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Study of a Distributed Wireless Multi-Sensory Train Approach Detection and Warning System for Improving the Safety of Railroad Workers

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16. Abstract
Safety is a key concern for the North American railroad industry, particularly for their employees. However, in one particular area there is an identified urgent need for a novel solution that helps protect them better than the current approach: track worker safety. Railroad employees and contractors are required to work on or near tracks. To prevent accidents, railroad personnel are tasked with acting as lookouts for oncoming trains. This is a tedious task and prone to failure, and statistics by the Federal Railroad Administration (FRA) published in 49 CFR 214 in 2008 indicate that the rate of accidents is in fact increasing! Current commercially available solutions to this problem are infeasible for adequately addressing this need. We have shown this as part of our research reported in this report, and attributed it to two primary factors: the reliance on single-detector approaches which are shown to be unreliable, and the need of most systems for destructive and semi-permanent installation methods to attach these systems to the railroad tracks.
Our solution we developed is built around a novel multi-sensory detection approach, where the benefits of each sensing method is leveraged and the drawbacks are resolved. We have shown that our method is highly reliable, with zero missed trains, and also detailed how our system achieves its modularity and ease of installation.
We strongly believe that the system we developed for this project can help save lives of railroad track workers and help increase operational efficiency of the railroads as well. We thank MATC and Union Pacific for their support of this research.

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List of Abbreviations

Advanced Telecommunications Engineering Laboratory (TEL)
Anisotropic Magneto-Resistive (AMR)
Analog-to-Digital Converter (ADC)
Automatic Train Warning System (ATWS)
Data Acquisition System (DAQ)
Federal Railroad Administration (FRA)
Global Positioning System (GPS)
Lookout Operated Waning System (LOWS)
Mid-America Transportation Center (MATC)
Nebraska Transportation Center (NTC)
Positive Train Control (PTC)
Printed Circuit Board (PCB)
Support Vector Machine (SVM)
Time Domain Reflectometry (TDR)
Transportation Research Board (TRB)
Transportation Technology Center, Inc. (TTCI)
Universal Serial Bus (USB)
Wireless Sensor Network (WSN)

Acknowledgements

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Disclaimer

Abstract

Safety is a key concern for the North American railroad industry, particularly for their employees. However, in one particular area there is an identified urgent need for a novel solution that helps protect them better than the current approach: track worker safety. Railroad employees and contractors are required to work on or near tracks. To prevent accidents, railroad personnel are tasked with acting as lookouts for oncoming trains. This is a tedious task and prone to failure, and statistics by the Federal Railroad Administration (FRA) published in 49 CFR 214 in 2008 indicate that the rate of accidents is in fact increasing.

Current commercially available solutions to this problem are infeasible for adequately addressing this need. We have shown this as part of our research in this report, and attributed it to two primary factors: the reliance on single-detector approaches, which are shown to be unreliable, and the need of most systems for destructive and semi-permanent installation methods to attach these systems to the railroad tracks.

Our developed solution is based on a novel multi-sensory detection approach, where the benefits of each sensing method is leveraged and the drawbacks are resolved. We have shown that our method is highly reliable, with zero missed trains, and also detailed how our system achieves its modularity and ease of installation.

We strongly believe that the system we developed for this project can help save lives of railroad track workers and help increase operational efficiency of the railroads as well.

Chapter 1 Introduction

Safety is one of the primary concerns within the North American railroad industry, highlighted by efforts in freight train Wireless Sensor Network monitoring and Positive Train Control (PTC). One area that requires more attention is track worker safety. Railroad employees and contractors are required to work on or near tracks. To prevent accidents, railroad personnel are tasked with acting as lookouts for oncoming trains. They are prevented from any distractions, like carrying mobile phones, conversations, etc. This is a tedious task and prone to failure. It is simply in the human nature to relax their attention.

Statistics by the Federal Railroad Administration (FRA) published in 49 CFR 214 [1] in 2008 indicate that the rate of accidents is in fact increasing. A modern, high-reliability technology-based solution is critically needed to address this problem and increase worker safety. The need for such a solution was expressed and emphasized by Union Pacific, and the lack of any feasible, portable, solution for all environments was verified by our own preliminary research.

Our team at the University of Nebraska-Lincoln's Advanced Telecommunications Engineering Laboratory (TEL) therefore proposed to research key aspects of a portable wireless sensor based system that can be used to alarm the rail workers of an approaching train in all environments of tunnels, hills, curves, etc. This will be a distributed system to accommodate detection on all tracks in the area collaboratively. Adjacent track incidents, according to 49 CFR 214, were also on the rise in recent years. Our research will be for a system that is rechargeable, communicates wirelessly, and will be able to interface with Positive Train Control infrastructure.

To address the above research goals this project aims to integrate research in multi-sensory distributed data acquisition and data classification into a new distributed multi-sensory train approach detection system. In general we can categorize train approach detection techniques into the following methods:

- detection by electric currents in rail;
- detection by train-induced track vibrations;
- detection by a train's acoustic "fingerprint", its characteristic sound, propagating over the air;
- visual detection of a train; and
- detection by RADAR and related ranging techniques.

Individually, each technique has a low reliability and detection sensitivity. For example, electric circuits could be disrupted by rail defects or rust layers on the wheel/rail interface. Vibrations have to be distinguished between train-emanated and other sources. Visual detection will not work around obstacles, tunnels, foliage, etc. Therefore, this project researched combining various techniques into a multi-sensory approach. Our intention was that our multi-dimensional data sensing and classification for train detection would produce a portable, accurate, and reliable system. Due to the need to monitor multiple tracks simultaneously, we envisioned our proposed system to be operating in a distributed fashion: collected data would be shared wirelessly in real-time among all system units, as would signal processing and data classification tasks.

The focus of the research was on two components vital for such a system: high-accuracy sensing and wireless distributed high-reliability processing for event classification.

Chapter 2 Review of Existing Train Approach Detection Methods

2.1 Reasoning for Conducting this Review

The current approach to railway safety in the United States presently consists and furthermore places the 'safety factor' entirely on the workers themselves, making 'safety' in this context be severely hindered by unavoidable human error brought about by many sources of distractions, which can include conversations with other co-workers, distractions by today's omnipresence of mobile electronic devices, tiredness and fatigue, or inability to react quickly.

The North American Railroads continuously have evaluated train approach detection systems that are commercially available and yet also have continued to decide against their deployment in the field. It is therefore of the utmost importance to understand why these systems are deemed infeasible for such deployments. It was this need that gave rise to reviewing these existing systems during this quarter at the onset of this research project. It provided us with the insight into the needs that such a system needs to address.

The goals of this initial research survey were twofold:

- Determine if the problem of early warning train detection has been addressed commercially.
- Provided that a commercial solution does exist, find out who manufactures it and what techniques for detection their system have been employed. This allows us to identify any potential shortcomings and risks pertaining to these systems.
- Determine if these systems specifically address the goals of our idea of the multisensory system and thereby being able to identify further areas of improvement.

Consequently, as a result of these initial efforts, in the following section we will:

- Discuss two commercially available ATWS/LOWS (Automatic Train Warning Systems/Lookout Operated Warning Systems) representing the current commercially available approaches to early warning train detection.
- Discuss two preliminary independent research studies revolving around the question of early warning train detection. These studies in particular focus on the evaluation of 'non-invasive' train detection systems that are partially aligned with the goals for our multisensory system we envision.

2.2 Automatic and Lookout Operated Train Warning Systems

The first task was on the identification of state-of-the-art commercial solutions that address the railway safety issue by providing an early warning. These systems are categorized as either ATWS or LOWS. An ATWS system is designed to be installed on the work site (i.e., red zone) and designed to operate without human supervision. The principle is simple; the train approaches, the system detects it (automatically), and issues a warning by way of a series of acoustical and visual cues designed to grab the attention by any means necessary of the railway workers. Upon human reception of these warnings, railway workers must immediately step out of the work site and await safe passage of the train. Once the train has left the red zone, the ATWS will automatically remove the warning, signaling the workers that it safe to re-enter the red zone.

A LOWS works exactly as the ATWS system with the only distinction that the system is now operated by a designated 'lookout'. In such an arrangement (or configuration) the idea is that the system will specifically warn the lookout. The job of the lookout is to confirm the presence of an oncoming train, at which point the operator must make the decision (by way of a hand-held controller) to trigger the acoustic/visual alarm that then signals the workers about the oncoming train.

Consequently, as far as the presence (or absence) of a lookout operator, which makes it an ATWS or an LOWS, both systems operate identically.

2.2.1 The Minimel ® 95

This research survey identified two commercial systems. The first such system is sold under the product name Minimel ® 95, which is manufactured by a company called Schweizer Electronic (Switzerland). [2] The Minimel ® 95 consists of a scalable ecosystem comprising of a series of portable (wired or wireless) modules, each designed to augment the safety of railway workers.[3]

Figure 2.1 Minimel 95, © Schweizer Electronic

The modular scalable 'ecosystem' for the Minimel ® 95 consists of the following:

- *Minimel95-RSK89: Rail Treadle (aka. Axle Counter)
- *Minimel95-EFK: Rail Treadle Radio Transmitter
- *Miniel95-ZE: Central Controller Unit

- Minimel95-EZE: Warning Signal Transmitter
- Minimel95-KWA: Power Distribution
- *Minimel95-EPW: In-Ear Personal Warning Device
- *Minimel95-EWK: Light/Horn Unit
- Minimel95-ACEDL: Self-powered Light/Horn Pole Unit(s)

The figure below gives a general overview on how some of these systems collectively work together to achieve the desired safety mechanism (not all components are shown):

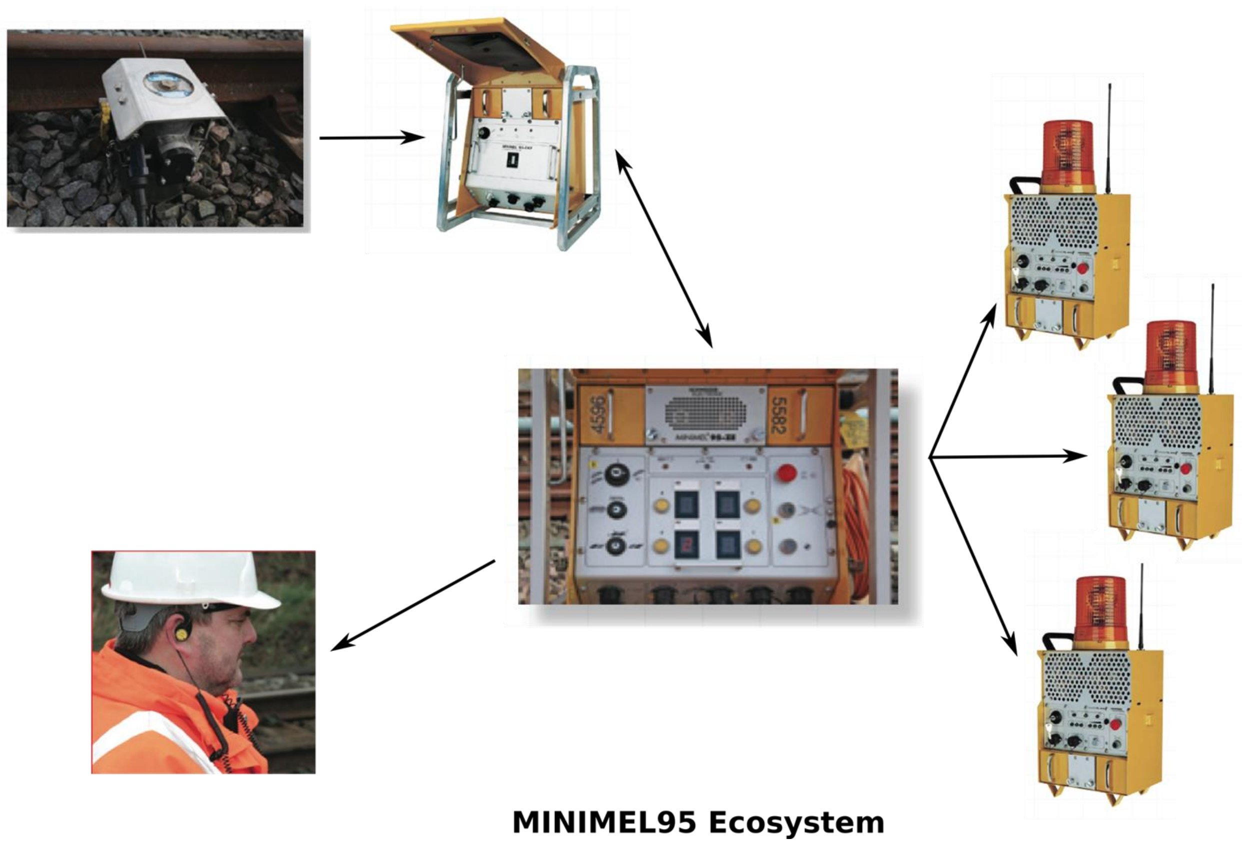


Figure 2.2 The Minimel 95 Component Ecosystem, © Schweizer Electronic

The operation of the Minimel ® 95 is rudimentarily grounded on the principle of a treadle (what is also called an axle counter). This device is installed at both the entry point (called the strike-in point) of the red zone and the exit point (called the strike-out point) of the red zone. These 'treadles' are sufficiently spaced apart so that when detection takes place considerable time is given to the workers to exit the red zone. The product video for the Minimel ® 95 quotes a 'large work site' to comprise up to 1000 meters (~0.65 miles). The treadle is simply a large mechanical switch that must be manually installed by attaching it beside each rail so that both the left wheel and right wheel both simultaneously make an impact with the 'strike points'. When the strike-in point is activated, it sends a wireless signal to the main controller unit whereby, when under automatic operation, it will signal the visual-acoustic alarms to notify the railway workers. Consequently, it is this treadle principle that resides at the core of the Minimel ® 95.

Schweizer Electronic has a couple of product videos illustrating the operation of the Minimel ® 95. The videos, which are nearly identical, show the Minimel ® 95 for 'small work sites' (which they quote as spanning no more than 500m) and 'large work sites', which as was already mentioned they quote as 1000m:

- Minimel ® 95 ATWS for small work sites: http://www.youtube.com/watch?v=KXlS9wzycMQ
- Minimel ® 95 ATWS for large work sites: http://www.youtube.com/watch?v=pcocfQjg12c

The videos specify that the Minimel ® 95 system can be installed by two workers in approximately two hours. Furthermore, it isn't presently clear whether the system is also able to detect both the speed and the direction of the oncoming train once it has been detected, which is a feature available in the second commercially identified product (discussed next).

Of bigger concern is the fact that in order to mount the treadles it is necessary to essentially excavate the track bed on both rails. A mounting bracket that holds the treadle device is installed by clamping it underneath the rail. This is a rather invasive procedure that may undermine the long-term stability of the track. It is also quite probable that this is not possible in most locations around North America. This raises valid concerns about the feasibility of the product and is in fact one reason why the railroads have rejected the use of this system. Another shortcoming is the limited range of the product, directly limiting the work site size. A 1000 meter warning zone size is not large enough to provide sufficient warning time to track workers.

This identifies two requirements for any new system:

- Significantly larger warning zone size and hence longer warning time.
- Less destructive, or ideally non-destructive mounting option if there is a need for rail mounting.

2.2.2 The Autoprowa®

Figure 2.3 Autoprowa, © Zoellner

The Autoprowa ® stands for Automatic Proportional Warning system, and it is also another form of an ATWS (Automatic Train Warning System). This system is manufactured by Zöllner Signal System Technologies (Germany). [4]

Like the Minimel ® 95, it consists of a series of scalable modular systems collectively working together to provide early warning of an oncoming train and signal the red zone workers for their safety. As with the Minimel ® 95, the Autoprowa ® can be operated in an ATWS or LOWS configuration. It is clear from both the product brochure and product videos that the engineering safety design mechanism implemented by the Autoprowa ® is nearly identical to that of the Minimel ® 95. Hence, it is believed that both the Minimel ® 95 and the Autoprowa ® systems are commercial product competitors.

The Autoprowa ® ecosystem consists of the following inter-operational modules [5]:

- *Autoprowa SSE2: Central Control Unit
- *Autoprowa WGH95/0: Stand-alone Horn Unit
- *Autoprowa WGL95/01E: Stand-alone Lamp Pole
- *Autoprowa-ZPW & ZPW120: Portable Light/Horn Units
- *Autoprowa F300: Treadle (aka Axle Counter) Device
- Autoprowa ZFH: Radio System
- *Autoprowa F500: Inductive Train Sensor
- *Autoprowa ZFE: Data Receiver
- *Autoprowa ZFS: Treadle Transmitter

An image of one possible configuration (out of many supported by the Autoprowa ® system) is showcased below:

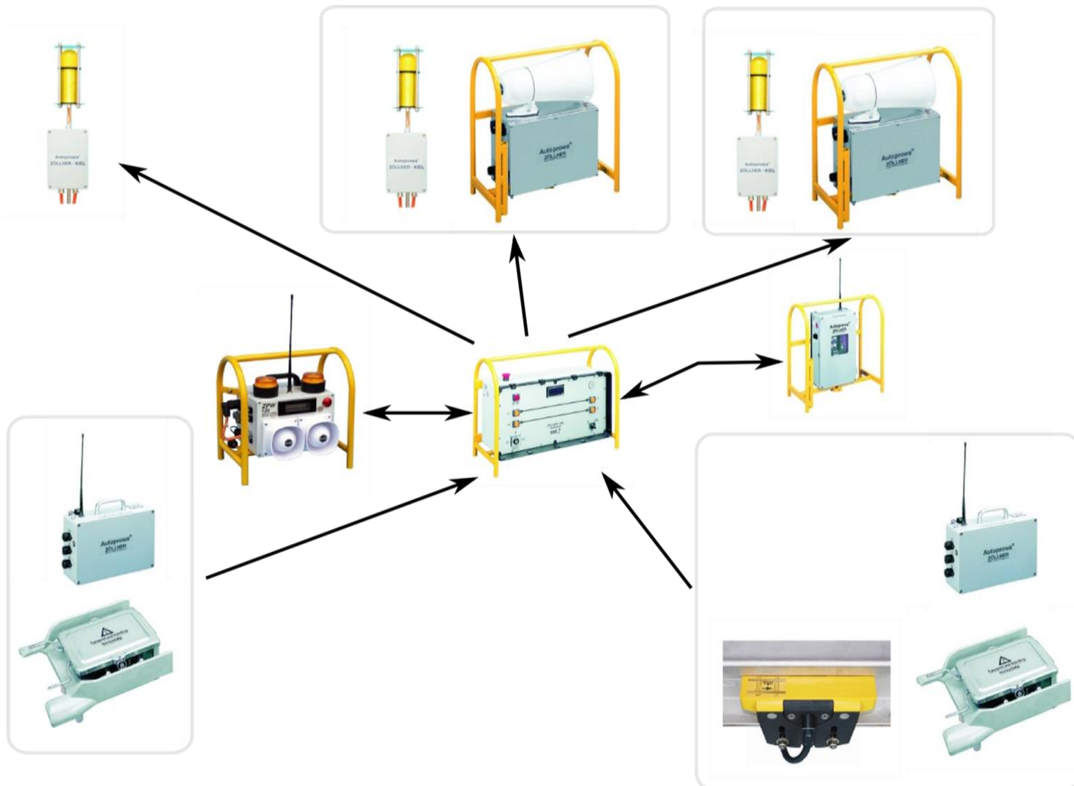


Figure 2.4 The Autoprowa Component Ecosystem, © Zoellner

The operation of the Autoprowa ® is nearly identical to that of the Minimel ® 95. That is, the early detection mechanism is firmly grounded on the principle of the treadle (strike-in/strike-out) mechanism. These have to be installed at the entry/exit point of the red zone.

However, the Autoprowa ® system adds an additional sensing mechanism to the mix and that is the installation of an inductive sensor (also installed at either side of a rail) whose purpose is to sense the speed and direction of the detected train. Recall the treadle (axle counter) is a simple 'mechanical' switch. The inductive sensor on the other hand is used to provide this additional 'telemetry information' regarding the on-coming train.

Another aspect that appears to make the Autoprowa ® system superior to the Minimel ® 95 is the ability of the system to continuously monitor all 'on-site' modules working together to provide safety. Any malfunction by any one unit in the ecosystem promptly issues a warning.

The 'proportionally' component of the Autoprowa ® system is also another positive aspect worth noting. This is illustrated in the video link listed below. One example of this 'proportionality' concept is the ability of the Autoprowa ® system to issue an acoustical warning that is proportional to the surrounding environmental noise levels. For example, a horn located at a site where heavy construction machinery is being operated will adjust its acoustic warning volume level upwards to ensure that it is heard amidst this 'environmental noise', whereas locations where other horns are not as exposed to high levels of noise will issue proportionally lower volume warnings. Thus, as already pointed out, the Autoprowa ® system seems somewhat more sophisticated than the Minimel ® 95.

As with the Minimel ® 95, Zöllner Signal System Technologies have a product video posted on YouTube (by Zöllner Signal System Technologies) showcasing the operation of the Autoprowa:

• The Autoprowa ® System Product Video: http://www.youtube.com/watch?v=Hz8OSQSIYoQ

A key observation about the Autoprowa® is that it shares the shortcomings already identified for the Minimel ® 95 system. As such, neither system is deemed suitable for use by the railroad industry in North America. In the following section we will list further observations obtained from conducting our review of commercial products for train approach detection.

2.3 General Observations

From the initial research survey regarding the early warning train detection systems, some observations are readily apparent:

- Both the Minimel ® 95 and Autoprowa ® systems while advertised as ATWS/LOWS systems, are simply “Just-in-Time” train detection solutions. The warning time of either system is deemed inadequate, but is limited by the system supported warning distance. For example, the maximum range quoted for the Minimel ® 95 of 1000m is significantly shorter than required for freight train operational deployments. A freight train moving at 40 mph can cover that distance in less than one minute!
- A tradeoff can be observed between reliability and warning zone size. Because of the desire for higher reliability of receiving trigger events from the treadles, cabling is used to connect the various system devices together. This is a significant inconvenience, as it means the required deployment of very long distances of bulky cable in order to secure a work site. Wireless options are available, but due to lower reliability seem to be rarely used and are also distance limited.
- Installation of these solutions is a semi-destructive process, requiring excavation underneath each rail where a treadle is to be installed. In fact, both systems require 'semi-permanent' installation of the treadles (axle counters) for the strike-in/strike-out points, while the Autoprowa ® system also adds the 'inductive sensor' to the mix, which must also be 'semi-permanently' installed at the rail(s).
- Both systems rely on the principle of the strike-in/strike-out point by way of treadles as their only sensors to detect an approaching train. Hence, the distance between the treadles and the work site determines the warning time available to the workers in

order to clear the track area and move to safety. This is a severe limitation of both systems.

- Both systems consist of heavy and bulky units that can take in the order of several hours to set up. This limits the time available to conduct actual work on each site and is very detrimental to the acceptance of any such systems by the railroads.

2.4 Research/Study of Non-Commercial Early Warning Systems

The second part of this research survey identified two independent research/studies concerning the use of train detection early warning systems for the achievement of track safety. The first system was primarily concerned with the safety of railway workers, while the second focused mainly in train detection at level-crossings (points where pedestrian traffic and train railways intersect).

What makes these systems interesting is the fact that these are local attempts here in the United States to address the issue of train safety and train detection. Section 2.0 of this report primarily addressed commercial systems that are both heavily prevalent in the European railway system, while initial research suggests that no such elaborate mechanisms exist or are heavily in use here in the United States.

