15')
save('OptKNxyz15','OptKNxyz15')
figure %1

subplot(2,2,1)
   title('Normal Cutting')
   hist(OptNxyz15(:,2),length(a));
    xlim([-6 6])
   xlabel('a values')
subplot(2,2,2)
```

```
    title('Normal Cutting')
    hist(OptNxyz15(:,3),length(a));
    xlim([-6 6])
    xlabel('b values')
subplot(2,2,3)
   title('KnotBump')
   hist(OptKNxyz15(:,2),length(a));
    xlim([-6 6])
    xlabel('a values')
subplot(2,2,4)
    title('KnotBump')
    hist(OptKNxyz15(:,3),length(a));
    xlim([-6 6])
    xlabel('b values')
```

9.4 Appendix A.3.2

```
%Code used during Phase 2, Bag of Words Analysis
clear
clc
load N.mat
N1=N(:,4);
thresh1=5:10:305;
countnorm=zeros(length(thresh1),length(N1)-51);
for II=1:length(thresh1)
  clc
      II
   for ii=1:length(N1)-51

%        ii
      temp1=N1(ii:ii+50);
      for jj=1:length(temp1)
%           count2(ii,II)=length(temp1(jj)>thresh1(II));
%               count1(ii)=count1(ii)+1;
%           end
         if temp1(jj)>thresh1(II)
            countnorm(II,ii)=countnorm(II,ii)+1;


         end
      end
   end
end

% This program uses a Bayesian Network (bag of words) to count the number
% of instances that occur above a given threshold. The minimum number of
% instances that would trigger a KB is 26 and the max is 50

clear
clc
load Kb.mat
threshkb=5:10:305;
count=zeros(length(threshkb),length(Kb(1,:)),length(Kb(:,1)));
%num is the number of measurements per sample that are greater than the
%given threshold.
num=26;
for I=1:length(threshkb)-1

   for i=1:length(Kb(1,:))
      temp=0;
      for j=1:length(Kb(:,i))
         if Kb(j,i)>threshkb(I)
            count(I,i,j)=temp+1;
            temp=temp+1;
            if temp==2
              mark(i,I)=j;
            end
         else
            count(I,i,j)=temp;
         end

%           if Kb(j,i)>thresh1(I) && Kb(j,i)<thresh1(I)+20
```

```
%               mark(i,I)=j;
%            end
%
%            if count(I,i,j)==num
%               mark(I,i)=j;
%            end
        end
    end
end
figure(3)
for k=1:length(threshkb)
    figure(3)
    subplot(4,8,k)
    temp=squeeze(count(k,:,:))';
    plot(temp)
    hold on
    plot([1 200],[26,26],'k')
    xlabel(sprintf('Threshold=%ddeg/sec',threshkb(k)))
end

%
% load NormBag.mat
% count1=full(count1);
% threshy=max(count1')

%% plot
load countnorm.mat
markmean=mean(mark);
markmax=max(mark);
markmin=min(mark);
figure
subplot(211)
bar(threshkb,max(countnorm'))
xlabel('threshold ^\circ/second')
ylabel('Max number of threshold counts')
title('Normal Cutting Bag of Words Results')
subplot(212)
plot(threshkb(1:length(threshkb)-1),(markmax-198)/5,'--.',threshkb(1:length(threshkb)-1)...
    ,(markmean-198)/5,threshkb(1:length(threshkb)-1),(markmin-198)/5,'--*')
legend('latest threshold cross','mean threshold cross','earliest threshold cross')
xlabel('Threshold (^\circ/second)')
ylabel('time before KB of first threshold cross (ms)')
title('Kickback Bag of Words Results')
ylim([-40 02])
```

9.5 Appendix A.3.3

```
%Code used for the Phase 2 Support Vector Machine Analysis, including the selective oversampling and
%classifier stakcing.
clear
clc
close all