The two research/studies on train detection and early warning come from two areas:

- IDEA Transit Project 55: This study evaluates an early warning system developed by ProTran1, LLC that is heavily influenced by the commercial Minimal ® 95 and Autoprowa ® ATWS/LOWS systems.
- Texas A&M Transportation Institute (TTI): Whereby a study was performed to identify low-cost and non-invasive train detection technologies to be used primarily at level-crossings, implementing sensor technologies for train detection in a non-

invasive way, which is also of a primary interest for our multisensory research project.

2.4.1 IDEA Transit Project 55

The Transit IDEA Program is part of the Transit Cooperative Research program, which is a cooperative effort of the following agencies:

- Federal Transit Administration (FTA) [provides funding]
- Transportation Research Board (TRB) [manages the program]
- Transit Development Corporation

One project performed circa 2008 that falls under this umbrella was the IDEA Transit Project 55 for the Transportation Research Board of the National Academies [6, 7]. The purpose of this study was to design, develop, test and evaluate a device to give early warning of an approaching train to both rail transit personnel and also give early warning to the train operator that this person is approaching a work zone.

The system is comprised of a scalable modular ecosystem that is very much inspired by the Minimel ® 95 and Autoprowa ® Automatic Train Warning Systems (ATWS) and Lookout Operated Warning Systems (LOWS). As with these systems, the detection system – developed by ProTran1, LLC – consists of the following modules:

- Portable Train Detector
- Personal Alert Device with in-ear Safety Blue Tooth
- Flagger (aka 'lookout') Supervisory Device
- Portable Warning Light/Horn Unit(s)
- Train-Mounted Early Warning Device

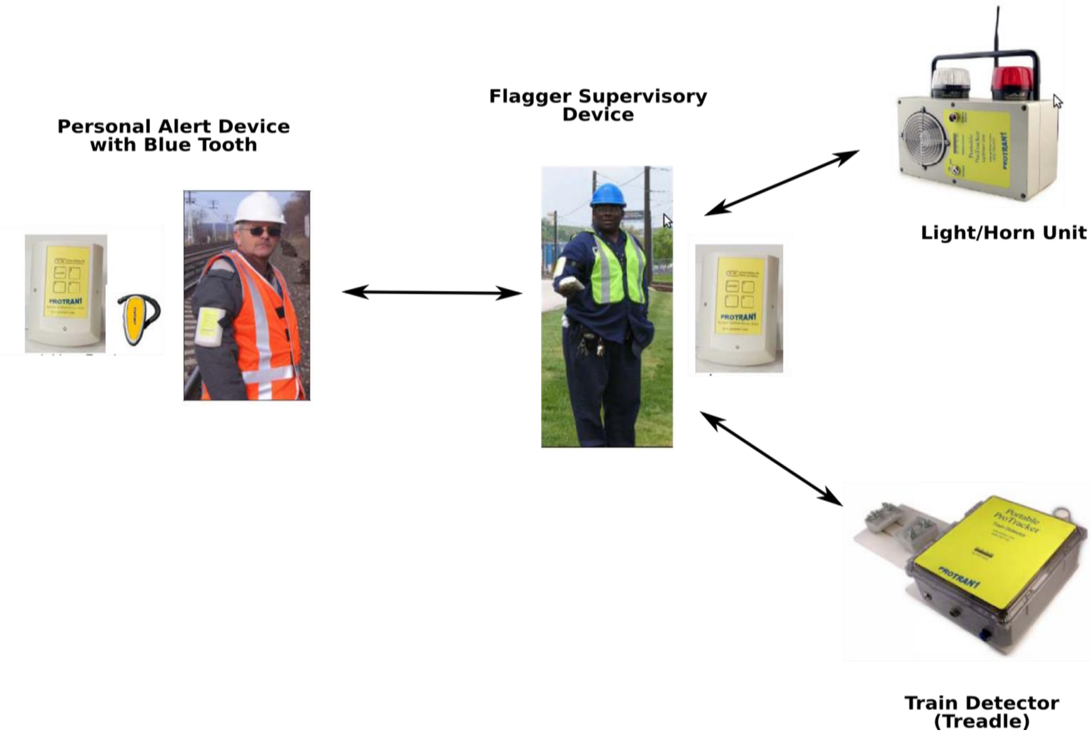


Figure 2.5 The ProTran1 system layout, © ProTran1 LLC

The image shown above gives a pictorial view of this ecosystem. It can be easily seen from the image that the system is indeed heavily influenced by the Minimel ® 95 and Autoprowa ® commercial products. This system, however is strictly a LOWS (Lookout operated) and thus is not designed to automatically operate on its own. Like their commercial counterparts, the system relies on a strike-point (treadle) consisting of a mechanical switch to detect the presence of a train when the approaching train enters the work zone.

A unique aspect of this system, however, is that the system was designed to primarily operate in a wireless fashion and discards the reliance on any cabling system. The system is more minimalistic in comparison to their commercial counterparts but embody the same principles.

Notice that on the above image, the “Personal Alert Device with Blue Tooth” is 'strapped' onto the upper arm. It is therefore presumed that the operator is notified of the oncoming way in three different ways:

- Visual-acoustic warning by way of Light/Horn Unit(s)
- Vibrating Mechanism via the 'arm-strapped' Personal Alert Device
- Auditory Warning via personal Blue Tooth in-ear device

As previously mentioned, the warning system requires the presence of a lookout operator (which they refer to as 'the flagger' in this study). The purpose of 'the flagger' is the same as in any LOWS: to confirm the presence of an on-coming train once notified by the system and then relay this warning to the workers in the red zone by activating their respective warning devices.

The ProTran1 device also introduces a unique component not previously observed in the Minimel ® 95 nor Autoprowa ® system. This system also adds a warning device that is mounted in the cabinet of the train operator as shown in the below image:

Figure 2.6 The ProTran1 in-cab warning unit, © ProTran1 LLC

The purpose of this device is two-fold:

- Warn the train operator that he/she is approaching a work zone when the device is within radio range of said work zone.
- The device in turn transmits a signal to the 'flagger' at the work site that said train is approaching, at which point, and upon confirmation he or she can issue a warning.

The system adds complementary warning to both the train operators as they approach work sites and the workers themselves, which is rather unique with the draw back that such are somewhat invasive as they would require installation onto train cars which might not be a viable option.

A last component that was also provided as an option for the ProTran1 system is the use of a wireless 'tripper' as showcased below:

Figure 2.7 The ProTran1 System's Tripper unit operation, © ProTran1 LLC

The purpose of the tripper (when in an up-right position) is to activate a braking system in cases where the train is expected to come to a full stop to prevent red zone entry. While not directly related to train detection in general, the device introduces an additional level of safety by both minimizing exposure of an operator (when setting the tripper) as well as workers presently inside of the work zone. However, this only works with systems that can successfully interoperate with such a tripper, which may not be the case for freight trains in North America.

2.4.2 Texas A&M Transportation Institute (TTI) Research/Study

Around 2006, the Texas A&M Transportation Institute (TTI) [8] performed a study (Project No. NCHRP 3-76B) prepared for the National Cooperative Highway Research Program, the Transportation Research Board, and the National Research Council with the purpose of identifying and evaluating what they refer to as two low-cost, off-the-shelf, non-intrusive, railroad 'right-of-way' alternatives to the traditional active-grade crossing warning systems.

This research is interesting since it was aimed towards a non-intrusive early warning system and utilizing different forms of sensing approaches, and not relying on the traditional treadle mechanism used in most current systems.

The study eventually narrowed down to selecting and evaluating two systems, which were identified during the 'Phase-I' portion of their study, while the evaluation procedure was considered as 'Phase-II.'

The two systems identified were:

- A Radar-based System
- An Acoustic Train-Horn Detection System

The manufacturers of these detection devices were not identified in the study for anonymity reasons as the study clearly reveals results that can evoke an unfavorable point of view of these products.

In the study, TTI gave each vendor a chance to agree on and identify a suitable 'test site' and to further perform a usual number of adjustments and 'tweaks' to fine-tune a system that is supposedly ready for commercial use. Once vendors were satisfied with any needed adjustments, the two systems were simultaneously evaluated and tested on the same site. The figure below demonstrates what these devices look like as well as the test setup.

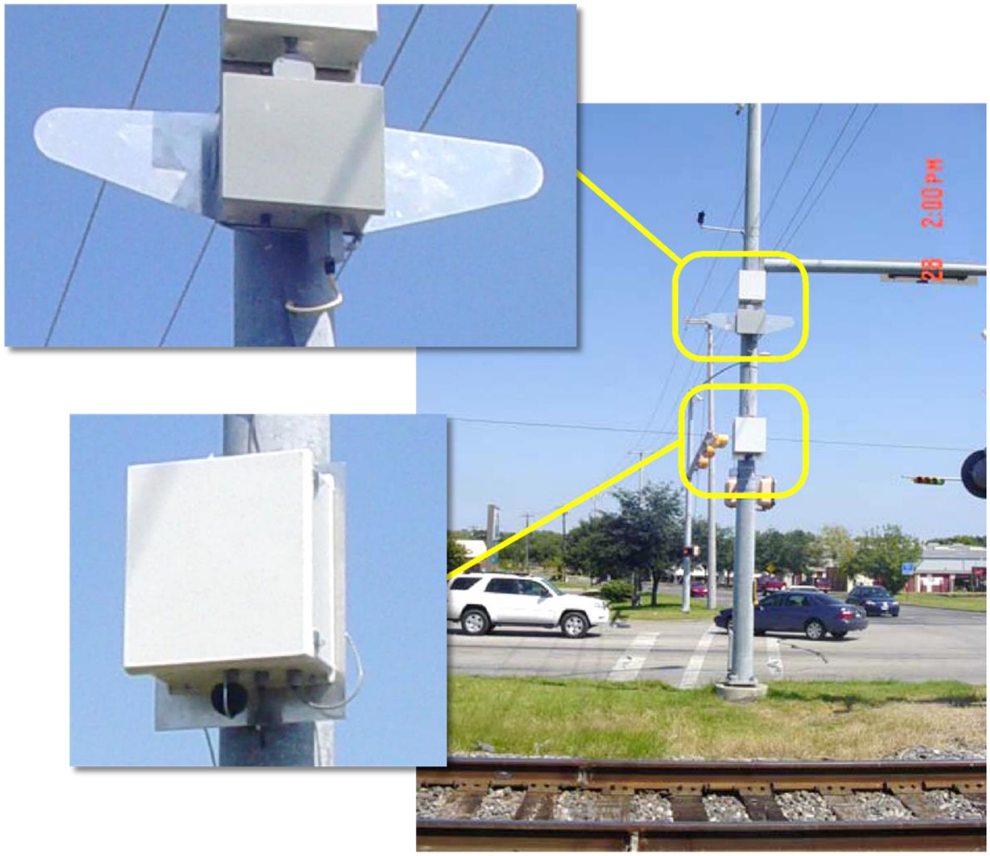


Figure 2.8 The TTI study's test setup

Both systems were mounted on a street pole at the 'crossing' where the railway is located. It must be re-iterated that the primary purpose of this system did not directly address the concern of 'worker safety,' but merely train detection at 'level crossings.'

The above image shows a radar detector with deflector shields that uses a 'radar return' signal (using the Doppler principle) from an approaching object to detect both the speed and direction of the approaching train. The system contains two radars (one of each side of the deflector) in parallel with the railway track. When a train approaches from either side, the radar system can pick up the 'radar return' and determine both direction and speed. In addition, a third radar is mounted so that it points perpendicular to the railway track in order to observe the 'blind-spot' should a train come to a complete stop at the crossing. Thus the radar system is a three-radar system. The purpose of the deflector shields is to avoid the radar signal from 'leaking' onto the adjacent street and falsely triggering the train detection mechanism from this adjacent vehicular traffic.

Below the radar system on the same pole, we see the acoustic train detection system. This detection system actually uses an omnidirectional microphone (which can be seen directly beneath the bottom-most cabinet, in black) for acoustic detection of the on-coming train. The manner in which this system identifies trains is by specifically listening for the train's horn signature, and comparing this horn signature against a library (contained in the system's memory) of 'train horn signatures.' The system uses this library to determine if a train is indeed approaching.

Clearly, a major draw-back of this system is that if the train fails to use its horn, the train will simply not be detected. Furthermore the system uses an omnidirectional microphone that is not acoustically focused to listen from sounds emanating in the direction of the on-coming train, making it susceptible to ambient noise by the adjacent traffic and the multi-path effect of the propagating sound wave.

Both systems have approximately the same size and both implement a logic control system, a microcontroller unit, a data acquisition system, and a power supply.

2.4.3 Results of the System Review

While both systems detected all the trains 100% of the time, both systems suffered from excessive generation of false positives.

- For the *Radar* system, 57% of all radar 'activations' were false positives (1973 false train activations out of 3459 total).

- For the *Acoustic System*, 94% of all 'activations' were false positives (24608 false train activations out of 26094).

Consequently, these sensors had a difficult time distinguishing between trains and external environmental features, which were the culprit of a lot of these false activations. Consequently, the conclusion settled upon by TTI at the end of their Phase-II study is that non-invasive train detection is possible. However, the real challenge is in successfully being able to only detect trains, and in a reliable manner without generating false alarms. This gives significant justification to our own proposed study to develop such a system.

Chapter 3 Desired Attributes of the Train Approach Detection System

Based on our research on similar railway safety technologies presented in the previous chapter, we desire our system to possess the following attributes:

- **Early Warning**: a system should be able to provide early warning. This means that the system should be able to detect that an oncoming train is approaching at a sufficient distance from the installation of the sensing device(s) located within the *work zone* to provide a minimum of 20 seconds warning, which is the minimum standard interval of highway-rail grade crossings in the U.S. Depending on the maximum speed of the train, this translates to a distance of between 1 to 2 miles from the point at which the sensor is installed. Note that early warning is preferred over approach detection. **Approach detection** simply means that the sensing device is installed “at the approach” at a distance (from and outside the work zone) such that when the train 'crosses' this 'trip-point' it will provide the 20-second warning of the oncoming train. However, the problem with approach detection is the requirement of the safety crew to have to travel a considerable distance (possibly on both sides of designated work zone) for the installation of the sensing device(s). Thus, under ideal circumstances, early detection is desired over approach detection.
- **Intrusiveness:** the system should preferably be designed such that detection can be achieved with minimal intrusiveness to the work zone and rail structure. This means avoiding the installation of sensing devices that result in overly complex 'rail attachments' that make installation and setup of the safety mechanism overly complex and lengthy (i.e., by having to dig a trench underneath a rail for clamping the sensor(s) to a rail).

- **Wireless**: the system should also be designed so that all the sensing devices perform the train detection task wirelessly: among sensors, sensors and look-out operator, sensors and maintenance crew, and any combination thereof.
- **Low Computational Complexity**: the detection methods implemented by the system should preferably implement low computational complexity. For example, train detection algorithms that rely on overly complex image detection methods should preferably be avoided as this translates into costly hardware and software design requirements.
- **Tampering:** the system should be designed to withstand intentional (human tampering) as well as unintentional tampering (animals knocking a sensor that sits on a tripod, for example), and any such conditions that can compromise the ability of the system do its job.
- **Robustness:** the system (and its sensors) should be capable of withstanding environmental conditions at the work zone. This includes EMI from overhanging electrical lines, mechanical vibrations induced by surrounding equipment as well passage of the train itself, and overcoming of the surrounding 'noise pollution' at the work site from all surrounding sources.
- **Fail-Safety:** most importantly, the system should implement stringent fail-safe mechanisms for all the implemented sensor technologies such that failure of any one sensing device, disturbance thereof, of any mechanism, and for *any* reason, that compromises the system's ability to do its job results in immediate notification of this serious and potentially fatal situation that is propagated to all maintenance crew using visual, auditory, or vibrational signaling or any combination thereof.

Chapter 4 Research Survey of Sensing Technologies

Having identified the desired attributes of the safety mechanism during the previous work for our MATC Multisensory Train Approach Detection project, the next stage of our efforts was to identify all of the sensor technologies and methods that held promise for implementation into the system for the purpose of train detection. The identification of these sensors and methods consisted of sensors that have either been used in the rail industry for similar purposes or from research performed by other agencies for the purposes of train detection, as well as other uses.

During the course of the research survey, the following sensing technologies and methods were identified. These are:

- Mechanical Treadle (Axle Counting)
- Inductive Sensors
- Infra-Red (IR) Beams
- Time-Domain Reflectometry (TDR)
- Anisotropic Magneto-Resistive (AMR) Sensors
- Accelerometer (Seismic/Vibration)
- Radar Technologies

For the rest of this section, a brief discussion on each of the identified devices and methods will be provided. Please note that some devices and methods are discussed at greater length than others. Also, note that not all of the above devices may necessarily address the primary concern of the system to achieve early detection as outlined in the attributes section in chapter 23. The goal here is to list and provide a brief discussion of all of the identified sensor technologies that hold promise in some form or other for implementation in the envisioned multisensory train approach detection mechanism.

4.1 Mechanical Treadle

The mechanical treadle is one of the most widely used mechanisms used for approach detection and is the primary detection mechanism used by the leading commercial Automatic Train Warning Systems (ATWS) such as the MINIMEL ® 95 and the Autoprowa [3, 5]. This is because the application of the mechanical treadle for axle counting has proven very effective for the detection of trains at the approach when it is about to enter the work zone and verification that it has exited the work zone.

Figure 4.1 Mechanical treadles

It is effective because the treadle is semi-permanently installed onto the rail structure, making it robust against tampering and environmental effects. In addition, the treadle mechanism provides a robust fail-safe approach because verification of entrance and exit of the train into and out of the work zone is done through axle counting. As the train crosses the treadle at the approach (called the strike-in point), the device counts the axles that make contact with the treadle mechanism. The train then exists the zone at the opposite side of the work zone when, and only if, the same number of axles have been accounted for at the strike-out point. This is illustrated in the figure below.

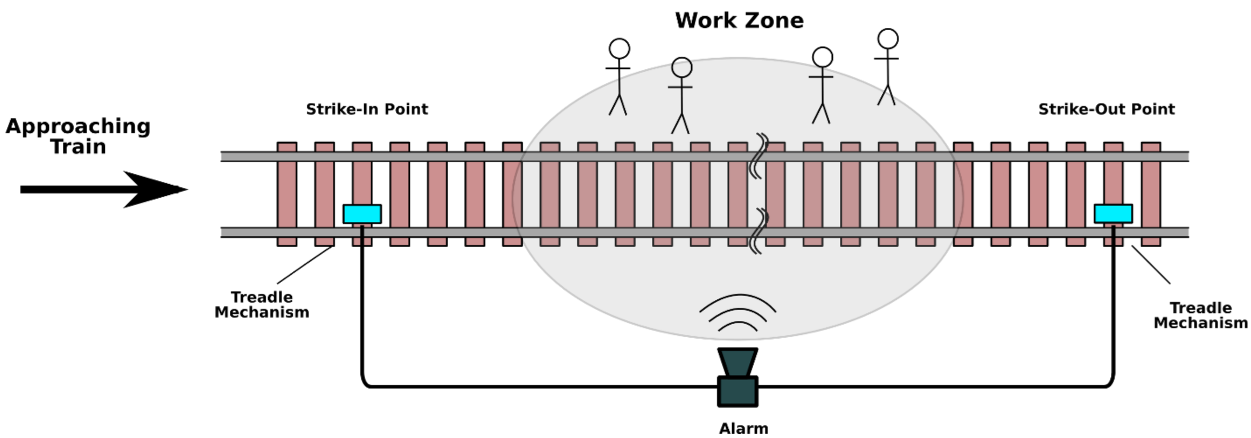


Figure 4.2 Work zone protection with strike-in and strike-out points

The problem with the treadle mechanism, unfortunately, also happens to be its strength (from a tampering standpoint). Usage requires installation by clamping the treadle onto the rail, which may require digging a small trench underneath the rail for placement of the cabling and clamping mechanism. This can add considerable length to installation, set-up, and removal times of the device. In addition, a single treadle mechanism by itself cannot provide other ancillary information about the oncoming train, such as direction, length of the train, nor its speed. However, direction and speed can be provided by the addition of a secondary treadle immediately following the first.

Still, and despite some of its shortcomings, the treadle/axle-counting mechanism is the most prevalent detection device of choice for leading ATWS systems.

4.2 Inductive Sensors

4.2.1 Inductive Sensing as an Electronic Treadle/Axle-Counter

Inductive sensors are used in everyday automotive traffic situations, so it makes sense that the application of inductive sensors for train detection be explored. In the study outlined in [9], the usage of two types of inductive sensors (one for each "System 2" and "System 4" investigated in the study) for the purpose of train detection. System 2 used an inductive sensor that is permanently (or semi-permanently) installed onto the rail structure as shown below:

Figure 4.3 Inductive sensor

An inductive sensor such as this serves the same purpose as the mechanical treadle/axle-counting device previously discussed, with the added benefit that such a device is not subject to the traditional wear-and-tear that is experienced by the mechanical treadle. As with all inductive-type devices, the sensor works by generating an electrical field in the vicinity of the sensor.

Then, as the wheel of the train passes near the sensor, it disturbs the electrical field, allowing the sensor to achieve detection.

As can be seen from the image, notice that as with the mechanical treadle, this sensor requires intrusive installation onto the rail structure, as well as the need to dig a trench underneath the rail for electrical wiring. A benefit of this type of sensor, however, is its ability to provide speed and direction information based on the 'signature' of the electrical signal generated when the wheel crosses the inductive sensor in one direction versus the other. However, the accuracy of such information provided by the sensor was not ascertained in this research survey.

4.2.2 Inductive Loops for Coarse Detection

Another type of inductive-type sensor is essentially an extension of the inductive-loop. Also as part of the study performed in [9], “System 4,” an inductive-based approach, was taken by installing a pair of inductive-loops back-to-back for train detection (at the approach), and also providing direction and speed information about the train. An image of the particular setup used is shown below:

Figure 4.4 Inductive loop installation and its problems

Note from the above image how the inductive loops are installed (as rods) alongside each rail, parallel to the rail structure. What is not visible from the above image is that these are loops (hence the term “inductive loop”), which means a portion of the loop component is buried in the ballast. Consequently, it is clear that a major drawback of this detection mechanism is the severe intrusiveness for this type of sensing device.

Another particular problem that is prominent with inductive loops is their sensitivity to EMI (electromagnetic interference) from electrical storms. If the system is not designed to account for impossible events (e.g., simultaneous 'trips' of two back-to-back loops), this could result in the generation of false-positives. Furthermore, electrical disturbances from other sources, such as nearby power lines, can induce 'ghost signals' into these types of sensing devices. This particular phenomenon was encountered in [9], for System 2.

4.3 Infra-Red (IR) Beam Sensors

Infra-Red beam sensors have been used particularly as electronic treadle mechanisms (axle-counters) to some degree. For example, a U.S. company by the name of Grace Industries, Inc. [10] has a train detection system that clamps onto the rail structure with an optical lens pointed against the side of the inner-rail to detect the passing wheel (see image).

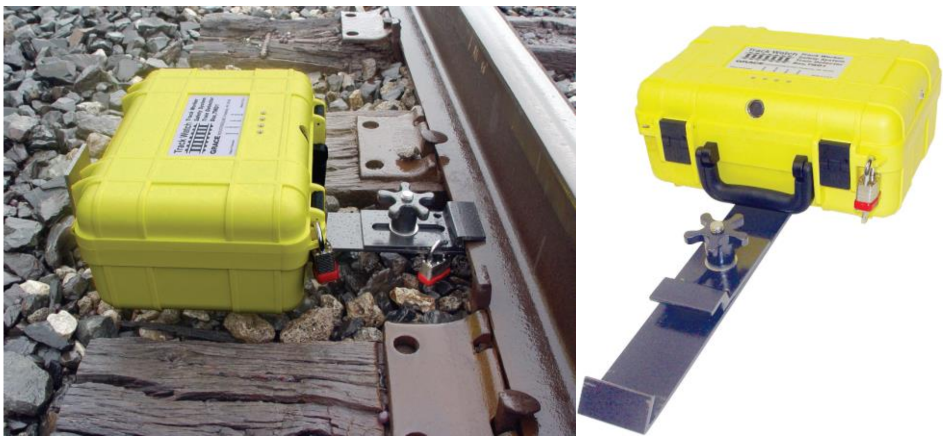


Figure 4.5 Infra-Red train wheel detector

Infra-Red beams make an inexpensive electronic treadle mechanism. However, they are easily susceptible to environmental disturbances, which include accumulation of dirt and dust onto the optical opening of the lens as well as misalignment resulting from the extreme mechanical vibration forces induced into the rail structure by the locomotive and accompanying rail cars.

4.4 Time-Domain Reflectometry

Time-Domain Reflectometry or TDR is not a 'sensor technology' per say, but a technique or method that can be applied to the principle of train detection. The general principle behind

TDR is actually rather simple, and the below image conveys the idea behind TDR using an electrical signal and a wire (modeling the transmission line) as an example:

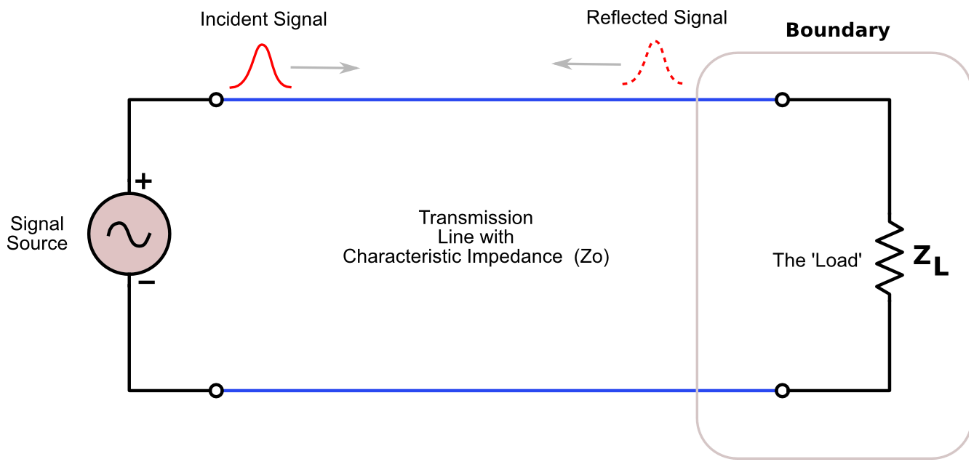


Figure 4.6 Time domain reflectometry principle

In the above figure we see a long, but finite, differential transmission line. Applying an electrical pulse at one end of the transmission line using a pulse generator will result in the pulse being introduced into the 'medium' (e.g., the transmission line) propagating along the medium at a propagation speed determined by the properties of the transmission medium. At some point, as the signal travels down the medium, it will reach the so-called boundary, (i.e., the end of the medium) and what happens to the signal when it 'hits' the boundary depends on the physical characteristics of the boundary as well as the medium. There are three possible outcomes that can result from this experiment:

- the signal will never return because it is absorbed and dissipated by a ‘load,’
- the signal will be reflected (bounced) back as a mirror image because the boundary is ‚open,’ or

- the signal will be reflected (bounced) back inverted because the boundary is 'shorted.'

These outcomes are conveyed in mathematically by the following equation:

$$\rho = \frac{E_r}{E_i} = \frac{Z_L - Z_o}{Z_L + Z_o} \tag{4.1}$$

where $\rho$is the so-called reflectivity factor; $Z_L$is the load's impedance; and $Z_o$is the characteristic impedance of the transmission medium.

Consequently, it can be seen that the resulting outcome is determined by how 'matched' the characteristic impedance of the transmission medium is to that of the load. If the two are equal (i.e., $Z_L = Z_o$), then $\rho = 0$, which means the signal will be fully absorbed by the load. On the other hand, if $Z_L = \infty$ (i.e., an open circuit), then the reflectivity will be equal to 1 given that the value of $Z_L$is so large that the contribution of $Z_o$is negligible, and thus, the equation reduces simply to $Z_L/Z_L = 1$. Finally, if $Z_L = 0$ (i.e., shorted), then the reflectivity will be equal to -1, which means the signal will be reflected, but inverted.

With this principle in mind, it easy to ask whether TDR can be applied for the purpose of train detection by treating the two rails as the differential transmission medium, with the short applied by the train's numerous axles (i.e., the shunt) to act as the boundary or 'load' (or 'boundary') at the other end of the medium. Then, using the known propagation speed of the signal, along with timing the flight time of this signal and back can – in theory – tell us the precise location of the train, provided that the rail provides a continuous contact from the point where the signal is applied and measured to the train’s current location. Furthermore, if we continuously send repeated coded pulses, we should be able to track the precise location of the train as it nears closer and closer, almost in a radar-like fashion.

It turns out that this very idea has been attempted by a study performed in [11], where the aim of the study was to examine the viability of Time-Domain Reflectometry as an alternative method for detecting oncoming trains as well as being able to predict the arrival times specifically for use in Highway-Railroad grade crossings. The principal approach proposed in this study was to use the two rails as a two-wire differential transmission line. Then, with the use of coded electrical pulses being injected into the track, the reflection of those signals in the presence of an oncoming train could, as a result of the train's axle shunting the two rails, be used to determine the distance to the approaching train by accurately measuring the round-trip delay of the reflected signals.

To test the viability of this idea, the electrical transmission properties of the rail were first determined, which included variations of 'tie' (or sleeper) type, track ballast quality, moisture content, etc. Using this information, an electrical model was constructed for bench-testing purposes – this model, as presented in **[5]** is reproduced below:

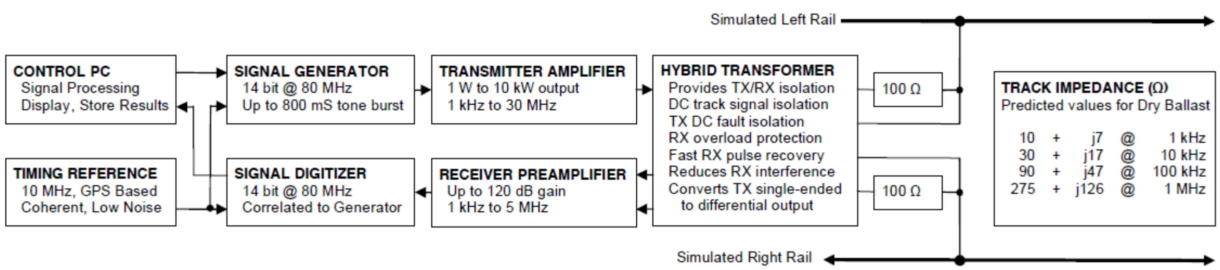


Figure 4.7 System block diagram for a TDR detector

During the bench-testing phase, a signal coding and modulation method was developed that allowed the use of short pulses, and preliminary results indicated that such signals were successfully recovered and furthermore correctly identified at theoretical track distances of up to 5 miles for dry conditions, and 3 miles for wet conditions, which is very promising for the purposes of early detection.

Experimental results, however, from the bench-test model generated, uncovered a few potential problems that need resolving. The first consisting of the significant signal attenuation resulting from ballast and tie conductance between the rails, resulting in a the rails behaving as a low-pass filter, which made it difficult to use the desired high-frequency signal pulses needed for accurately predicting the train's position. In fact, this created a dilemma; lower-frequency pulses can travel longer distances (to overcome the attenuation effect), but positioning accuracy became more difficult, while higher-frequency signals, being able to provide that accuracy, could not be transmitted as far, thus shortening the time in advance at which the oncoming train can be detected.

To make matters worse, the tie/ballast conductance problem under real track conditions made this situation worse as a result of accumulation of dirt, mud, and moisture, which is very common of most railway systems (see image):

Figure 4.8 Image of a problematic TDR environment

Consequently, as a result of this problem, even lower frequency signals had to be used with the consequence that the incident pulses injected into the track rails were overlapping with the reflected pulses, making it difficult to determine the pulse's flight-time (or round-trip) accurately, defeating the project's very purpose.

Still, despite these difficulties, Time-Domain Reflectometry is certainly an approach that should continue to be researched for the following reasons:

- While attenuation of the coded pulse signals may be severe, TDR still works. In fact, TDR techniques could be implemented as sort of a hybrid train detection approach that sits between being categorized as an early detection system and an approach detection system.
- TDR can be implemented exclusively for approach detection purposes; it can serve as an alternative track occupancy detection mechanism. Even if the detection distance is limited, train detection is most certainly achievable within the span of a track segment.

- It is a train detection technique that – provided solutions are found to the present challenges – holds premise for early train detection. That is, detection of an oncoming train at distances greater than a mile without having to install the sensing device at such distances, and have instead, the sensor be localized AT the work zone, as opposed to being remotely installed.

Of course, TDR cannot be applied to all detection scenarios as it assumes that there is a continuous (and electrical) contact between the source, where the signal is 'injected' into the rail, and the oncoming train (i.e., a continuously-welded rail). Attenuation becomes a significant problem for jointed rails, and furthermore, isolated jointed rails fix the maximum detection distance for train detection.

4.5 Anisotropic Magneto-Resistive (AMR) Sensors

Anisotropic Magneto-Resistive (AMR) sensors are unique in their capability. A study outlined in [12] was performed to determine the feasibility of these types of sensors for railroad and highway equipment detection. The study focused primarily on characterizing the unique features of a digital Anisotropic Magneto-Resistive sensor manufactured by Honeywell®, such as temperature drift, signal repeatability, and EMI resistance, as well as some tests that were performed in the context of railroad technology.

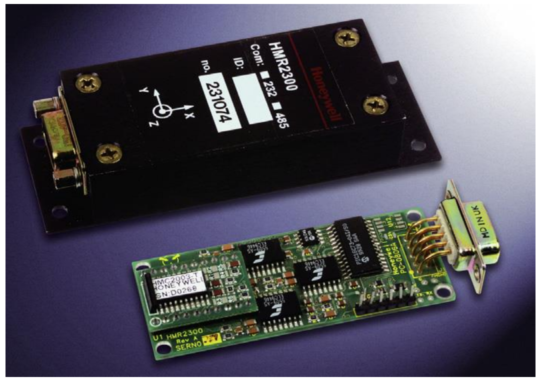


Figure 4.9 Anisotropic Magneto-Resistive Detector Module

An Anisotropic Magneto-Resistive sensor's operation is fairly easy to understand. These types of sensors essentially detect the change in the Earth's ambient magnetic field caused by the presence of metallic objects. When a large ferrous objects is present in the vicinity of the sensor, it creates perturbations in the magnetic field lines, which are picked up by the sensor. The image shown below conveys the general idea:

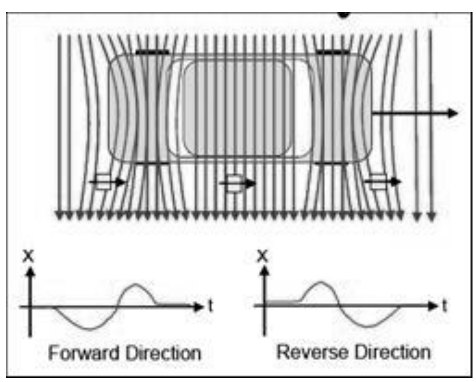


Figure 4.10 Direction detection using AMR [12]

A particularly fascinating aspect of this type of magnetometer is in its ability to pick up unique magnetic signatures generated by the metallic object, but more importantly, the repeatability of this magnetic signature. For example, in the above image, we see an oversimplified signature being reversed in direction when the object retracts its previous motion (think an audio signal playing backwards). This capability has all sorts of interesting potential uses. For example, the following image shows the actual magnetic signatures picked up by the AMR sensor being characterized in the study when a Lexus SUV was driven back and forth three times in the vicinity of the AMR sensor:

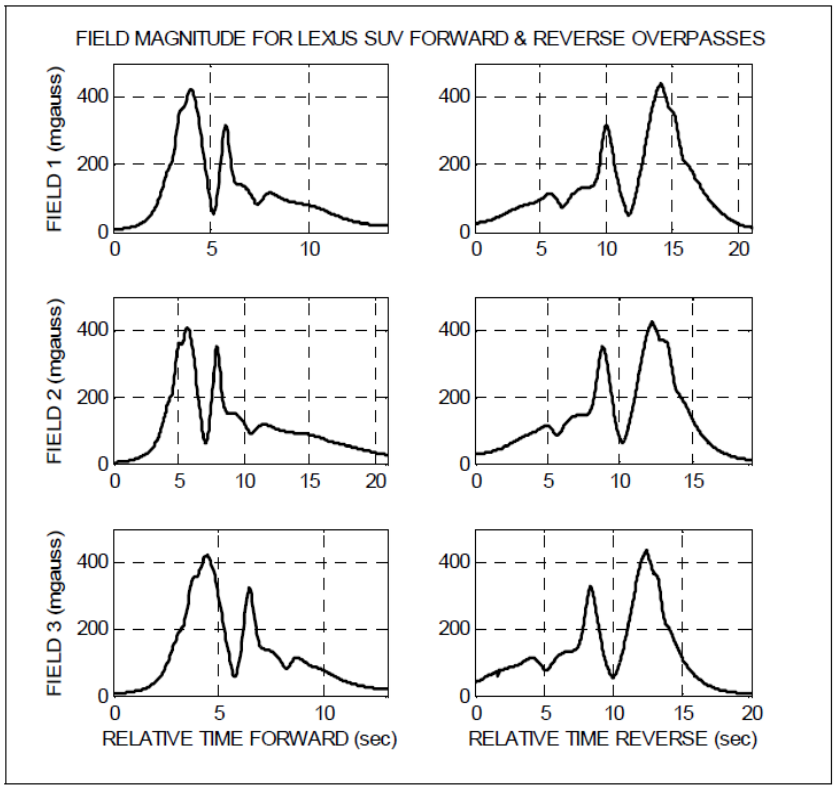


Figure 4.11 AMR sensor applied to detection of Lexus SUV "fingerprint" [12]

Such devices, once again, could be used as electronic axle counters, but they can even potentially be used to actually determine the length of the train. For example, it is theoretically possible to record the overall signature of a passing train at the approach as it enters the work zone, and only signal “clearance” to re-enter it once the same entire signature has been fully verified at the strike-out point, and thus, it can allow for more 'axle-counting-like' sophisticated methods, because we're now not only counting axles, but also tracking rail cars.

Therefore, magnetometer type sensors make an interesting sensor technology for approach detection (as opposed to early detection). Finally, the magnetometers of the Anisotropic Magneto-Resistive type are unique in their capacity for fast signal response and fading, which is necessary to pick up useful, discernible, and unique signatures.

4.6 Detection through Rail Vibrations with Accelerometer Sensors

Another sensing approach that also seems particularly logical to try and investigate for train detection is by 'listening' for the mechanical vibrations induced onto the rail structure, taking advantage of the fact that train-induced mechanical vibrations always precede the oncoming train.

It turns out that this approach was precisely attempted in [13]. The objective of this study was to investigate the potential utility to the railroad industry by exploiting the train-induced rail vibration signals by listening and recording the vibrational patterns using a piezoelectric-based accelerometer with a mounting magnet exhibiting a relatively flat frequency response around the band of interest. During this study, it was found that trains stimulate a rich vibrational signature that is related to several characteristics of the train itself. For example, it was found that train-induced vibrations contained, both broadband and narrowband information. The broadband content observed was a result of the physical irregularities of the track itself, randomness of wheels bouncing and re-establishing contact with the rail, rail cars making contact against each other, etc. The narrowband, on the other hand, is attributed from repeatable consistent patterns, such as from irregularities from the wheel of a locomotive, for example, and as a result, the narrowband content was observed to be proportional to the train's speed. This phenomena can be observed from the following figure:

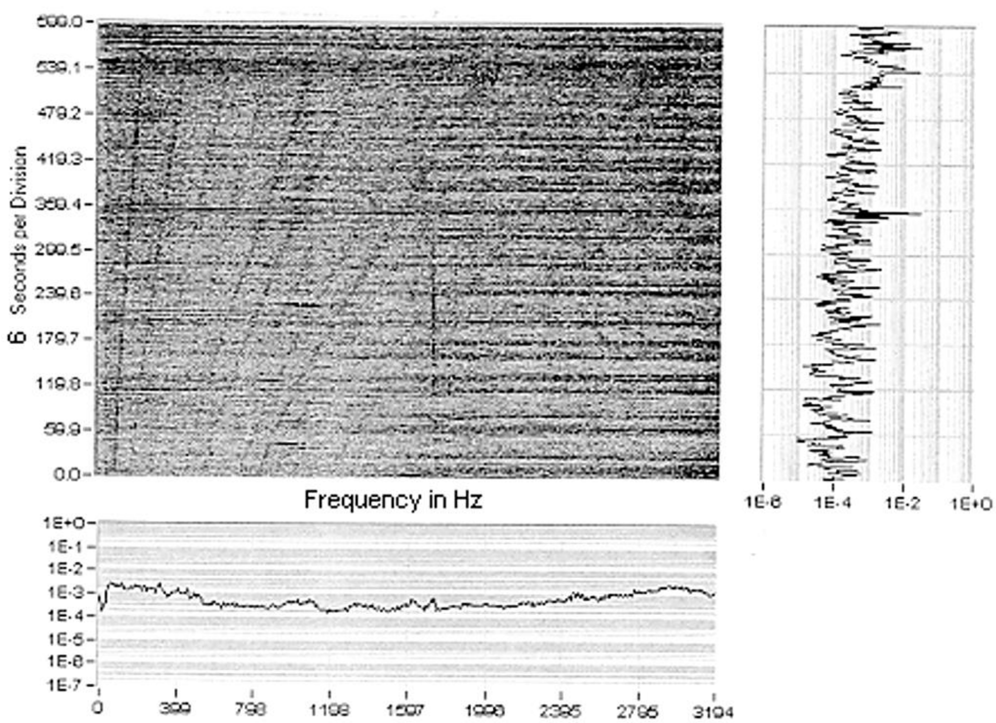


Figure 4.12 Representation of the accelerometer signal in the frequency domain [13]

Features of the train related to irregularities resulting from the wheels (e.g., flat spots or chips) that lead to repetitive vibrations ranged between 3 to 15 Hz.

Another interesting characteristic observed during the study showed how the power recorded of the induced vibrations did not seem significantly different as the train approached at different speeds. This can be seen on the data below before correlation for the power of the mechanical vibrations recorded for a freight train approaching at 35mph versus one approaching at 50mph:

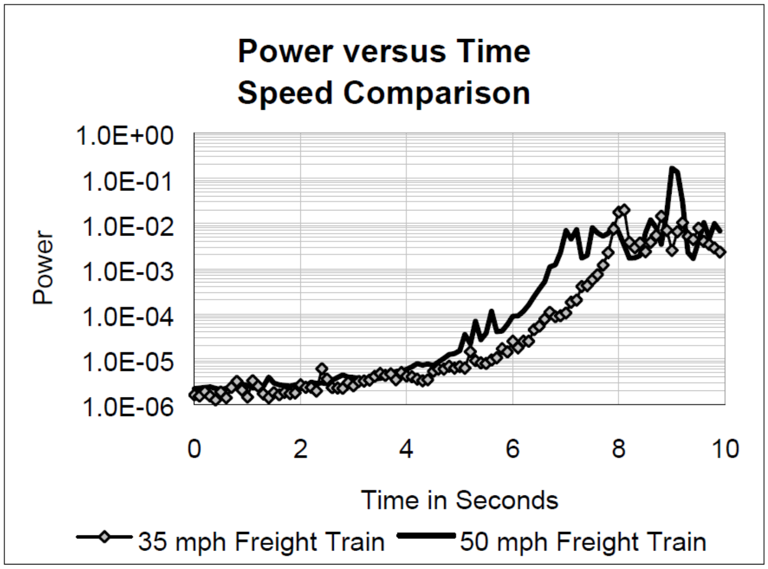


Figure 4.13 Power profile before correlation [13]

...and after the same data has been correlated:

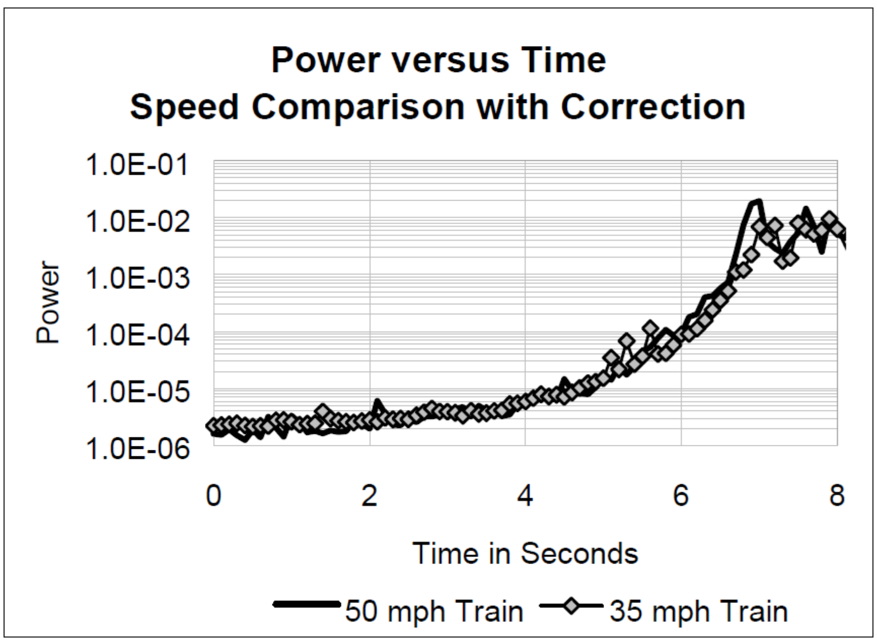


Figure 4.14 Power profile after correlation [13]

Other general findings from the study included the following:

- Relative to the noise floor baseline of the equipment used to gather data recorded energy levels of up to 70dB.
- An attenuation factor from estimated data was found to be around 0.03dB/ft for the best case and 0.08dB/ft for the worst case. This can be seen in the graph below:

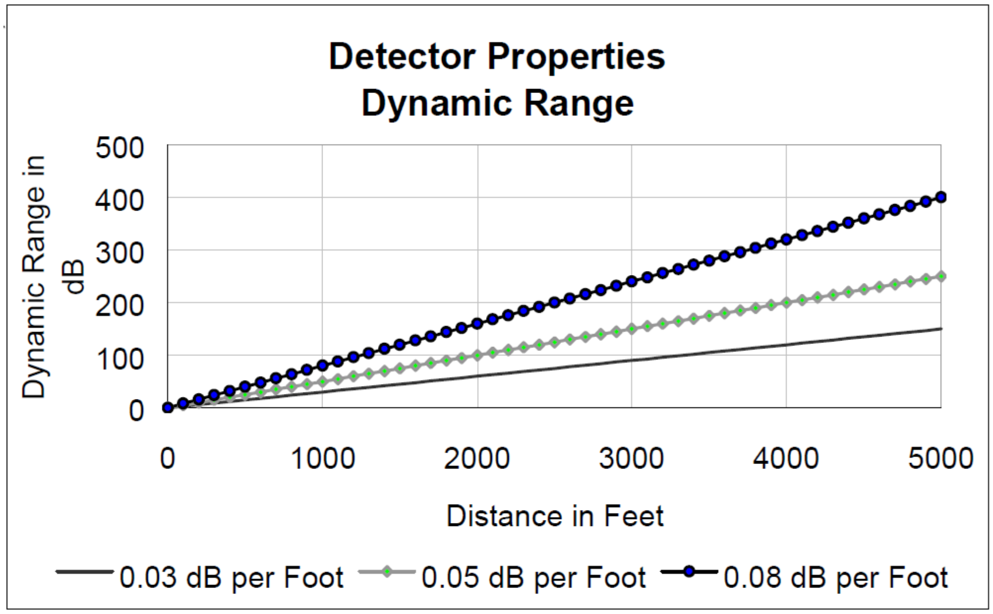


Figure 4.15 Range limitation as a result of attenuation [13]

This information was derived under ideal assumptions based on the data collected by the investigators during the course of the experiment, and it is useful in understanding the dynamic range requirements of a system that measures these vibrations as a function of distance.