%% load data
load N.mat  %Normal Cutting Data
% load Ka.mat
load Kb.mat
kb=Kb;
N=round(N*1000)/1000; %This gives 3 decimal places which helps to find vectors later
%n is the number of KB instances we want to look at. There are only 24 sets
%of KB data.
L=49;%This depends on the number of samples examined in each kb file(50 for now)
l=L+1;%(used because there ends up being 50 data points)
n=86; %This is the number of data vectors in each permutation
runs=10000;
% NormSVbszg=zeros(runs,30);
% NormSVbmagzg=zeros(runs,30);
dist=[61 71 81 91 101 111 121 131 141 151];%Distance from peak=200-dist
lo=dist; hi=dist+L;

% Setup SVM
% The support vector machine has to be "reinstalled" for ever use. The
% folder labeled matlab has to be mapped using the CD command. Once this is
% done, the command "make" will generate the SVM code to be used. If the
% data is cleared, so is the SVM.
%Windows:  use this path on the on a school windows machin
% cd C:\Users\pdda73388\Desktop\GyroImbalance\libsvm-3.11\libsvm-3.11\matlab
%linux: Use this command on my linux workstation
% cd /nfs/mohr/parmigiani/arnolddr/Blount/Data/GyroImbalance/libsvm-3.11/libsvm-3.11/matlab/
% mac: Use this command on my laptop
cd /Users/drewarnold/Desktop/GyroImbalance/libsvm-3.11/libsvm-3.11/matlab/
make

for  I=1:runs



%% n1-n2
   %n2-n4 are random numbers from the vector that is the data taken from normal cutting
   %each time the program runs, a new set of random values from the k2-k4 data
   %is taken.
      n1(:,I)=randsample(length(N)-l,n*3);

%% Training
%This loop builds the "Instance Matrix" (X) which is full of feature
%vectors (X_i) and the Associated labels vector (y). The KB feature vectors
%have corresponding labels of 1, the rest are 0.
% X=sparse(n,4*l);
for D=1:length(dist)
   clc
   I
   D
```

```
for i=1:n

    Xb(i,:)=kb(lo(D):hi(D),i);
    Xb(n+i,:)=N(n1(i,I):n1(i,I)+L,4);
    Xb(n*2+i,:)=N(n1(i+n,I):n1(i+n,I)+L,4);
    Xb(n*3+i,:)=N(n1(i+2*n,I):n1(i+2*n,I)+L,4);
    yb(i,1)=1; yb(i+n,1)=-1; yb(i+2*n,1)=-1; yb(i+3*n,1)=-1;

end

Xb=full(Xb); % Matrices were sparse bust must be made full
modelb=svmtrain(yb,Xb,'-s 0 -t 0 -b 1');
I
D

    pcountxb=0;
    for pxb=1:length(modelb.sv_coef)
        if modelb.sv_coef(pxb)<0
            pcountxb=pcountxb+1;
            NormSVbb(I,D,pcountxb)=findsubmat(N(:,4),(round(full(modelb.SVs(pxb,:))*1000)/1000)');
            NormSVbmagb(I,D,pcountxb)=modelb.sv_coef(pxb);
        end
    end

clearvars dec_values accuracy X Xt y yt wXsort
end
end

save(workspace)
%
clear
clc
load ImbalWkSpc.mat
NormSVb=NormSVbb;


close all
clc
bins=5000;
num=200;
clearvars bin1 bin2 bin3 bin4 bin5 bin6 bin7 bin8 bin9 bin10 bin11...
    bin12 bin13 bin14 bin15 bin16
% Collect Data After
temp1=squeeze(NormSVb(:,1,:));
temp1=reshape(temp1.',[],1);
temp1(temp1==0)=[];
[bin1(:,1),bin1(:,2)]=hist(temp1,bins);
bsort1=sortrows(bin1,1);

temp2=squeeze(NormSVb(:,2,:));
temp2=reshape(temp2.',[],1);
temp2(temp2==0)=[];
[bin2(:,1),bin2(:,2)]=hist(temp2,bins);
bsort2=sortrows(bin2,1);

temp3=squeeze(NormSVb(:,3,:));
temp3=reshape(temp3.',[],1);
temp3(temp3==0)=[];
[bin3(:,1),bin3(:,2)]=hist(temp3,bins);
```