- From the experiment, preliminary results demonstrated that train vibrations were detectable above the 'noise baseline' at a range of over 3000 ft, or approximately 0.5 miles.
- It was also found that vibrations levels were relatively higher around turns, possibly due to the increased contact between the lateral side of the rail in addition to the normal vertical contact as a result of the wheel resting on the track's rail.
- Energy levels recorded were greater in front of the train (preceding it), than behind it.

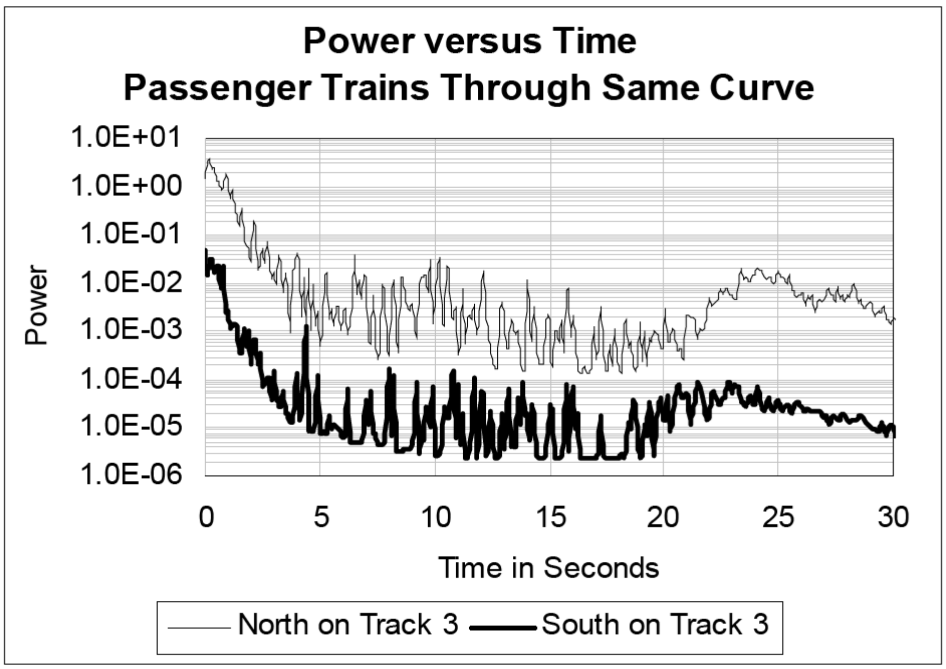


Figure 4.16 Power over time profile [13]

Thus, the analysis of induced mechanical vibrations makes a potentially useful method for train detection purposes. Such mechanisms could be simply be used – in a multi-sensor context, for example – to determine when other sensing devices should be activated to also 'listen' in their particular ways. This would be the most simplistic use of vibrational analysis. A more elaborate approach would implement pattern classification methods, for example, to determine if unique features exist within the vibrational signature to discern and classify the signature as an oncoming train versus false alarms resulting from other non-train related vibrations.

Vibrational analysis also holds promise because it consist, yet, another alternative train detection method where early detection may be desirable (as opposed to approach detection). Provided that the point where the sensing takes place, a continuous rail exists all the way to the oncoming train, such detection mechanisms could be easily exploited. However, as with Time-Domain Reflectometry, the signal attenuation of the mechanical vibration will be heavily attenuated in the presence of jointed rail systems, or even worse, insulated-joint rail systems. In fact, this also was observed in the study (below).

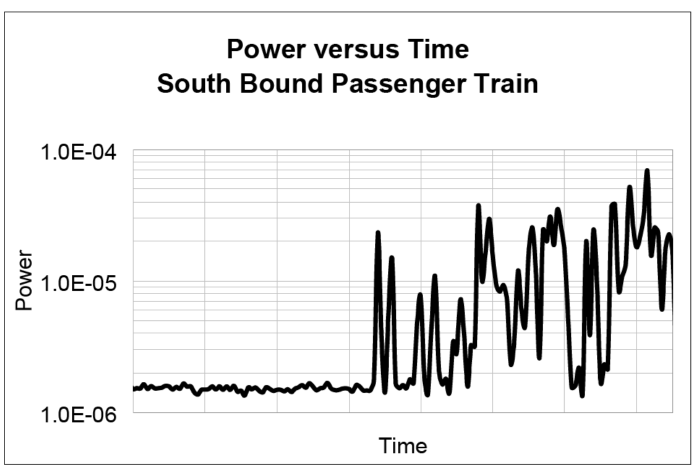


Figure 4.17 Signal cutoff problem as a result of improperly jointed rails [13]

Accelerometers make excellent devices for experimental work in vibration analysis because they are compact, small, inexpensive, and are suitable for frequencies in the 50 to 5kHz range. For lower frequency analysis, seismometers are more suitable as these measure velocity, which is suitable for measuring lower frequency signals. An important technical detail to keep in mind is that a single type of sensor may not be sufficient because of the wide dynamic range in changes of power levels as the vibrational forces increase. This technical detail is effectively illustrated in the below figure, taken from an article in [14]:

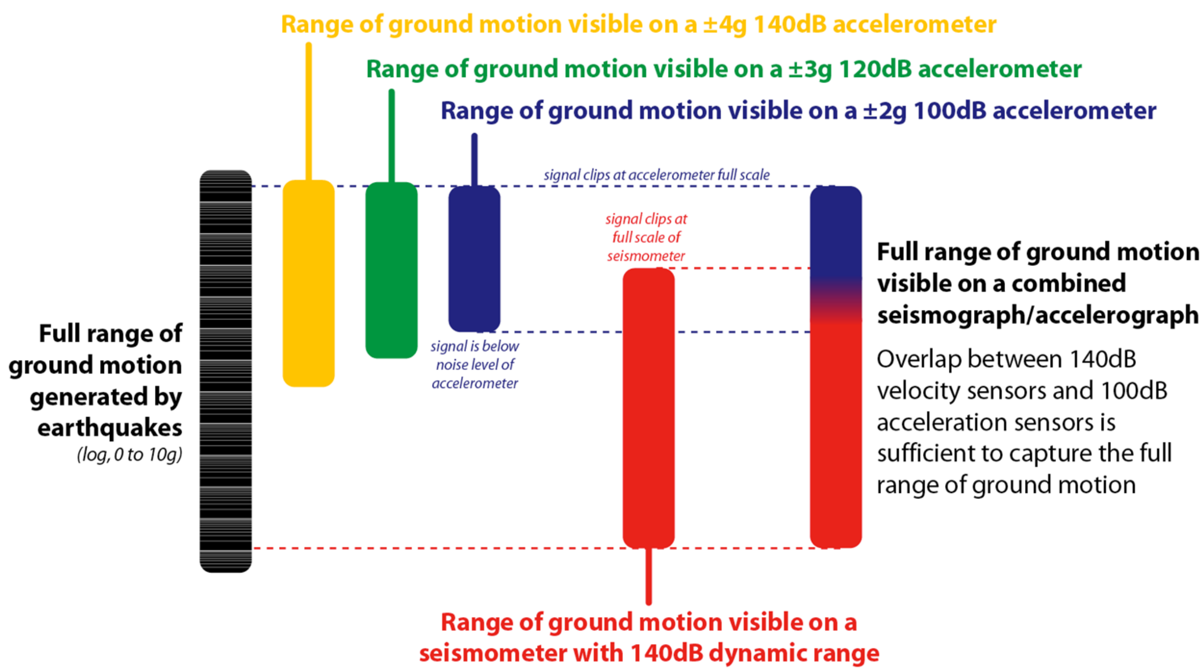


Figure 4.18 Range Comparison of different signal sources [14]

4.7 Radar Technologies

4.7.1 Background

The last category of sensor technologies that can be used for purposes of train detection is the class of radar-based sensors. Radar technology has always been closely associated with vehicular technology, as well as the rail industry, so it makes perfect sense to take a brief look at these for consideration.

Radars operate by emitting a microwave signal onto the air which travels at the speed of light. When this signal hits a metallic object it will bounce back, resulting in a small portion of that signal being picked up by the radar's receiver. Uses of this application include ranging (the determination of an object's distance) as well as speed determination, which can be achieved in various ways (e.g., distance-rate-time formula, or Doppler Effect).

Several varieties of Radar technologies exist:

- **Doppler Radars**: The 'plain-vanilla' Doppler radar is so-called because it uses the Doppler Effect for the determination of an object's radial speed, or velocity, to be exact. Such radars may operate by continuously emitting a microwave signal by a transmitter, with the receiver picking up the reflected signal. These radar types are properly called Continuous-Wave Doppler Radars.

  These types of radars are only good for determining the object's velocity, but not the distance to the object itself because they only see moving objects – not stationary ones, given that they rely strictly on the Doppler Effect. However, that can be a plus in cases where object detection is necessary in the presence of other stationary clutter, as Doppler-type radars.

Another problem with the Continuous-Wave Doppler Radar is that if the object being tracked is moving such that it creates a sufficient phase shift in the emitted frequency of the microwave signal, the signal may fade as a result of destructive interference between the transmitted and reflected waves. It is for this reason the Pulse-Doppler Radar was realized.

- **Pulse-Doppler:** The Pulse-Doppler Radar attempts to overcome some of the limitations of the Continuous-Wave Doppler. Instead of sending a continuous-wave, the radar instead sends short brief coded pulses. Several benefits arise from this approach. First, power savings are realized by the system because the radar device is not continuously active. This also prevents the 'signal cluttering' from the scattering effect that would otherwise overwhelm radar systems from a persistent continuous wave. Second, the radial velocity of the target object can still be determined from the Doppler Effect observed from the received pulse. Third and last, this now provides the radar with ranging capabilities, because the flight-time of the transmitted and received pulse can now be measured, giving the radar the capability to determine its distance-to-target. Consequently, today, when most people liberally speak of Doppler Radars, they are most likely referring to the Pulse-Doppler type.
- One drawback of the Pulse-Doppler is that, for distance-to-target measurements, highly accurate timing electronics are required due to the propagation of the microwave at the speed of light. Thus, an error in timing measurements as much as a microsecond off can result in an error of +/- 300 meters – this is a huge difference, say between an approaching vehicle, and one that has already crossed the intersection. Thus, to overcome

the strict technical requirements of the Pulse-Doppler the Frequency-Modulated Continuous-Wave Radar was developed.

- **Frequency-Modulated Continuous-Wave (FMCW) Radar:** An FMCW Radar, like the Pulse-Doppler is capable of ranging (distance-to-target measurements) as well as radial velocity determination. The velocity determination is easily done through the Doppler Effect, just as with the plain-vanilla Continuous-Wave Doppler. The ranging capability is achieved by frequency-modulating the emitted microwave signal at a known rate. By measuring the frequency of the emitted signal and comparing it against the frequency of the received signal, a distance-to-target measurement can be effectively achieved in a similar fashion to that of the Pulse-Doppler, but without the strict requirements in timing electronics from it.

  FMCW Radars are a perfect match for beam-breaking applications, where the radar signal from the continuous wave can be used as a beam and signal an event when the radar beam is broken by the object of interest. Furthermore, FMCW radars can be paired with a retro-reflective device for this very purpose and aids in extending the maximum ranging capability of the beam.

4.7.2 Usage in Rail Detection Applications

The use of radar technologies for train-detection applications is not new, and the rail industry has and continues to implement them in various ways. In a study outlined in [16], a radar-based train detection device was tested for the activation of Highway-Rail Intersection (HRI) crossings using a three-radar system. In this configuration, two Doppler-type radars pointing in opposite directions (but parallel to the rail track), were used to detect when the oncoming train approached and left the HRI. Shield deflectors were used to guide the microwaves as well as reduce interference from adjacent traffic.

Figure 4.19 Radar installation for approach detection [16]

A third radar – of the FMCW type – looking down onto the track (perpendicular to it) was used to observe the blind spot for the case where the train would stop mid-way for whatever reason. This allowed the system to both see the train entering or leaving the zone in question, but also know if the train remained inside of the zone of interest. Consequently, this system is a perfect example of a system that uses a combination of numerous radar technologies for the purpose of train detection.

Detection by radar technology alone, however can be unreliable. In that particular study, 57% of all radar activations were false positives – that is, out of 3459 train activations, 1973 were false activations. However, all those activations consisting of train activations were successfully detected. Consequently, the problem here was not in showing the use of radar technology for train detection, the problem was in the ability of the system to only detect trains.

Another use of radar technology for train-detection purposes uses the beam-breaking approach, which accomplishes a function similar to the mechanical treadle mechanism. Examples of such usage have been showcased by Banner Engineering, who manufactures a FMCW adjustable-field radar called the "R-Gage" for this particular purpose [16]. The use of FMCW radars in this context is also discussed in the article in [17].

Figure 4.20 Depiction of an R-Gage [17]

They a have a couple product demonstrations videos (posted on *YouTube*) showing the device in action:

- Demonstration of slow and fast response (but not limited beam field adjustment capability): http://www.youtube.com/watch?v=LkI3Qaz7A9s
- Demonstration of response time as well as beam field adjustent capability http://www.youtube.com/watch?v=MvOitLmkCbI&feature=relmfu

What makes radar technology particularly suitable for usage in the train industry is that unlike most sensors, radar technologies have multiple applications, depending on how they are used. For example, they can be used for detecting the presence of an oncoming train. Within this capability, the ability to acquire velocity and distance information (from the sensor) can be gathered. When used in a beam-breaking configuration (such as suggested by Banner Engineering), it can be used as an electronic treadle mechanism and it can also furthermore be used, when use in conjunction with other sensors, to determine the length of the train.

Radar systems are also very robust against environment effects. Their electronics are usually well enclosed, have no precise alignment requirements such as Infra-Red (IR) Beams, and are fairly immune to EMI interference (rain, thunderstorms, snow, wind, dust/dirt accumulation). Finally, since radars react to metallic objects only, these devices are not as prone to interference from cluttering or other sources within its beam field, such as animals, humans, etc. Thus, radar systems make formidable sensor technologies for application of train-detection as well as implementation for solving other types of common vehicular problems. The only real limitation is that their usage must be carefully considered – for example, detection of an oncoming train will require a direct Line-of-Sight (LOS) with the target. Furthermore, their maximum ranging distance for most commercial units is only a few hundred meters, or even less than that (e.g., less than 50 meters), which limits their applicability when used entirely by themselves. However, when combined with other sensor technologies, it makes a formidable option.

4.8 Recommended Sensor Selection for the Multisensory Train Approach Detection System

Looking at the tables, and as a result of this research survey, it is believed that a suitable set of sensing technologies make a potentially viable fit for implementation into our proposed train approach detection project. The sensors recommended for further investigation have been chosen as such because these are suitable devices with the potential to achieve a system that provides early warning of an oncoming train by application of early detection. These sensing devices and methods are:

- Seismic/Vibrational Analysis through the use of accelerometer-type sensors.
- Localization (or presence) detection of a train through Time-Domain Reflectometry (TDR).
- Application of radar technologies for velocity and/or occupancy determination of oncoming trains, which can also include the determination of train length.

The manner in which these devices will be used together for the safety mechanism are numerous and will form part of the in-depth technical research that is planned as a result of the findings summarized in this research survey report.

One last notable mention is the Anisotropic Magneto-Resistive (AMR) sensor, which, with its unique ability to pick up repeatable and discernible magnetic signatures, presents some potentially interesting uses with endowing the ability of a system to 'finger-print' rail cars, for example, and to keep track of them using this approach.

Chapter 5 System Component Selection for Prototype

Having performed the initial research survey, and having furthermore chosen the train detection technologies and methods for further exploration into the multi-sensor system, the next phase consisted of a suitable selection of devices to achieve the above tasks. These devices were chosen primarily to design and realize a system that would serve as a proof-of-concept for further exploration. Thus, it was important for this first execution phase that the components of choice were suitable for performing preliminary tests (and corresponding measurements), and furthermore that such tests can be performed at low-cost with minimal monetary investment. The goal here is for the proof-of-concept system to aid us in determining if the project and its multi-sensor system demands further exploration into the next phase, or if the project should be abandoned. The selection of these devices also included finding a suitable low-cost data acquisition system (DAQ) for data collection purposes, as this is the ultimate goal for the construction and realization of this first-stage proof-of-concept system: mainly to collect data, analyze it, and see how its features can be leveraged for train detection and classification tasks. Nothing further can be ascertained until this stage is successfully completed.

Thus, what follows now is a brief detailed description of the chosen devices, providing motivation for their choosing as well as how these devices fit into the proof-of-concept system, including a discussion of the chosen low-cost data acquisition system for data collection purposes.

5.1 Analysis of Induced Mechanical Vibrations with Accelerometers

The first device chosen will be used specifically to measure the mechanical rail vibrations induced by the locomotive and its railcars. For this, the CTC AC216 accelerometer (shown below) has been chosen for this task. This is an analog internal electronics piezoelectric accelerometer (also called IEPE) for measurement of rapid vibrations with g-forces up to ±80g and a sensitivity tolerance of ±5% at 100mV/g.

Figure 5.1 AC216 Analog IEPE Accelerometer

The device has a relatively flat frequency response up to 7kHz (at ±5% tolerance) and up to 10kHz (at ±10% tolerance), which is a desirable characteristic given that we will be collecting real-time data that may span the entire audio spectrum. We estimate, however, that the spectrum of interest will be focused in the 0 to 5kHz, which is known to consist of both broadband as well as narrowband frequency components. It operates from a voltage source of 18 to 30VDC with a constant current source that can be set anywhere between 2 to 10mA.

The intended usage for this device will be to measure and record the train-induced mechanical vibrations in to the data acquisition system for further analysis. In the simplest case, the accelerometer signals from oncoming locomotives could be used to 'wake up' the rest of the system to make it aware of an oncoming train. In the more sophisticated case, signal processing and pattern matching techniques could be applied to determine if the vibratory signatures correspond to that of an oncoming train as opposed to other sources of vibration that are non-train related.

5.2 Proximity Sensors with Ultrasonic Distance Sensors

The next device has been chosen to fulfill or stand in for what ultimately represents a device to operate in the form of a beam-breaking configuration. As previously discussed, this device can be anything from an inexpensive infra-red (IR) sensor beam, to a sophisticated frequency-modulated continuous-wave (FMCW) radar. For this task, however—and as a preliminary proof-of-concept—we have chosen the MaxBotix weather-resistant precision ultrasonic range finder, model MB7386.

Figure 5.2 MaxBotix Ultrasonic Range Finder

This compact sensor, which is approximately 3” in length, uses ultrasonic waves to measure distances to objects within its field-of-view up to 10 meters away with a resolution of 1mm and it can operate easily from a 5V supply, drawing around 3mA, which is not much.

It provides simultaneous output measurement signals, which include: Serial TTL (or RS232, depending on the model), a digital PWM signal whose pulse-width is proportional to the distance-to-target measurement, and an analog voltage signal with a sensitivity of ‘Vcc/10240’ volts/mm with a resolution of 5mm.

Ultrasonic ranging sensors are commonly used in robotics applications for object detection. Consequently, we wish to employ this ultrasonic sensor in our proof-of-concept system to detect when a train reaches a particular point along the track where the ultrasonic sensor is positioned. This can be used as further confirmation for train detection, augmenting the use of the accelerometer sensors, or to further alert other sensor devices down the track. The device is weather resistant, relatively inexpensive, and simple to use. Its multiple-output options allow us to easily interface this with an analog channel of a data acquisition system, but easily integrate this with a microcontroller device as part of an embedded controller system in the more sophisticated case.

5.3 Measuring Magnetic Anomaly with Anisotropic Magneto-Resistive Magnetometers

Another sensor technology we wish to employ in our proof-of-concept system is the use of anisotropic magneto-resistive (AMR) magnetometers using off-the-shelf components manufactured by Honeywell®. These parts are the HMC1002 (dual-axis) and HMC1001 (single-axis) magnetometers, which provide a ±2 gauss dynamic range of 3.2mV/Vcc/gauss. They operate from 5VDC and as depicted below, they are available in surface-mount components.

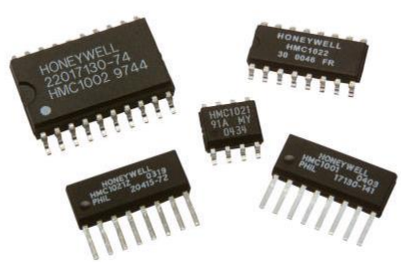


Figure 5.3 Honeywell’s ® line of AMR, chip-based magnetometers.

Our strategy here is to design a custom 3-axis magnetometer solution by providing the necessary signal conditioning and analog output signals to maximize the dynamic range of the selected data acquisition system. Honeywell® provides extensive literature and technical reference documents surrounding their magnetometer components that greatly aid design engineers in realizing a custom magnetometer-based solution. While Honeywell® does offer complete “off-the-shelf ready” digital and analog evaluation units, these are very costly for our initial goals. A custom design solution would permit us the freedom to accommodate our specific design needs from concept to realization.

5.4 Train Detection through Time-Domain Reflectometry (TDR)

The approach regarding train detection using time-domain reflectometry (TDR) is still under review given some of the technical challenges that need to be overcome. These challenges include the precise technical and engineering approach of TDR for train detection as well as technical challenges that may impede the use of TDR due to various environmental conditions that contribute to parasitic and considerable conductance between the track rails as a result of moisture in the track ballast, tie/sleeper conductance, as well as conductance from rain and snow accumulation between the rails, which, provided a solution is found to circumvent these issues, the TDR mechanism is very likely to be complex in the context of the other three detection methods: accelerometer, magnetometer, and proximity/beam-braking.

5.5 Data Acquisition System (DAQ) for Data Gathering

The last component selection surrounds the data acquisition system (DAQ) itself, which will be needed to simultaneously digitally acquire and record continuous data from all three analog sensors (accelerometer, proximity, and magnetometer) for further analysis. To achieve this task, we have chosen the USB-6009 data acquisition system from National Instruments, pictured in figure 5.4.

Figure 5.4 National Instruments USB-6009, low-cost Data Acquisition System

This device provides eight analog inputs (8 in single-ended mode/4 in differential mode) with the differential mode supporting a variety of voltage scale ranges that can be captured at a sample rate of 48kS/s at 14-bit resolution, which is sufficient for the frequency spectrum we expect to observe across all sensor groups previously discussed.

The software comes with the 'lite edition' of *LabVIEW SignalExpress* (called 'SignalExpress LE') and is designed to work with the entire LabVIEW software suite from National Instruments thanks to the NI-DAQmx driver. Because of this industry-standard driver, we also have the ability to operate and make use of this data acquisition system with MATLAB's ® SIMULINK software either as a primary software analysis tool, or as backup software should the primary software from LabVIEW be found unsuitable for our needs.

Note: ‘LabVIEW’, ‘SignalExpress’ and ‘NI-DAQmx’ are trademarks of National Instruments. ‘MATLAB’ and ‘SIMULINK’ are registered trademarks of MathWorks, Inc.

The system also provides a +5VDC with 200mA output capability, which we hope will accommodate the power supply needs for all three sensors with the help of some power conditioning and DC-DC regulation (i.e., up-converters or boost switching regulators).

Chapter 6 Evaluating the Initial Prototype System

Having decided on the detection methods and the corresponding devices for employment into the proof-of-concept system, the next task was in functionally characterizing all of these devices, including the data acquisition system itself. This was accomplished by devising a series of functional and characterization tests meant to verify the specifications claimed by their vendors, but to also establish a starting point with regard to data collection purposes and to gain experience in utilizing the sensing devices to their full potential.

These tests were also designed to help us uncover any potential pitfalls or design revision requirements that might arise in the process. In addition, the tasks performed in these stages aided us in setting up the data acquisition platform that would be effectively used for data collection purposes throughout the following quarters.

6.1 DAQ/MATLAB/SIMULINK Test Bench Setup

The first task in the device testing process was in setting up the bench-test configuration that would be used for the collection of data of all the sensors discussed thus far. Thus, it consisted of setting up the chosen data acquisition system (i.e., the National Instruments USB-6009 system) and configure it to be used in conjunction with the chosen software component to control it.

For the software component we chose to use the MATLAB simulation software. This numerical analysis tool is extensively used in engineering research and academia. It contains a component called SIMULINK, which is a block diagram environment for multi-domain simulation and model-based design. Because the NI DAQ system provides an industry-standard driver called NI-DAQmx, MATLAB is able is able to control this device via SIMULINK using the data acquisition toolbox. The following image illustrates the SIMULINK project model used for interfacing with the NI USB-6009 DAQ system.

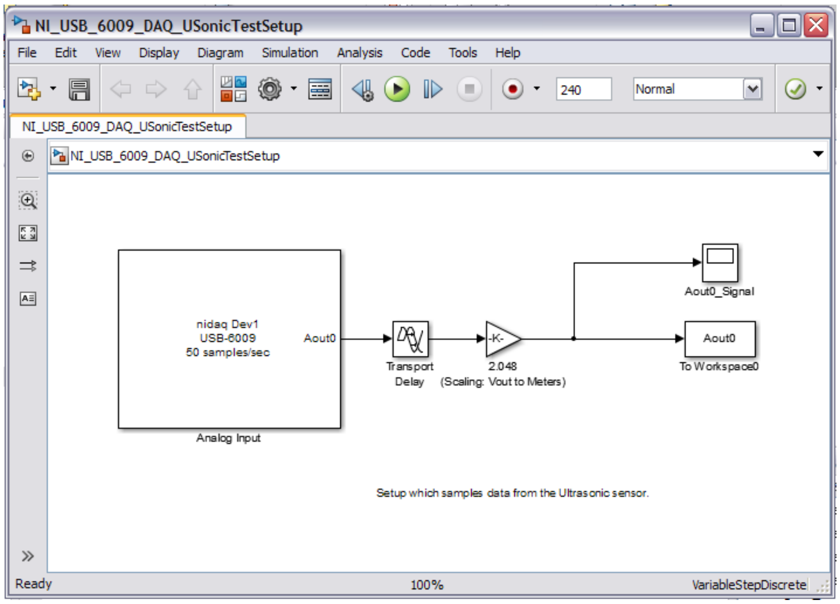


Figure 6.1 Screen capture of MATLAB/SIMULINK Setup for NI-DAQ USB-6009

The above figure shows the traditional MATLAB/SIMULINK model configuration used for most of the tests performed in characterizing each of the sensors and for which data was collected. While the above figure was specific to the ultrasonic setup configuration, a similar configuration was applied for all other sensor variants. That is, there was a source block consisting of the DAQ system a sink block for visualizing data ("Scope") and a sink block for saving this data into a workspace variable. Anything in between these components was for scaling the data accordingly, while the main goal was simply to log data.

6.2 Amplitude Characterization of the DAQ System

The first task, having setup the MATLAB/SIMULINK/DAQ system, was on characterizing the DAQ system itself. There were two key questions we wanted to verify against the manufacturer's claimed specifications:

- The absolute worst accuracy of the device.
- The absolute worst frequency response of the device.

Consequently, the first task was in measuring the absolute accuracy of the device. During the characterization of this phase, a sine wave at 100Hz was applied to the NI DAQ system with an amplitude set to 10mV, which was the smallest [immediately] available voltage level from our present lab equipment here at the University of Nebraska's electronics labs at the Peter Kiewit Institute.

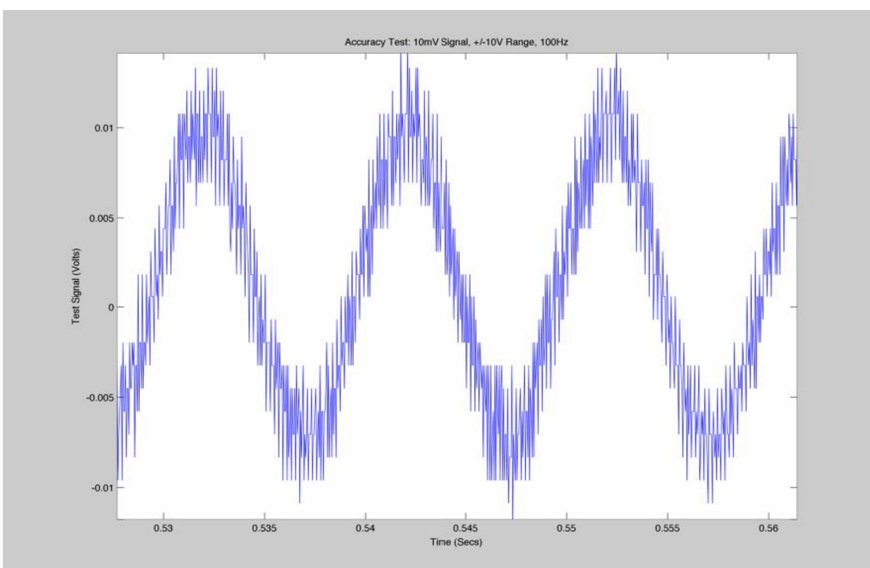


Figure 6.2 DAQ System Absolute Accuracy Test with 100Hz wave 10mV set at +/-10V range

This waveform was applied to the inputs of the DAQ system configured as differential mode. Data was then collected and recorded at various voltage range scales (for the DAQ), which were 10V, 5V and 2V respectively. The figures show the results:

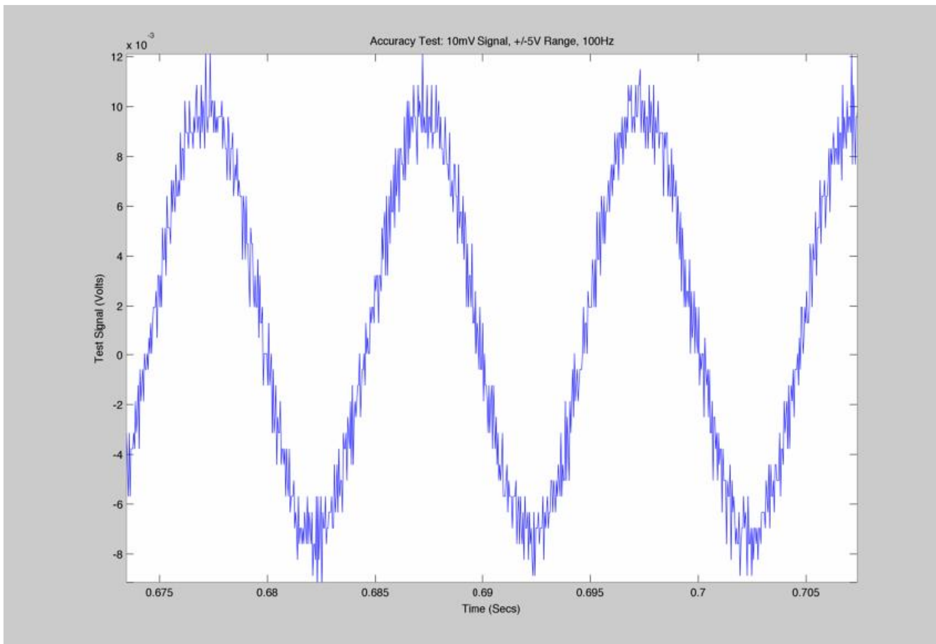


Figure 6.3 DAQ System Absolute Accuracy Test with 100Hz wave 10mV, set at +/-5V range

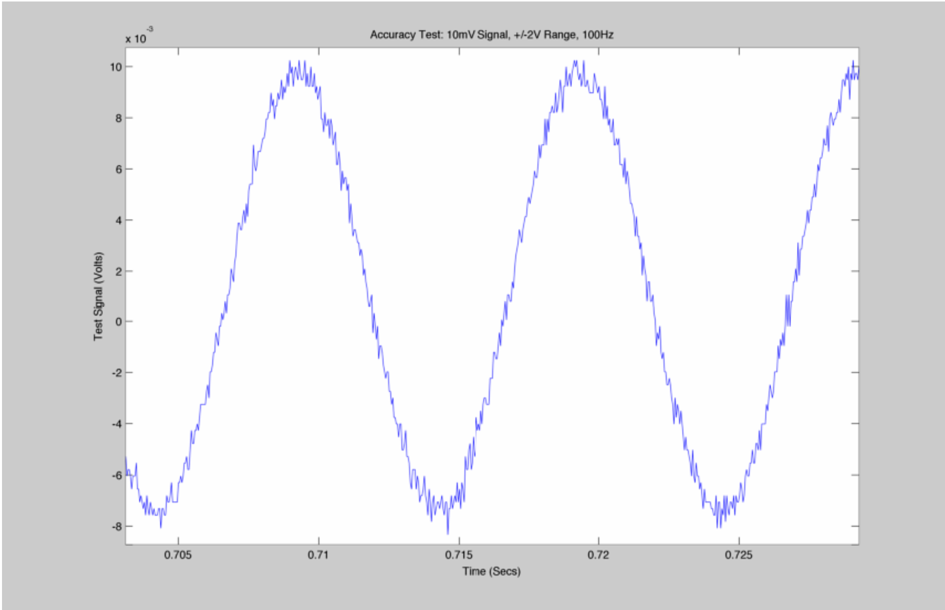


Figure 6.4 DAQ System Absolute Accuracy Test with 100Hz wave 10mV, set at +/-2V range

What we can observe from the previous three figures is how the absolute accuracy improves as the measurement range of the DAQ system is lowered from 10V, 5V, and 2V respectively. For the 10V range, the absolute accuracy using full-scale differential mode was around 6.5mV (on average). This agreed with the manufacturer's claimed specifications for this range, which is rated at 7.73mV. Furthermore, looking at the 2V range, the absolute accuracy using full-scale differential mode was around 1.5mV. This also agreed with the manufacturer's rated specifications, which was 2.21mV.

Thus, the conclusion from the characterization for this series of tests with regard to absolute accuracy is that not only did the DAQ met the manufacturer's stated specifications, but it even exceeded them by a small margin. This means that at +/-2V range, for example, we are capable of measuring signals as small as approximately 4mVpp and getting a fairly discernible signal that can be easily analyzed and filtered from this noise.

6.3 Frequency Characterization of the DAQ System

Having characterized the absolute accuracy of the DAQ system, the next step was on determining the frequency response of the DAQ system. The primary motivation here is that two of the selected sensor technologies (i.e., the accelerometer and magnetometer devices) can potentially produce signals that are wide bandwidth (anywhere between 0 Hz to 10kHz). The DAQ system is specified at providing 48kS/s (Samples per second), and we wanted to see – especially in regard to the Nyquist sampling criterion – how this specification translates in practice. Thus, to perform this test we applied a sinusoidal signal of 1Vpp at various frequencies of 200Hz, 400Hz, 2kHz, 4kHz and 8kHz. These results are showcased in the following figures:

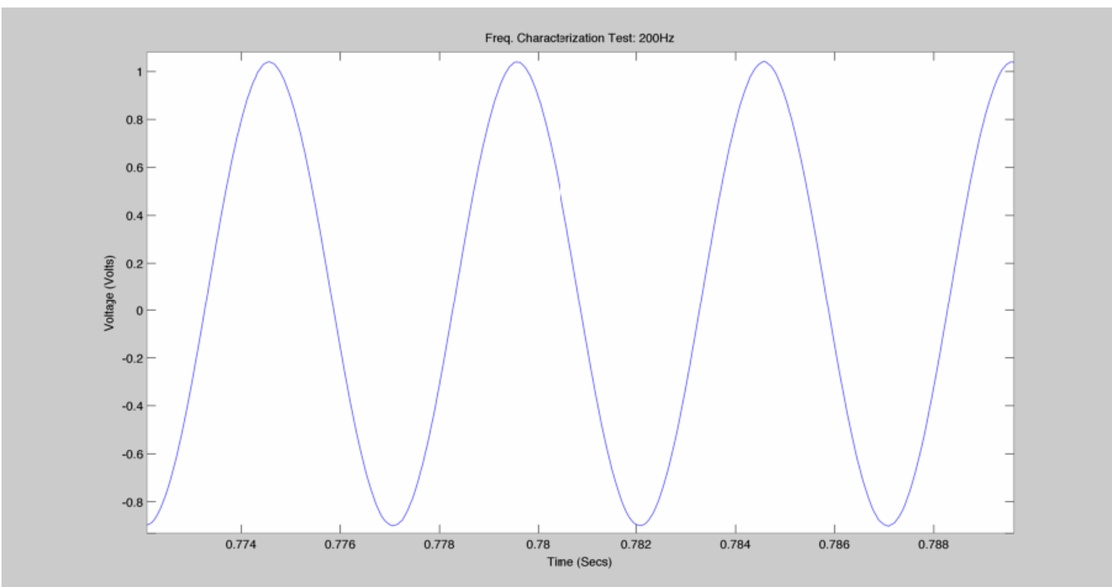


Figure 6.5 DAQ System Frequency Response Test w/ 200Hz Signal, 1V peak

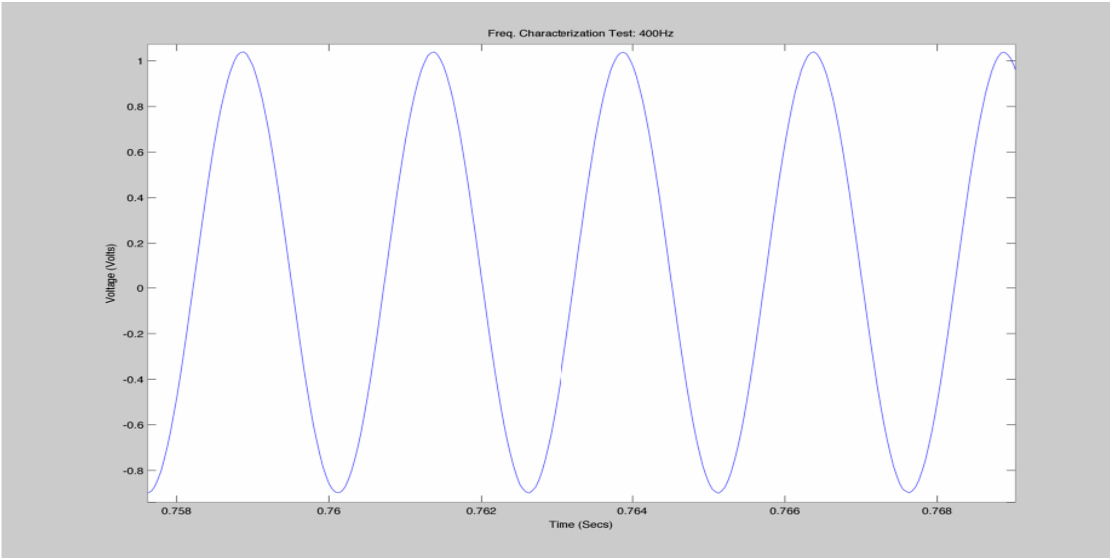


Figure 6.6 DAQ System Frequency Response Test w/ 400Hz Signal, 1V peak

Thus far, the above two figures show a fairly good reproduction of the original signal. This is to be expected, as we are well below the Nyquist criterion frequency. However, the following figure shows what happens as we move to higher frequencies in the kilohertz range.

It is clear that at higher frequencies the signal's definition begins to degrade. An important lesson to gather from this experiment is that while the Nyquist criterion states that for proper signal reproduction one should sample at twice the frequency of the original component, note that this is only true from a mathematical perspective. That is, this criterion, which is properly called the sampling theorem is a necessary condition to avoid what is referred to as aliasing. However, this condition by itself is not sufficient for properly reproducing the original signal with a high degree of definition. Intuition would lead one to believe by Nyquist criterion alone that we can sample at 24kHz because the DAQ system is capable of up to 48kS/s. But clearly, signal definition is heavily degraded even at 8kHz. This is a factor of “6,” which is much greater than a factor of “2.” This is a key observation from performing this particular characterization test.

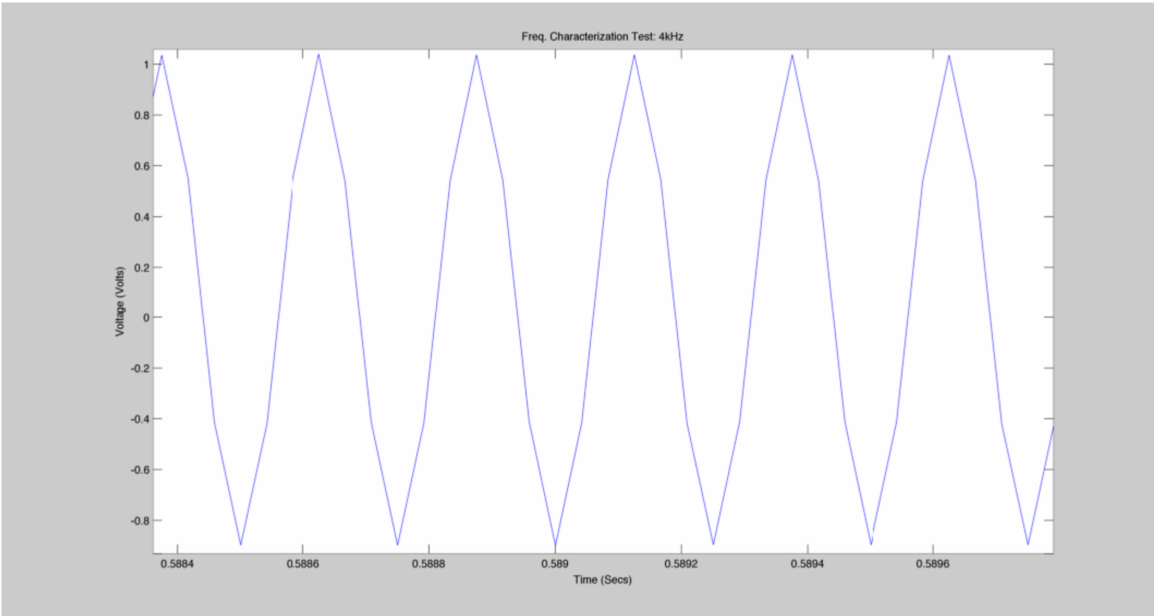


Figure 6.7 DAQ System Frequency Response Test w/ 4kHz Signal, 1V peak

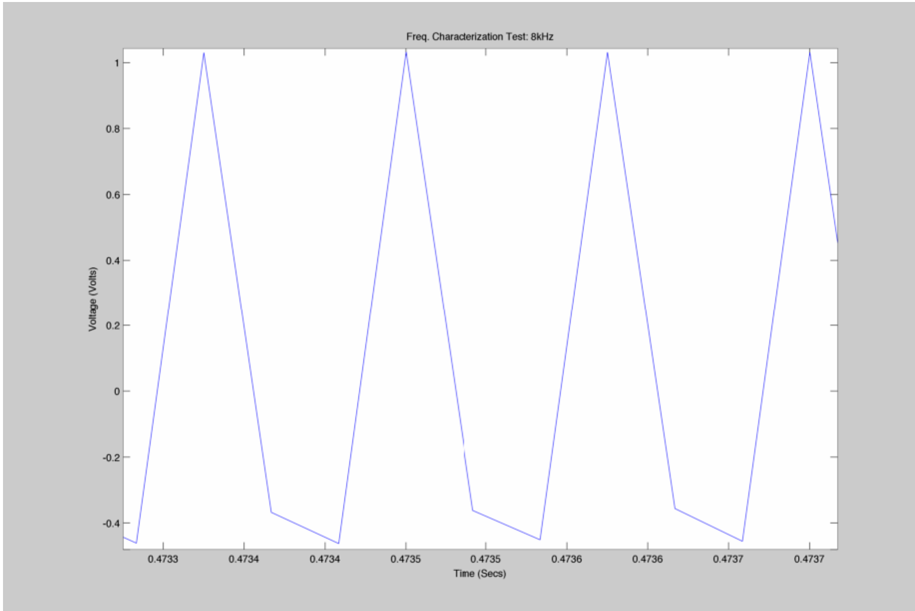


Figure 6.8 DAQ System Frequency Response Test w/ 8kHz Signal, 1V peak

6.4 Characterization of the Ultrasonic Sensor

Having successfully completed the testing and characterization of the data acquisition system itself, the next step was to characterize the ultrasonic sensor itself. As discussed in the previous quarter's report, we chose to use the MaxBotix ultrasonic ranging sensor. This sensor provides multiple output options in both digital and analog form. For this characterization setup, we simply connected the analog output of the sensor directly to the NI-DAQ acquisition system. Because the DAQ system provides a 5VDC output supply, we were able to use this to power the analog sensor.

When operated in this manner, the sensor is operating in what is called free-running mode. In this mode, the ultrasonic sensor is continuously ranging and detecting objects at a rate of 1.5Hz. The analog output voltage is proportional to the distance. This voltage can then be converted to a distance in meters based on the equation given by the following equation:

$$d_m = 2.048 \cdot V_{out}, \text{ when Vcc} = 5V \quad (6.1)$$

The figure below shows a photo taken of the setup produced to characterize the ultrasonic sensor. Phono jacks were used to provide power (i.e., 5VDC) supplied from the DAQ system to the ultrasonic sensor, and another one for acquiring the analog signal output to one of the analog inputs of the DAQ system.