```
bsort3=sortrows(bin3,1);

temp4=squeeze(NormSVb(:,4,:));
temp4=reshape(temp4.',[],1);
temp4(temp4==0)=[];
[bin4(:,1),bin4(:,2)]=hist(temp4,bins);
bsort4=sortrows(bin4,1);


temp5=squeeze(NormSVb(:,5,:));
temp5=reshape(temp5.',[],1);
temp5(temp5==0)=[];
[bin5(:,1),bin5(:,2)]=hist(temp5,bins);
bsort5=sortrows(bin5,1);

temp6=squeeze(NormSVb(:,6,:));
temp6=reshape(temp6.',[],1);
temp6(temp6==0)=[];
[bin6(:,1),bin6(:,2)]=hist(temp6,bins);
bsort6=sortrows(bin6,1);

temp7=squeeze(NormSVb(:,7,:));
temp7=reshape(temp7.',[],1);
temp7(temp7==0)=[];
[bin7(:,1),bin7(:,2)]=hist(temp7,bins);
bsort7=sortrows(bin7,1);

temp8=squeeze(NormSVb(:,8,:));
temp8=reshape(temp8.',[],1);
temp8(temp8==0)=[];
[bin8(:,1),bin8(:,2)]=hist(temp8,bins);
bsort8=sortrows(bin8,1);

temp9=squeeze(NormSVb(:,9,:));
temp9=reshape(temp9.',[],1);
temp9(temp9==0)=[];
[bin9(:,1),bin9(:,2)]=hist(temp9,bins);
bsort9=sortrows(bin9,1);

temp10=squeeze(NormSVb(:,10,:));
temp10=reshape(temp10.',[],1);
temp10(temp10==0)=[];
[bin10(:,1),bin10(:,2)]=hist(temp10,bins);
bsort10=sortrows(bin10,1);

figure

subplot(5,2,1)
plot(bsort1(bins-num:bins,2),bsort1(bins-num:bins,1),'*')
hold on
plot(N(:,4))
title('1')

subplot(5,2,2)
plot(bsort2(bins-num:bins,2),bsort2(bins-num:bins,1),'*')
hold on
plot(N(:,4))
title('2')
```

```
subplot(5,2,3)
plot(bsort3(bins-num:bins,2),bsort3(bins-num:bins,1),'*')
hold on
plot(N(:,4))
title('3')

subplot(5,2,4)
plot(bsort4(bins-num:bins,2),bsort4(bins-num:bins,1),'*')
hold on
plot(N(:,4))
title('4')

subplot(5,2,5)
plot(bsort5(bins-num:bins,2),bsort5(bins-num:bins,1),'*')
hold on
plot(N(:,4))
title('5')

subplot(5,2,6)
plot(bsort6(bins-num:bins,2),bsort6(bins-num:bins,1),'*')
hold on
plot(N(:,4))
title('6')

subplot(5,2,7)
plot(bsort7(bins-num:bins,2),bsort7(bins-num:bins,1),'*')
hold on
plot(N(:,4))
title('7')

subplot(5,2,8)
plot(bsort8(bins-num:bins,2),bsort8(bins-num:bins,1),'*')
hold on
plot(N(:,4))
title('8')

subplot(5,2,9)
plot(bsort9(bins-num:bins,2),bsort9(bins-num:bins,1),'*')
hold on
plot(N(:,4))
title('9')

subplot(5,2,10)
plot(bsort10(bins-num:bins,2),bsort10(bins-num:bins,1),'*')
hold on
plot(N(:,4))
title('10')

Nimb(1,:)=bsort1(bins-num:bins,2);
Nimb(2,:)=bsort2(bins-num:bins,2);
Nimb(3,:)=bsort3(bins-num:bins,2);
Nimb(4,:)=bsort4(bins-num:bins,2);
Nimb(5,:)=bsort5(bins-num:bins,2);
Nimb(6,:)=bsort6(bins-num:bins,2);
Nimb(7,:)=bsort7(bins-num:bins,2);
Nimb(8,:)=bsort8(bins-num:bins,2);
Nimb(9,:)=bsort9(bins-num:bins,2);
Nimb(10,:)=bsort10(bins-num:bins,2);
```