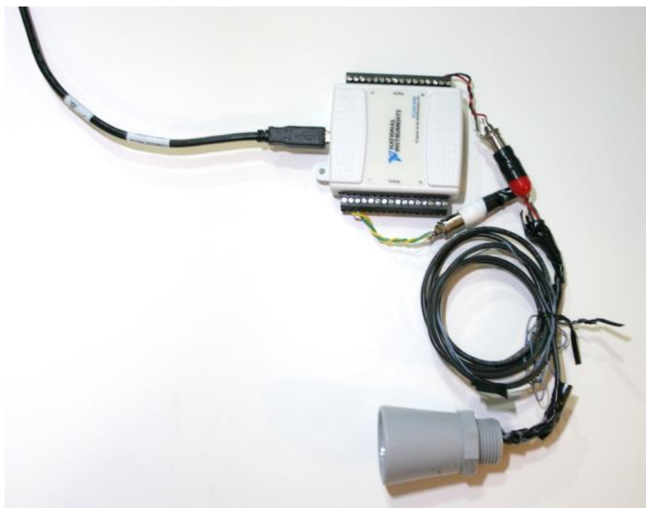


Figure 6.9 Ultrasonic/DAQ Setup

It should also be noted the DAQ system is connected to a laptop running MATLAB/SIMULINK via USB.

6.5 Indoor Tests: PKI Lab

Some of the early tests were performed indoors in a lab setting in room PKI-311 at the Peter Kiewit Institute (PKI) of the University of Nebraska. During this testing phase, the sensor was in the middle of a room, mounted on a tripod, and pointed directly at a wall. The figure below shows the collected data from this experiment.

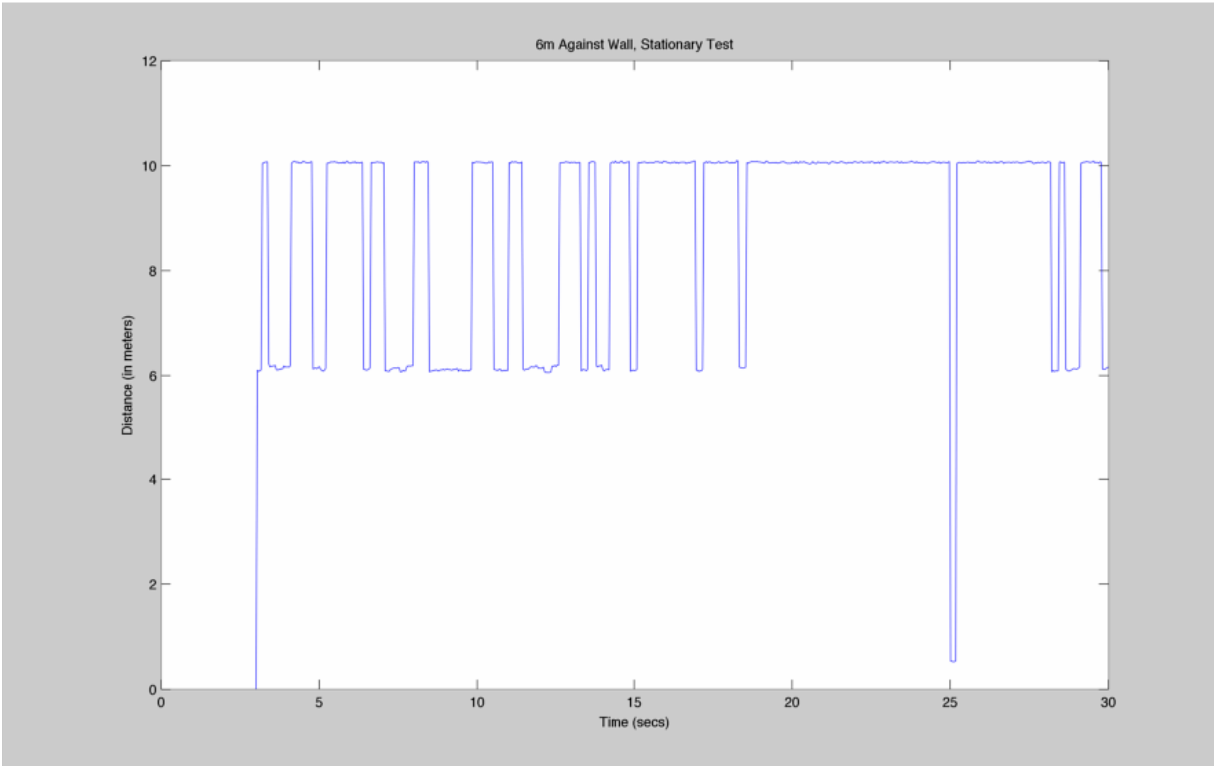


Figure 6.10 Ultrasonic stationary test (indoor), 6m from wall

It can be observed that the ultrasonic readings were intermittent. Notice that the 6m target wall is indeed being picked up (as pointed to by the arrow), but that for unknown reasons the readings would jump between actual distance and maximum distance of 10m. Other indoor tests demonstrated similar behavior.

One possible reason for the observed readings could be from a back-scattering effect of using an ultrasonic sensor designed for large, outdoor object detection in an indoor setting. In another similar test, the sensor was slowly pulled away from the wall, for about a meter. This can be observed in the figure shown below, in which the arrow points to the starting point of this event.

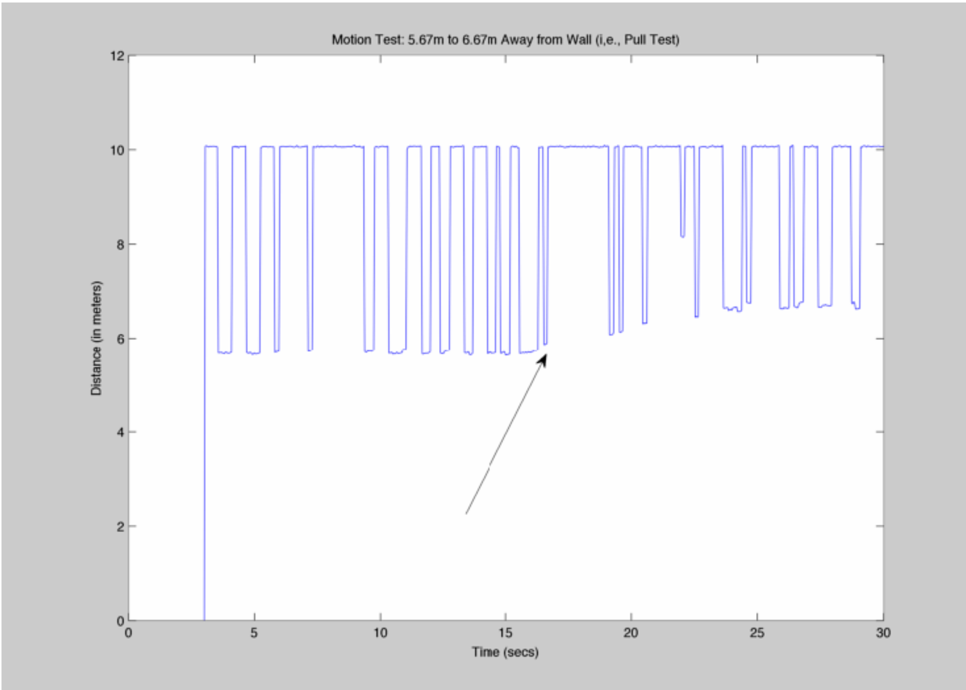


Figure 6.11 Ultrasonic indoor pull test 5.67m to 6.67m

The arrow points to the point in time when the "pulling away" is being done. Once again, the reader should observe the sensor's ability to pick up this event taking place. However, as before, it is intermittent, with the readings jumping back and forth between actual data and max distance [by the sensor].

<u>6.6 Outdoor Tests: PKI Parking Lot</u>

The ultrasonic indoor tests were followed by outdoor testing. This was necessary to characterize the sensor in the setting that it was designed for, as claimed by the manufacturer of the device. For the first round of tests, we focused on a large, box-like, generator structure outside of our lab's building, pictured on the right. Note that this image is for reference only and does not represent the actual structure we used. However its smooth surface walls and scale are of similar nature.

Figure 6.12 Structure used in outdoor tests to simulate the size and scale of a passing train

The key idea behind the use of this structure in our tests is that its size and shape approximate that of an actual railcar or locomotive in scale. This allowed us to get a feel for the performance of the sensor in similar conditions.

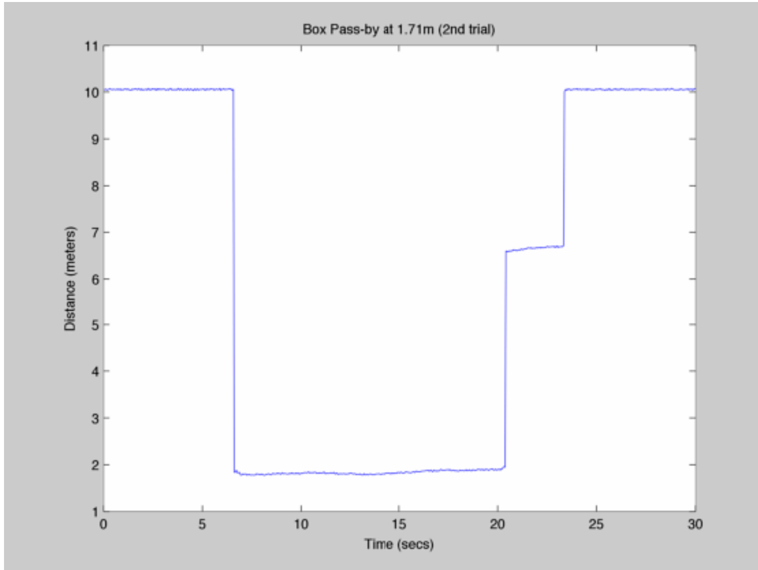


Figure 6.13 Ultrasonic outdoor test, using simulated railcar structure on PKI parking lot

One of the tests consisted of us holding the ultrasonic sensor at a fixed distance and height from the above structure and walking past it, simulating a rail car pass-by. The data collected is seen in the next figure.

It can be observed in the figure that unlike the indoor tests performed at the PKI lab, these readings were much more stable and consistent. Notice that at around 6 seconds, the structure is “picked up” by the ultrasonic at about 2 meters. Notice, the stair-like effect at about 20 seconds. This is the result of the sensor picking up a second structure that was behind the first one, at a distance of almost 7 meters away. The result of these outdoor tests matched our expectations much better.

Some additional tests performed included determining the incidence angle formed between the ultrasonic sensor and the surface normal of the structure being tracked. During this test it was consistently found that the ultrasonic sensor could track an object's distance so long as the angle was less than 35 degrees on average. It did not matter whether this angle was varied in a horizontal fashion, or vertically.

6.7 Outdoor Tests: RailsWest Railroad Museum

Having observed generally positive results from the outdoor tests performed at the PKI building, we obtained permission to perform additional tests at the RailsWest Railroad Museum located in Council Bluffs, Iowa. The museum contains a few outdoor railcars where we could repeat the previous outdoor experiments and measure data by simulating the passing by of a low-speed train by moving the sensor past each railcar while the railcar itself remained stationary. See the figure below.

Figure 6.14 Jose Santos and Pradhumna Shrestha, Ph.D. students, performing various field tests using the ultrasonic sensor at the RailsWest Railroad Museum in Council Bluffs, Iowa

At the RailsWest museum, various tests were performed whereby the sensor was moved past each railcar at numerous distances and heights. This also included seeing how low to the ground and at what angles the sensors could be used while reliably being able to still track the rail car. For example, the above figure shows the data collected by the ultrasonic by doing a walking pass at approximately 1.5m distance and a height of 5 feet, pointed strait at the railcars.

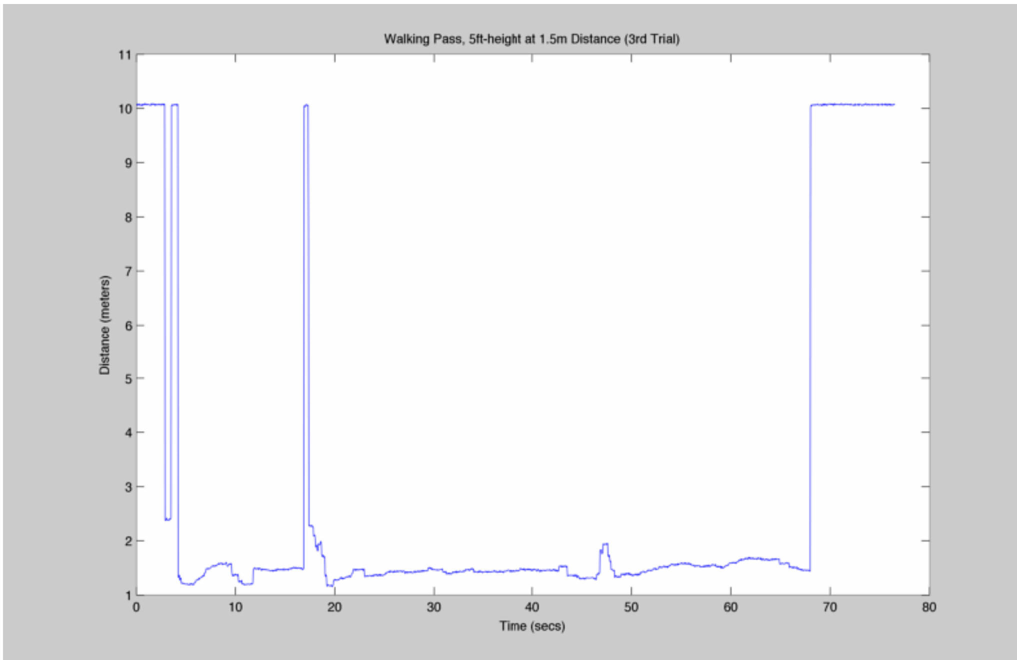


Figure 6.15 Ultrasonic outdoor test at RailsWest; walking pass at 1.5m distance and 5 feet height

Once again we see more consistent results than compared to the sporadic indoor test readings that were observed. Notice in the previous figure there are some slight increases in distance such as that observed in the time interval of 15 to 20 seconds, and again in the time interval between 45 to 50 seconds, which represented the gaps between each rail car.

The below figure shows the same experiment, but this time while doing a “running pass”. That is, we ran past the train while holding the ultrasonic sensor at a fixed distance and height.

Once again, it can be observed the sensor readings being much more stable even under such circumstances.

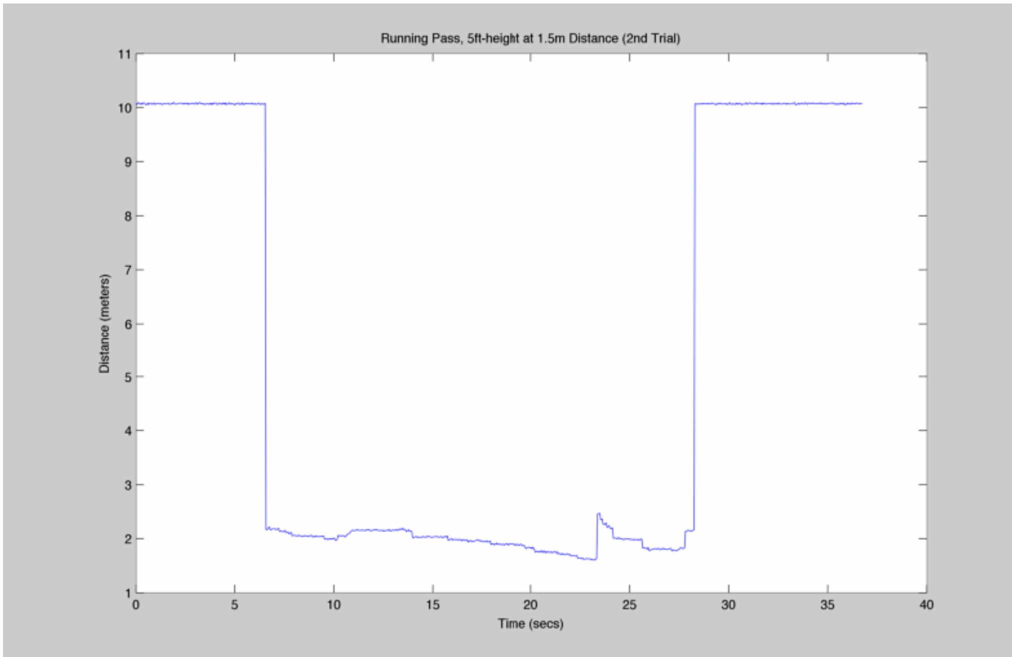


Figure 6.16 Ultrasonic outdoor test at RailsWest, running pass at 1.5m distance and 5 feet height

Another important test performed was determining how low we could set the sensor with a proper angle, aimed at the rail car to determine if the ultrasonic still was able to track objects. As can be seen from the figures shown below, the results were mixed. The first figure represents one of the best passes obtained during that particular test set, with the sensor at about a foot of height, held at a distance of 0.5m, and angled at 45-degrees upwards aimed at each railcar. The test shows the sensor was able to indeed pick up the rail car, but it would have occasional jumps in the process. While somewhat successful, the obtained test result is not quite as clean as when the sensor is aimed perpendicular to the surface of the rail car.

Note that the second attempt shows a little more instability between actual distance and maximum distance.

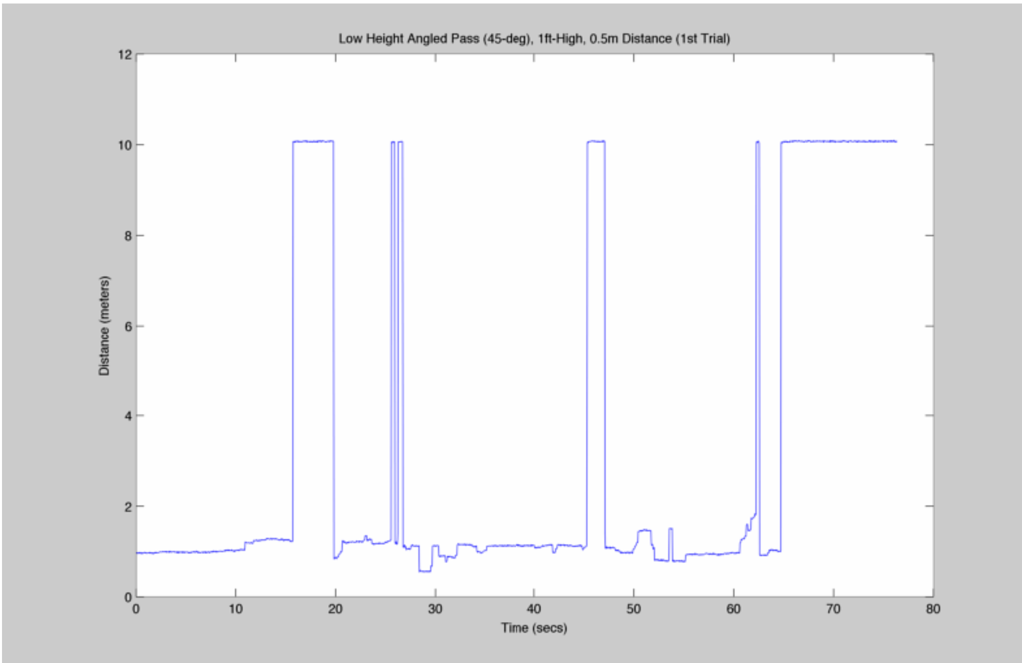


Figure 6.17 Low-height walking pass, at 45-degrees looking up; 0.5m distance, 1ft height (first attempt)

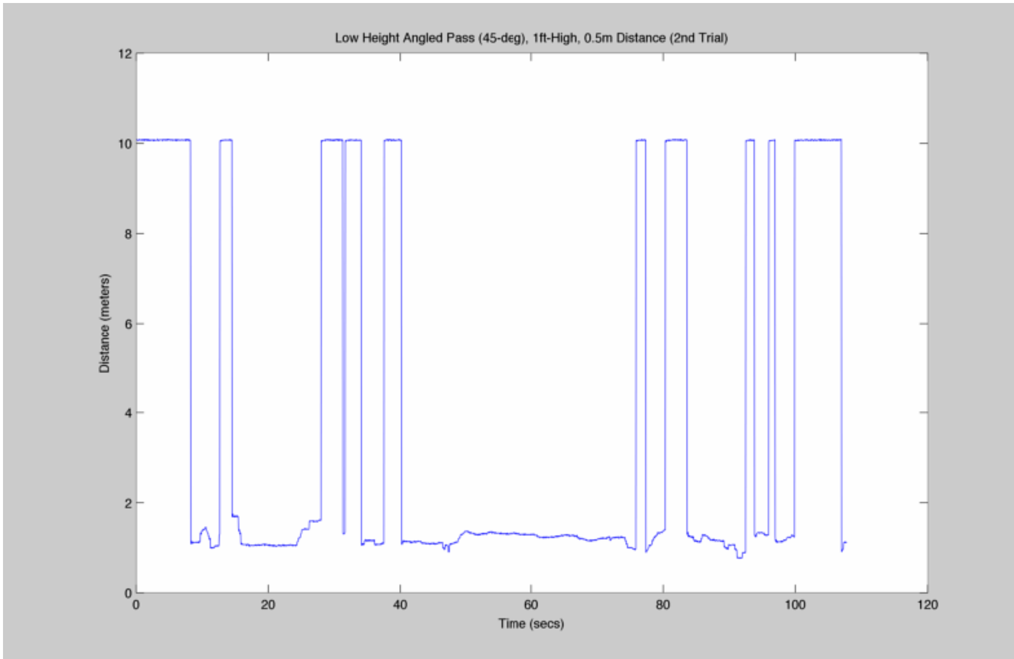


Figure 6.18 Low-height walking pass, at 45-degrees looking up; 0.5m distance, 1ft height (second attempt)

These tests clearly demonstrate the feasibility of using the proximity sensor for train detection. It also shows that there are some irregularities in the sensor reading. This effect is the reason for utilizing multi-sensor approaches in this project – to overcome the inaccuracies and discrepancies in sensor readings obtained from a single source. We are currently in the process of evaluating the sensor data obtained from our tests using the accelerometer. This data will be included in the following quarter's report, together with the results from the planned multi-sensor train detection algorithm work.

Chapter 7 Field Test at TTCI of the Prototype System

With the unexpected and very welcome opportunity to test our train approach detection system and the individual sensors at the Transportation Technology Center, Inc. in Pueblo, CO our planned activities during the summer of 2013 had to be rearranged.

In the first few weeks after receiving news of this opportunity, we began the process of test planning and arranging the equipment to be deployed, packaging for a more ruggedized system unit that could be deployed on actual railroad tracks, with data acquisition and power supply units protected from the elements for prolonged test operation.

These preparations were then put to the test at the RailsWest Museum in Council Bluffs, IA. It showed that the system setup was suitable for deployment at TTCI and also afforded us the opportunity for additional data collection from our sensors.

With all of our devices, test equipment, etc. ready for the trip to TTCI, we were ready to head to Pueblo, CO in late August 2013. We spent two days at the TTCI facilities.

We were provided with a train that consisted of two locomotives, 36 hopper railcars, and 1 caboose. The tests were conducted on a 9 mile test circuit. On a segment of this track we deployed our train approach detection system. The train then began its rounds around the test track, passing by our test site repeatedly at various test speeds. These test speeds were chosen as 15 mph, 30 mph, and 45 mph.

The following photographs show some of the impressions from our tests at TTCI. The first several shots are from our test train.

Figure 7.1 Test train at TTCI (from a distance, and up close)

Figure 7.2 Testing extended well into the night

These next several photographs illustrate the test deployment of our sensor suite and data acquisition setup. The tripods are equipped with ultrasonic rangefinder sensors and camera sensors for train approach detection and timing. On the side of the rail we also attached two accelerometers using neodymium magnets, for easy and secure attachment without welding or lengthy installation procedures.

Figure 7.3 Our test setup for the proximity and accelerometer sensors

Figure 7.4 The test measurement enclosure, with the accelerometer visible attached to the rail

The enclosure houses the data acquisition module. It also performs the duties of an analog to digital signal converter, as well as provides the power and signal conditioning circuitry for the sensor. The cable leading out of the enclosure is a USB connection to the data acquisition laptop for recording of the sampled data. One of our team's students is shown near the sensor attached to the rail, while another student monitors the data acquisition at the laptops.

Figure 7.5 A long day of test monitoring

The tests continued until late into the night.

Figure 7.6 Night time at TTCI

We would once again like to take the opportunity to thank the Federal Railroad Administration, the Association of American Railroads, as well as TTCI for giving us this opportunity. We would also like to thank the Mid-America Transportation Center (MATC) and Union Pacific for supporting this project and our research efforts.

Figure 7.7 Group photo of TTCI staff and the TEL team

Chapter 8 Evaluation and Processing of the Data Recorded at TTCI

One of the primary objectives for this phase of the project was the processing of all the raw data we collected during our field tests at TTCI. Using signal analysis and signal processing, we have post-processed the results to obtain some meaningful insights from them. Some of these results have been accepted for publication in the Proceedings of the Joint Rail Conference, 2014.

8.1 Proximity Sensor

This sensor type is one of several planned for our system. It is currently integrated into our prototype and was utilized in the tests at TTCI. It was positioned next to the track and was directed perpendicular to the track, such that a passing train would also pass in front of the proximity sensor's detector.

Figure 8.1 shows the measurements of the proximity sensor as the train passes in front of it at different speeds. We performed multiple tests at the same speed, but we have presented only one of them, selected at random, as they can be similarly described. The zero in the time axis represents the time when the front of the lead locomotive just crosses the sensor, while positive time indicates the train has passed the sensor. As mentioned in our earlier reports, the sensor functions by detecting ultrasonic energy emitted from sensor and reflected back to the sensor by the surface of the object passing in front of it. If no reflected energy is detected, or the object is at a distance larger than 10m, the sensor records a distance of 10m. Thus, 10m represents the absence of a train. If the reflecting object is within the distance of 10m from the sensor, it reports the distance accordingly. We had placed the proximity sensor at a distance of 10ft (3m) from the tracks.

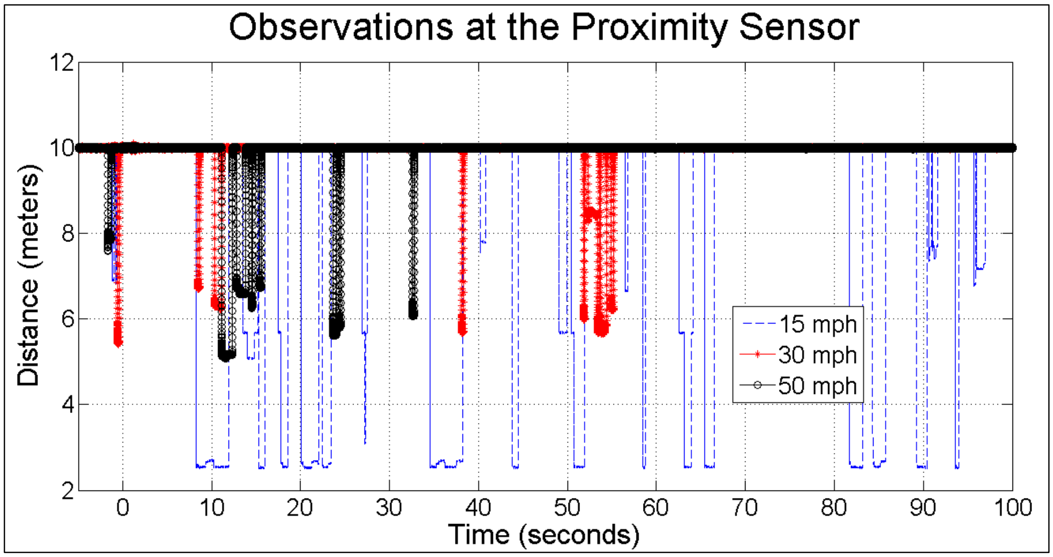


Figure 8.1 Estimation of the distance of the train from the proximity sensor at various train speeds

We can see that the sensor can reliably detect the presence of a passing train for all speeds, as indicated by the distance reduction shown in the curves. After the train completely passes the sensor, the reported distance return back to 10m. It is important to note that for the higher-velocity tests the distance between sensor and track was increased to safeguard the sensor from the effects of a train passing in close proximity at high velocity. The fluctuations in reported distance around 6-8 meters is the result of the gap between two railcars, effectively looking over the coupler and through between the railcars, being measured as the partial absence of a train. As a result, the amount of ultrasonic energy reflected back fluctuates, thus resulting in the results shown above. This allows us to process the information and extract railcar counts and length of train information.

The time taken by the train to completely pass the sensor directly correlates with the speed, taking the least amount of time at 50 mph and the most amount of time at 15 mph. The change in speed has been well captured by the expansion or compression of the profile with respect to time in proportion to the ratio of change in train speed. For example, in the case of 30 mph, the train takes approximately 1.6 times longer to completely pass the sensor as compared to the case when train speed is 50 mph, which correlates closely to the ratio of speed as well.

Furthermore, it can be asserted that the ultrasonic sensor can reliably estimate the time duration taken by the train to completely pass the sensor by observing the first dip and the final rise in the reported readings. Using these values, the system will be able to calculate the approximate length and the speed of the train. In our future work, we also plan to integrate an AMR sensor in the sensor system. Since the AMR sensor is capable of estimating the length of the train, we expect to combine these readings from the sensors to obtain estimates for train characteristics

8.2 Accelerometer

8.2.1 Time Domain Analysis

The accelerometer sensor measures the vibration by actually measuring minute amounts of acceleration within the sensor device. The sensor itself is mounted to the side of the rail using a magnetic mount bracket. This allows for easy installation and removal without damaging the rail. In this configuration the accelerometer measures and reports the vibration of the rail tracks due to the impact of a moving train on them. The vibrations are converted to a voltage by the sensor. The readings obtained from the sensor are in a voltage vs. time format. But, using the information of the speed of the train and the exact time instant when the front of the train actually crosses the sensor (obtained from video recordings), the time axis can be transformed to a corresponding distance axis. Figure 8.2 shows the impact of a train moving at a speed of 30 mph. The zero value in the x-axis corresponds to the time when the front of the train exactly crosses the sensor. The negative value corresponds to the time before the train crosses the sensor, and shows the distance of the train from the sensor. Similarly, the positive values correspond to the time after the train crosses the sensor and represents the distance of the front of the train from the sensor. It is clear that the impact on the sensors due to the moving train is significant. In fact, there is some signal registered when the train in almost 40 yards away from the sensor.

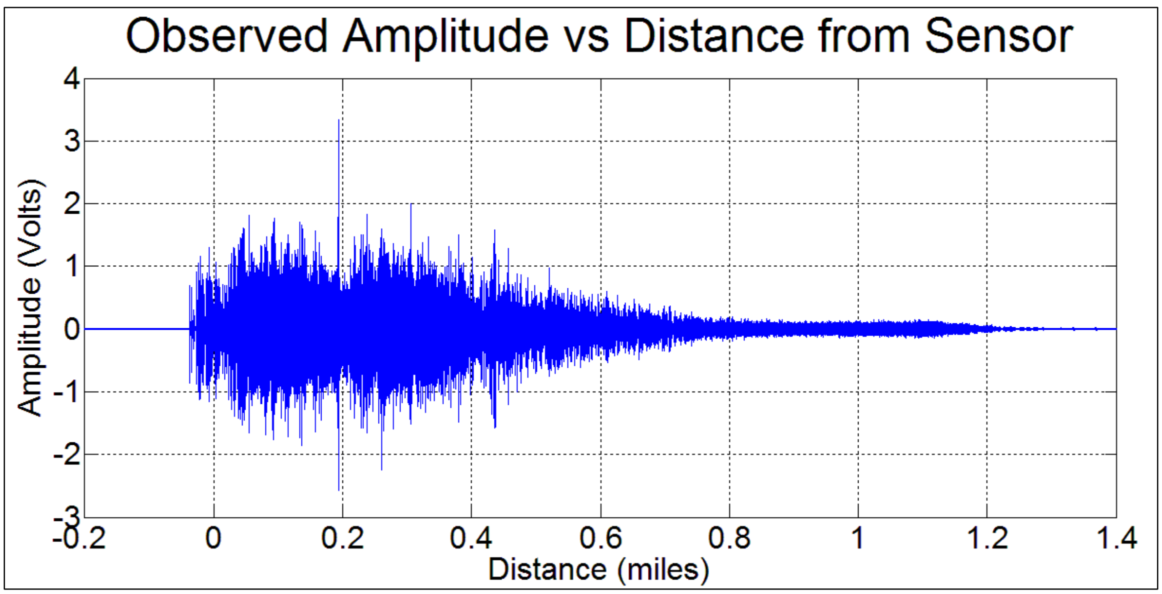


Figure 8.2 Voltage amplitude at the accelerometer due to impact of train movement at 30 mph

However, we could not extract any further insights from this time domain information. It is seen that the impact of the moving train on the accelerometer sensors did not have any definite pattern with respect to its speed. For example, figure 8.3 shows the average voltage recorded by the accelerometer when the front of the train is at different distances from the sensor at various speeds. Since multiple observations were registered at the same speed, those speeds are repeated in the figure as well for added consistency and reliability.

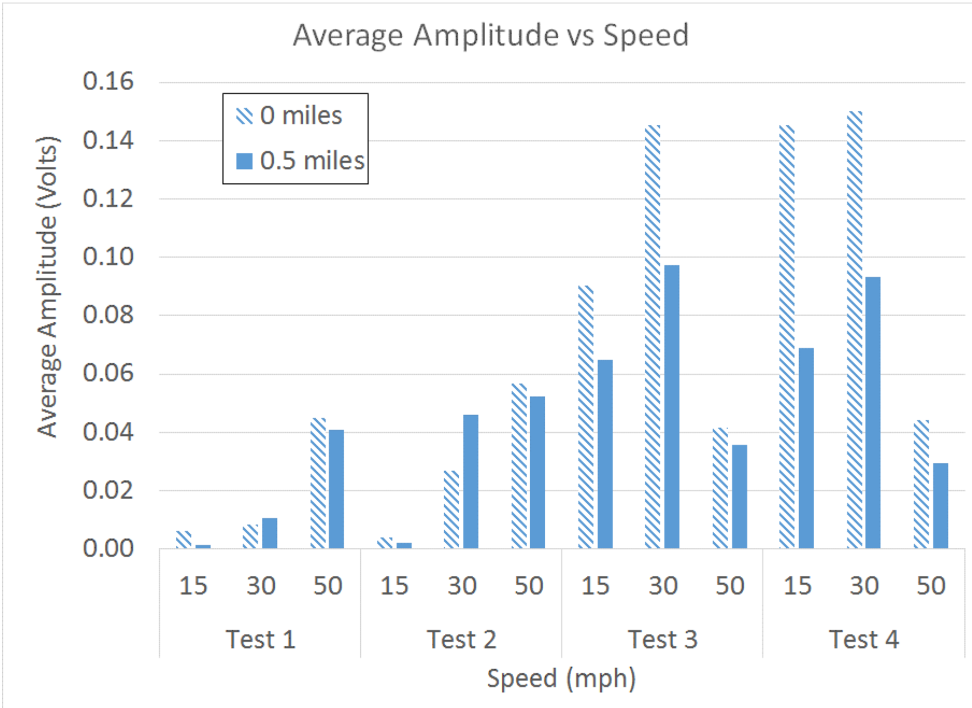


Figure 8.3 Average amplitude recorded by the accelerometer at various velocities for different separations between the sensor and the front of the train

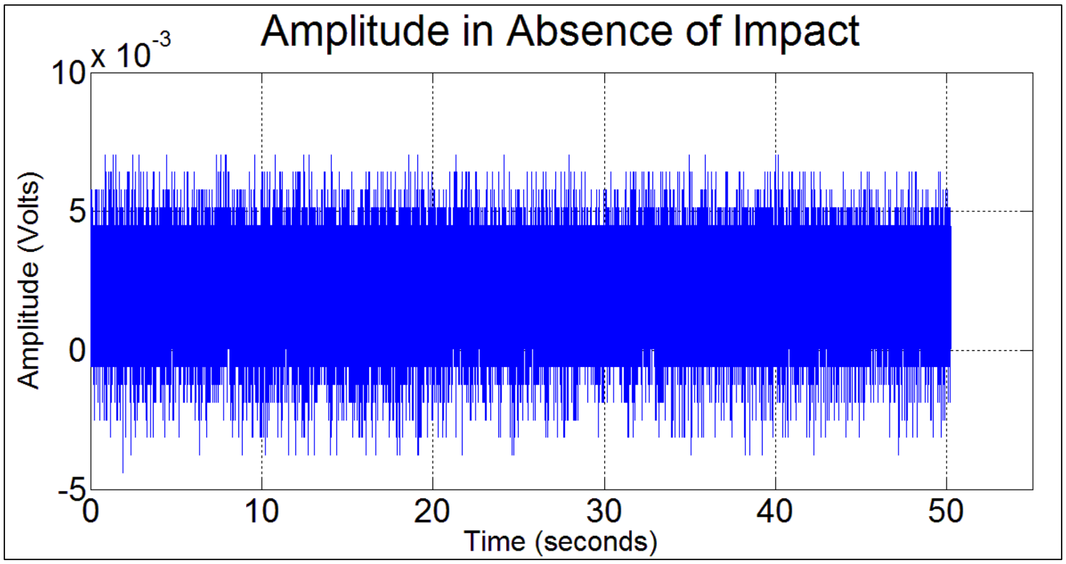
The voltage was averaged around ±0.01 miles of the designated distance from the sensor to reduce the effects of noise. For example, the amplitude value for 0.5 miles is averaged from 0.49 to 0.51 miles. It is clear from the figure that the impact is not uniform even for the same speed. Furthermore, the impact of the moving train on the sensor and the speed of the train are not highly correlated. In other words, the observed average amplitude neither increases nor decreases consistently with respect to the speed of the train. Therefore, we cannot estimate the speed of the train from the time-domain accelerometer readings in a reliable way.

Our future work is therefore focused on advanced processing techniques applied to the signal in the frequency domain. This will allow us to gain significant insight into train characteristics not available from the time-domain representation of the signal.

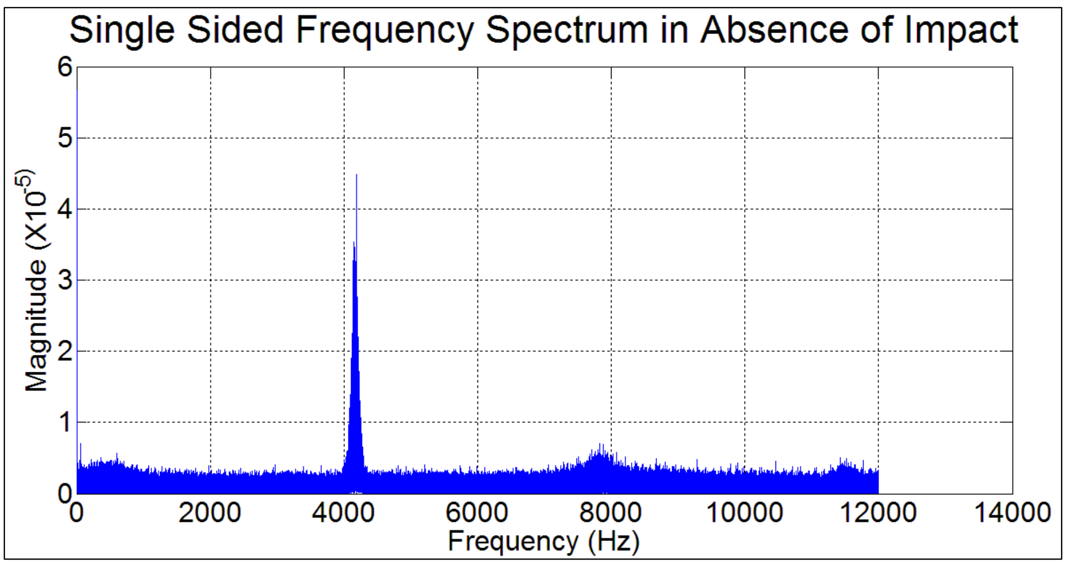
8.2.2 Noise Analysis

As with any sensing device, the presence of noise energy in the measured signal is unavoidable. One of our tasks was therefore to investigate the impact of the noise on the measured data and the reliability of the system.

As is expected, the accelerometer still reports a low-amplitude signal even in the absence of any vibrations on the rail track. We treat this spurious signal as noise. Figure 8.4(a) shows the noise from the accelerometer readings. We can see that the noise power is very small compared to signal power, as indicated by the fairly low amplitude values. Figure 8.4(b) shows the frequency domain representation of the noise signal. The DC component of the signal has been eliminated. We see that the noise is band-limited. This phenomenon is consistent over all observations in absence of vibration of the sensors. However, the noise band is seen to be shifting within 4 KHz to 6 KHz for different observations. This band-limited nature of noise allows the possibility of filtering it out using a band stop filter or simple high pass filter. However, we have noticed that filtering out this noise band brings little advantage to the overall quality of the readings. First, the noise power is very small and there is little advantage to complicate the system by adding filters for this small gain. Furthermore, filtering will also result in loss of some signal power. However, it is important to acknowledge the possibility of filtering for noise removal, especially when we process the data from all the sensors, not just the accelerometer.



(a)



(b)

Figure 8.4 Time profile (a), frequency profile of the accelerometer in absence of any impact (b)

9.1 Sensor Design and Development

The other core effort of the current quarter was the integration of a new sensor device into our system prototype. This sensor is an anisotropic magneto-resistive sensor. This sensor type has the potential to provide significant additional measurements and capabilities for our system, including the ability to ‘fingerprint’ a passing train.

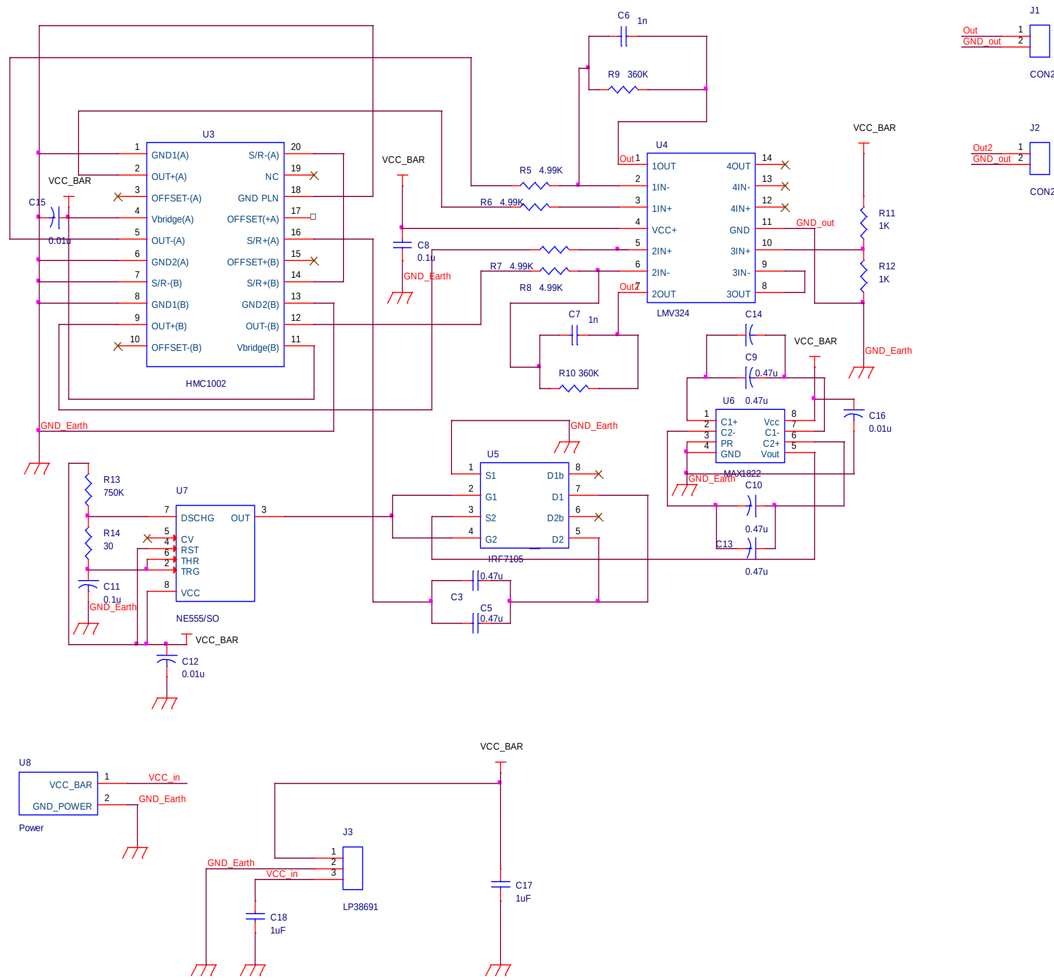


Figure 9.1 Circuit design for a two axes magnetometer based on HMC1002 sensor

We therefore decided to integrate an AMR sensor into our sensor system to improve reliability of detection, and measure and utilize these additional characteristics of the incoming train. The AMR sensor measures the fluctuations in the Earth's magnetic field when large objects, like a train, passing by the sensor produce small but measurable distortions in this field. We used Honeywell's HMC1002 AMR Sensor for this purpose. The HMC1002 AMR sensor is a 2-axis magnetometer for low magnetic field sensing.

Based on the specifications published by Honeywell for this sensor, we designed a PCB to drive it and interface with our data acquisition setup. We used Cadence Allegro Design Entry CIS to draw the circuit diagram, as shown in figure 9.1. The HMC1002 is the 20-pin chip shown the top left part of the figure. It has two main accessory circuits. The first one is the amplification stage circuit based on LMV324 instrumentation amplifiers. The output of the magnetometer is connected to this circuit for amplification, before being tapped out for digitization and further processing. The second circuit is a so-called Set-Reset Circuit, which is an inherent requirement of an AMR sensor. The set-reset circuit clears the magnetic memory of the sensor, by passing a momentary pulse of large DC current to demagnetize the sensor and clear the previous effects. The set-reset circuit is comprised of a MOSFET switch, whose power is supplied by a MAX1822 chip. The MOSFET switch supplies the power to set/reset the magnetometer. The gates of the MOSFET are controlled by an NE555 timer to regulate the interval of the set-reset operations. After the circuit design was complete, we started the PCB fabrication process. Figure 9.2 shows the PCB layout of the board. The work on the PCB schematics and layout have been completed. An initial prototype has been produced and additional prototypes of it are currently undergoing fabrication.

Figure 9.3 shows an initial version of the sensor board made for testing purposes. The final board will look similar, but also provide for additional power regulation and signal input/output capabilities.