```
figure
plot(N(:,4),':')
hold on
plot(bsort9(bins-num:bins,2),bsort9(bins-num:bins,1),'r*')


figure
plot(N(:,4))
figure
plot(N(:,2))

%

% Having 5000 bins makes it so there are about 50 data points for each bin.
% having 500 leaves about a 5000 wide chunk of data that could be

clear
clc

load Nimb.mat
load Kb.mat
load N.mat
N=N(:,4);
chunk=[61 71 81 91 101 111 121 131 141 151];

% Setup SVM
% The support vector machine has to be "reinstalled" for every use. The
% folder labeled matlab has to be mapped using the CD command. Once this is
% done, the command "make" will generate the SVM code to be used. If the
% data is cleared, so is the SVM.
%Windows:  use this path on the on a school windows machin
% cd C:\Users\pdda73388\Dropbox\THESIS\Plots\SVMgyro\libsvm-3.11\libsvm-3.11\matlab
%linux: Use this command on my linux workstation
% cd /nfs/mohr/parmigiani/arnolddr/Blount/Data/GyroImbalance/libsvm-3.11/libsvm-3.11/matlab/
% mac: Use this command on my laptop
cd /Users/drewarnold/Desktop/GyroImbalance/libsvm-3.11/libsvm-3.11/matlab/
make

for i=1:length(chunk) %i sets the specific distance from the ID point
  clc
  i
   %Build KB vectors of only specific time ranges
   X=Kb(chunk(i):chunk(i)+49,:);
   y=ones(1,length(X(1,:)));
   %Build Balance compensated Normal Cutting Matrix
   for j=1:length(Nimb(i,:)) %j is the numbe of normal selected points
      Nx(:,j)=N(Nimb(i,j):Nimb(i,j)+49);
%        Ny(j)=-1;
   end
   Ny=ones(1,length(Nx(1,:)))*-1;
   %Build feature set with class vector
   X=[X Nx];
   y=[y Ny];

   model=svmtrain(y',X','-s 0 -t 0 -b 1');
   w(:,i)=full(model.SVs)'*model.sv_coef;
%     clearvars Nx Ny X y
End
```

```
load w1.mat
load Kb.mat
load N.mat
N=N(:,4)';
% Find the thresholds for w
We are going to determine the thresholds such that the highest kickback
% event does not set it off.
cnt=1;
for i=1:length(N)-50
   if cnt==1000
      clc
      i
      cnt=0;
   else
      cnt=cnt+1;
   end


      n1=N(i:i+49)';
      normclass(i,:)=n1*w1;
end

% next run
thresh=max(normclass).*1.1;
chunk=[61 71 81 91 101 111 121 131 141 151];
for l=1:length(chunk)
   kb=Kb(chunk(l):(chunk(l)+49),:)'*w1;
   kbmin(:,l)=min(kb);
end
class=zeros(length(Kb(:,1)-50),length(Kb(1,:)));
class2=zeros(length(Kb(:,1)-50),length(Kb(1,:)));
class3=zeros(length(Kb(1,:)),1);
for m=1:length(Kb(:,1))-50 %m is position in kickback
   for n=1:length(Kb(m,:)) %n is the given kickback event
      input=Kb(m:m+49,n)'; %this is the 50 sample window (m,n)
      check=input*w1; %Apply the stack of 10 classifiers
      for p=1:length(thresh) %look at each classifier in the stack
         if check(p)>thresh(p) %If greater than the threshold, kickback occurs
            class(m,n)=class(m,n)+10^p; %Stores which classifiers are marked
                                  %because more than one can trigger for a given input
            class2(m,n)=class2(m,n)+1;  %Simply stores how many classifiers have triggered
         end
%           if p==1
%              if class(m,n)>0
%                 class3(n)=m;
%              end
%           else
%              if class(m,n)>0 && class3(n)==0
%                 class3(n)=m;
%              end
%           end
      end
   end
end
%Find where kickback is detected earliest
for q=1:length(class2(1,:))
   for r=1:length(class2(:,1))
      if class(r,q)>0 && class5(q)==0
```

```
         class5(q)=r;
      end
   end
end


class3=sort(class3);
class4=sort(class3);
class5=sort(class(class~=0));
```