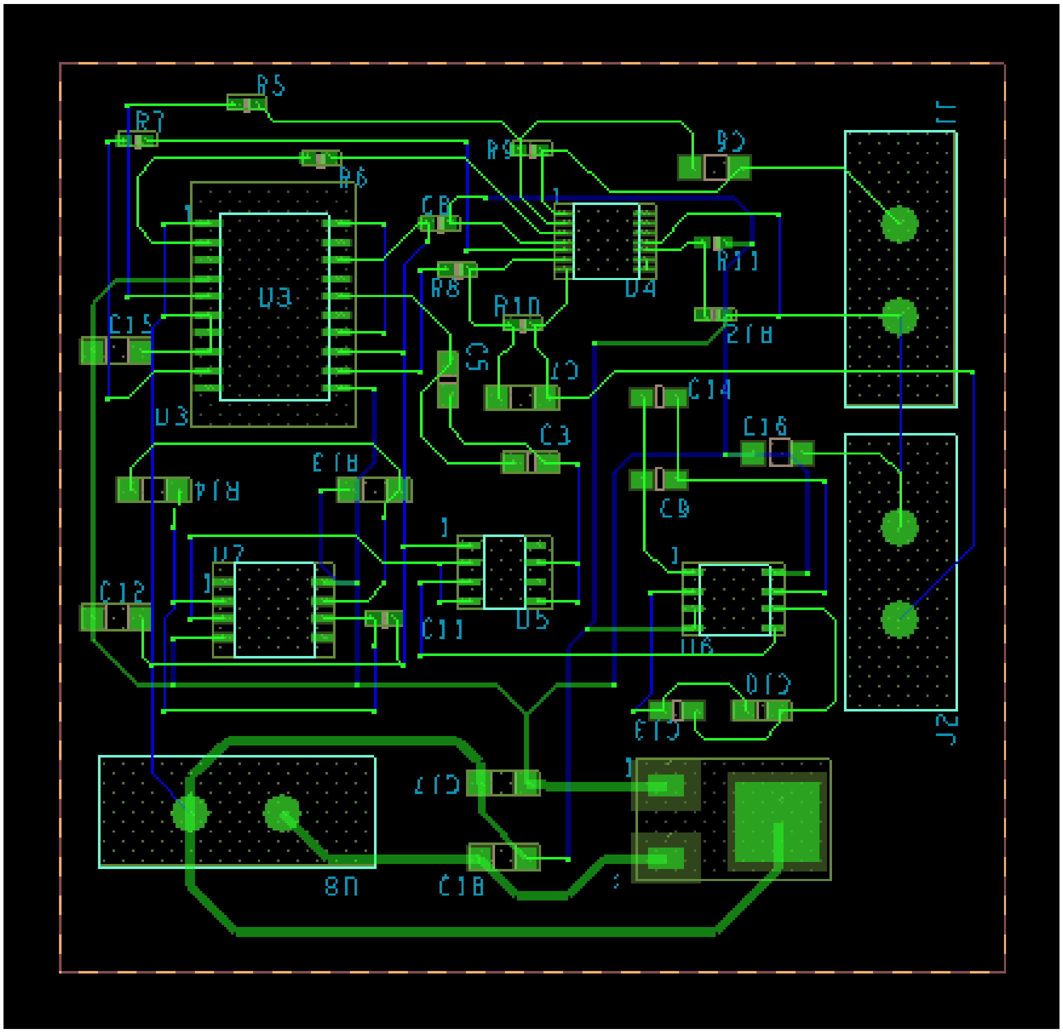


Figure 9.2 PCB Layout of the HMC1002 AMR Sensor Board

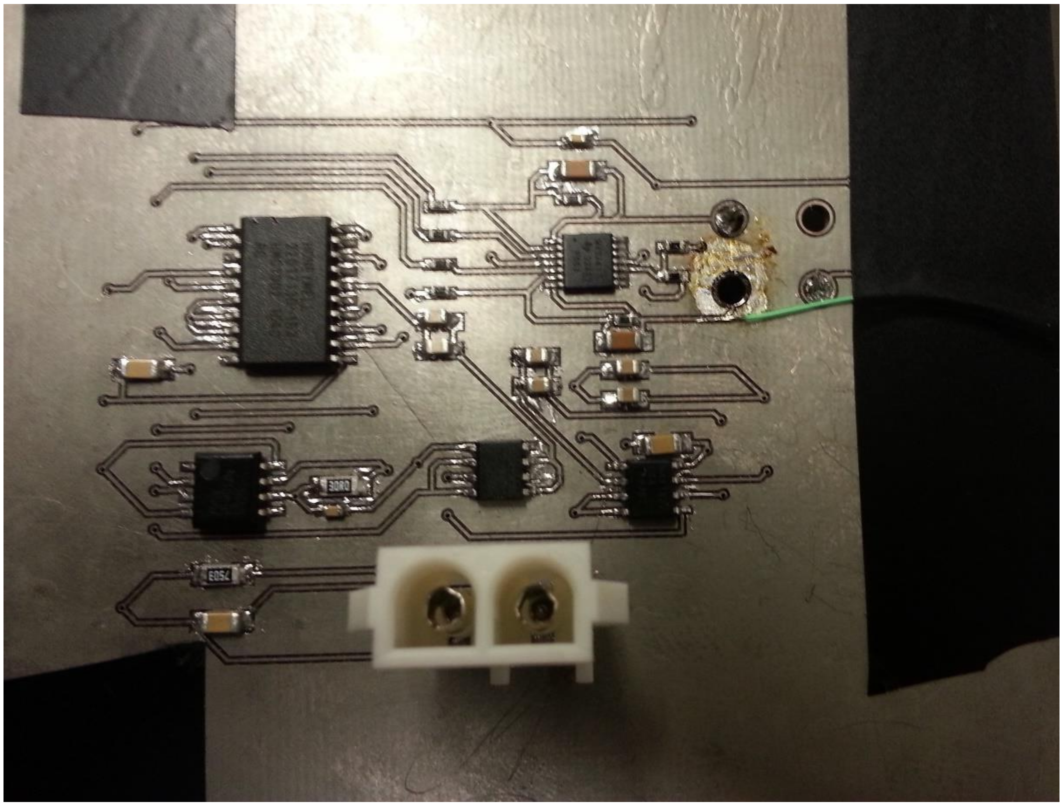
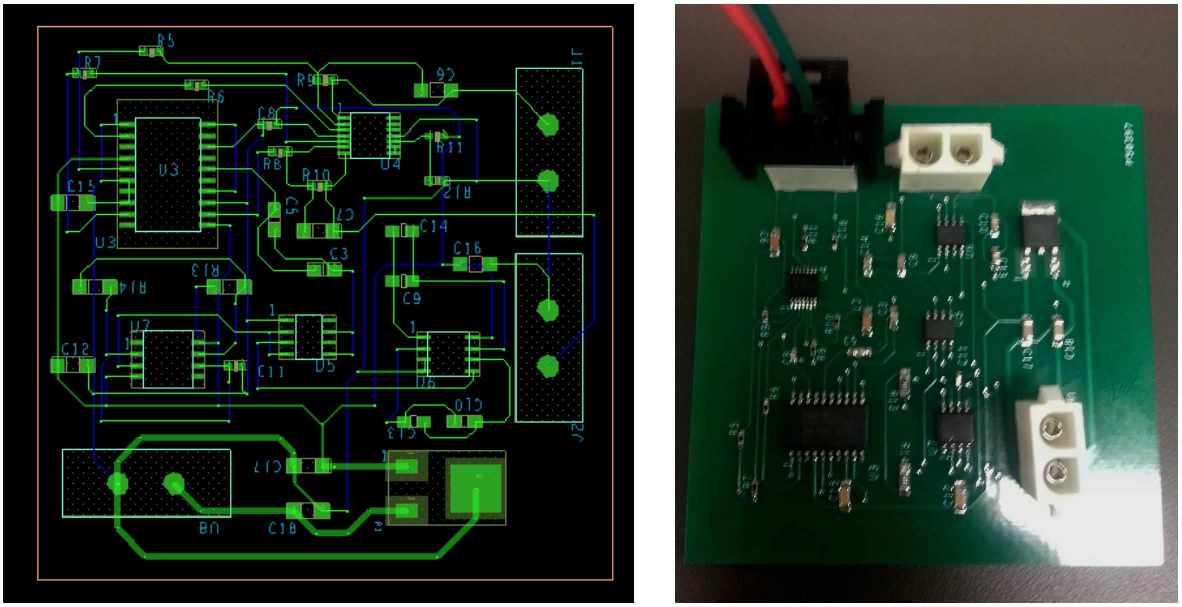


Figure 9.3 First version of the AMR Sensor Board

After we conducted our preliminary design and testing of the AMR sensor board in late fall of 2013, we leveraged the insights from these preliminary tests to engage in a redesign of the AMR board in order to achieve better performance and handling flexibility.

We redesigned the power circuit with the goal of facilitating a dedicated power supply by using a 6V battery connected to it via onboard power connectors. In our new design, the battery power is now filtered through a voltage regulator based on the LP38691 for circuit protection and better noise characteristics. The analog signal used by the data acquisition system is highly susceptible to noise, and with this redesign our primary goal was to improve the conditioning of the input power supply. Additional connectors were also added to the design such that it now is significantly easier to connect the AMR sensor board to our data acquisition system.

Figure 9.4 shows the PCB layout and an image of the updated AMR board:



(a) (b)

Figure 9.4 Upgraded AMR board design (a), PCB Layout snapshot (b)

9.2 Parking Lot Tests

To study the performance of the new AMR board, we conducted extensive tests in the parking lot at the Peter Kiewit Institute. The objective of these tests was to measure the signal produced by driving a car nearby the sensor board. The board was located on the curb of a parking lot traffic island and we drove past the board repeatedly at various speeds. Figure 9.5 shows the set-up of the test.

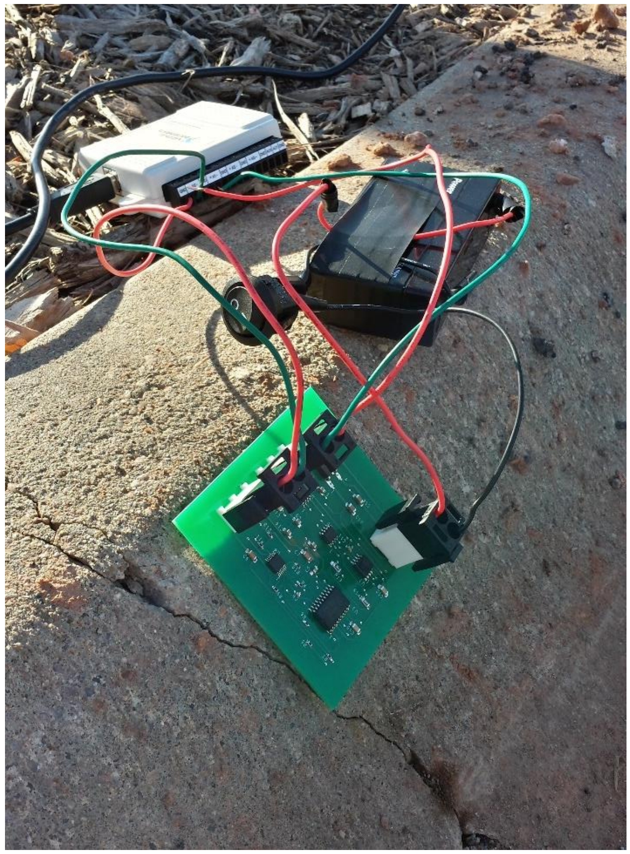
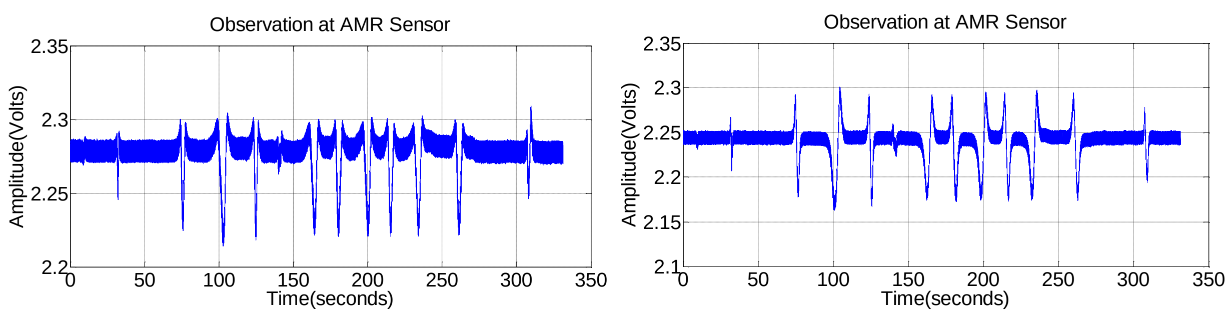


Figure 9.5 Setup of AMR Sensor board and DAQ in PKI parking lot

9.3 Time Domain Characteristics

The AMR sensor is designed to detect the changes in the magnetic field in the two horizontal orthogonal axes (x and y axes). The two analog signals share a common ground. Using connectors, the two signals are routed to two separate DAQ channels. We used MATLAB Simulink to record both the digitized signals from the DAQ with respect to time.

In figure 9.6, we are showing one example of our test results. As shown in the figure, the sensor was clearly able to detect the car passing by it. The spikes correspond with the moment when the axle of the car passes the sensor, hence changing the magnetic field around it. Since the spikes correspond to the axles the spacing between two consecutive spikes represents the time duration for the car to pass the sensor axle-to-axle. Using this time information, if the length or the speed of the car is known, the other feature can be estimated. The spikes in the figure are regularly spaced, reflecting upon the fact that the car was driven at a uniform speed during this test set. Also, the patterns repeat regularly, which points at the relative stability of the monitoring operations and reliability of the sensor.



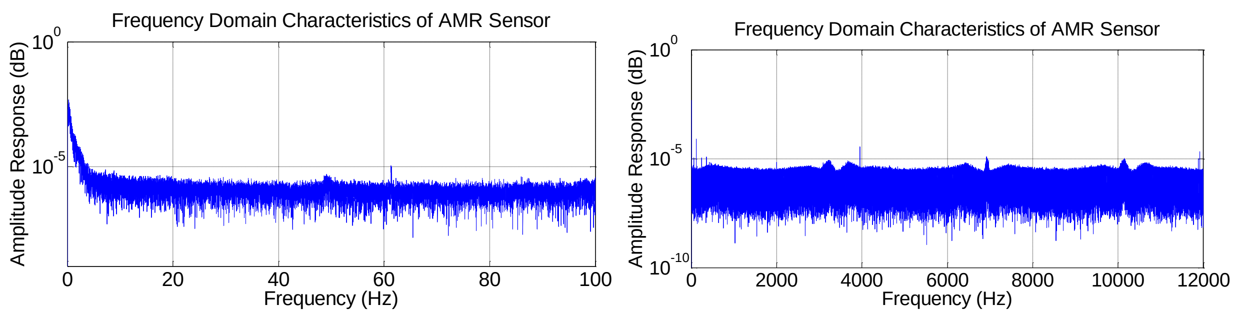
(a) (b)

Figure 9.6 Amplitude registered at the AMR sensor; channel 1 (a) channel 2 (b)

9.4 Frequency Domain Characteristics

In figure 9.6 above, though the spikes are clearly visible, occasionally they may be buried in noise. In fact, in the response of both signals, the signal-to-noise ratio at the earlier part of the observation (before 50s) is quite low. Also, it is evident that the noise mostly lies in the high frequency band. To analyze the frequency domain characteristics of the signal, we computed its Fourier Transform. The amplitude response of the signal in figure 9.6 (a) is shown in figure 9.7 (a). Figure 9.7 (b) is the same figure, but zoomed in below 100 Hz. As we can clearly see, most of the signal power is in the low frequency domain.

A moving average filter was used to remove the high frequency noise. The amplitude of the signal in figure 9.6 (a) is shown in figure 9.8. The averaging window size was 100 samples. The moving average filter averages out the high frequency noise and the signal to noise ratio is improved. However, there are some unavoidable losses of the signal as well.



(a) (b)

Figure 9.7 Amplitude Response of the signal at channel 1 (a), zoomed-n view below 100 Hz (b)

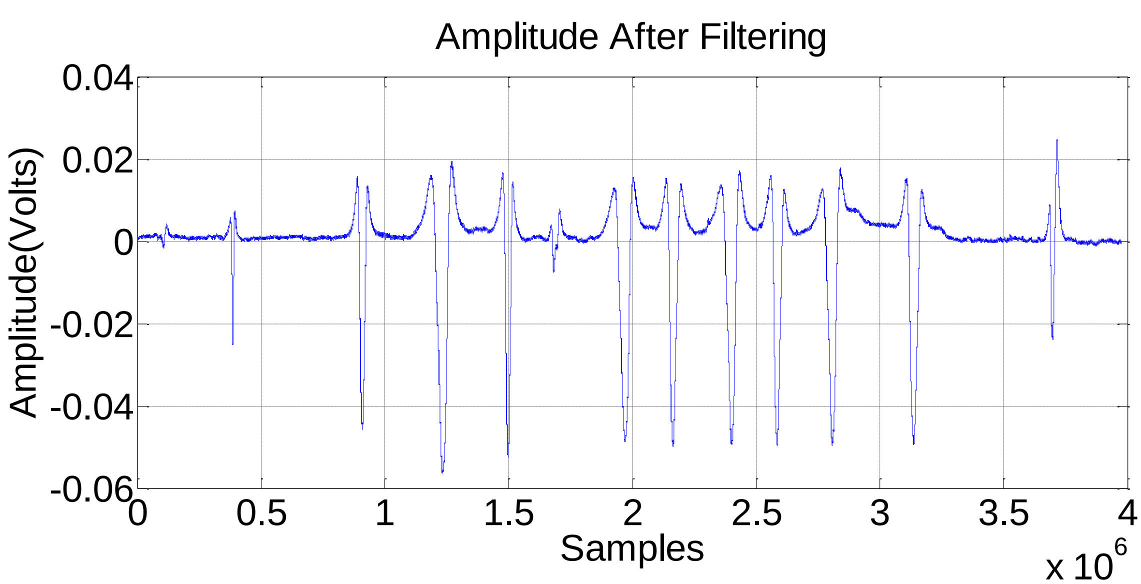


Figure 9.8 Amplitude of the signal after passing thorough a moving average filter

Chapter 10 Classifier-Based Detection

One of the primary objectives of our project is to enable multi-sensory train detection. To do so, we need to research methods to combine the features of different sensor elements for reducing false detection, improved reliability, and feature estimation. A common mathematical tool that is able to perform this operation is classification. A classifier is a function that maps an entity, or an event in this case, to a member of the set of fixed and pre-defined possible outcomes, called classes, based on the set of distinguishing characteristics, also referred to as the feature points of the event.

Based on our data collection and scenario analysis, we concluded that events in our application we are observing belong to one of the following four possible classes:

- Class A: Train approach detected
- Class B: Something else triggered the proximity sensor (deer crossing, etc.)
- Class C: Something else triggered the accelerometer (maintenance, drilling, hammering, etc.)
- Class D: Something else triggered the AMR (any metallic object in proximity)

Similarly, the following physical variables will be defined as the feature points:

- Amplitude registered at the accelerometer
- Power of signal at the accelerometer at various bands
- Triggering of the proximity sensor
- Time duration between first high and last low from proximity sensor
- Amplitude registered at the AMR sensor
- Power of low frequency component for AMR sensor

We have identified MATLAB as the tool for prototyping the classification methods. MATLAB provides several sophisticated algorithms and tools, with their own sets of advantages and disadvantages, and built-in functions for classification operations. We decided to study each of the algorithms to determine which algorithm or tool would be best suited for our data. In the following paragraphs, we shall briefly describe the essence of the algorithms and how we plan to use them for our project.

There are two forms of classification: supervised learning and unsupervised learning. In supervised learning we train the classifier on the set of data that associates a set of feature points to a class. It is expected that the classifier will be able to predict the class of a new set of feature points based on what it learned from the provided training data. In unsupervised learning, the classifier is simply given sets of feature points and the classifier is expected to divide them into distinctive zones or groups or classes based on those features. In this project, supervised learning is more relevant since we have the information about the class of each set of feature points for use as training data.

MATLAB provides multiple supervised learning algorithms. In the following sections we introduce the most important ones.

10.1 Classification Trees

In a classification tree, the value of each feature point determines which branch an event will take at each node. At the end of the leaf node, the event is finally classified and a decision is made.

A simple classification tree is shown in figure 10.1, where there are two classes—class ‘0’ and class ‘1,’ and two feature points, x1 and x2. At the root node, one of the branches is taken depending on the value of x1. If x1<0.5, the sample belongs to class 0. If not, it takes the branch on the right, in which case the value of x2 is used to determine which branch it takes further on. If x2<0.5, it is classified as class 0, else it is classified as class 1. The order in which features are used and the threshold of the features at each node is determined by the classification algorithm.

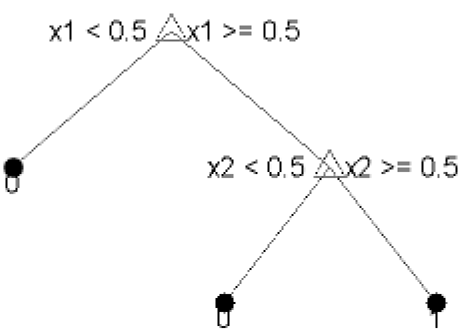


Figure 10.1 Simple classification tree example [18]

Consider Y be a decision variable that has to be categorized by knowing the value of another discrete variable A. The mutual information between Y and A is given by

$$I(Y;A) = \Sigma_a\, Pr(A = a)\, I(Y;A = a) \tag{10.1}$$

where, $I(Y;A = a) = H(Y) - H(Y|A = a)$ and $H(.)$ are the corresponding entropy values. Here, $I(Y;A = a)$ represents the amount by which the uncertainty about Y reduces by knowing that $A = a$. Similarly, $I(Y;A)$ represents by how much the uncertainty of Y decreases on average by knowing the value of A.

For classification, A is not necessarily one of the predictors, but rather an answer to some questions about one of the predictors X i.e. $A = 1_{\mathcal{A}}(X)$ for some set $\mathcal{A}$. The first question is chosen in the root node of tree so as to maximize $I(Y;A)$. The question at the subsequent nodes in the tree needs to be asked keeping in view what we already know by that time. For example, when we reach node C and if we already know $A=a$ and $B=b$, we look for a question that maximizes

$$I(Y;C|A=a,B=b)=H(Y|A=a,B=b)-H(Y|A=a,B=b,C) \qquad (10.2)$$

To maximize $I(Y;C|A=a,B=b)$, we need to minimize $H(Y|A=a,B=b,C)$ as the other term does not depend on C.

A tree can make two kinds of predictions. A point prediction that establishes the class of entity under investigation, or a distributional prediction that gives the probability of each class.

In distributional prediction, each terminal node gives a distribution over the classes. If the terminal node corresponds to a sequence of answers $A=a,B=b,C=c,\dots,R=r$, then the terminal node will give the probability $Pr(Y=y|\ A=a,B=b,C=c,\dots,R=r)$ for all possible values of y. This probability can be simply estimated by using the empirical distribution of the sample. However, if the number of classes is too small relative to the sample size, the sample distribution may no longer reflect the actual distribution accurately and may even show the probabilities for some classes to be zero, which may not be true in reality.

In point prediction, the strategy depends on the loss function. If we are using the misclassification rate, we choose the class that has the highest conditional probability at the leaf node. With other loss functions, we need to choose the class that minimizes the loss function.

There are three major ways of measuring errors when using classification trees: misclassification rate, loss, and cross-entropy.

The misclassification rate is simply the proportion of instances that has been wrongly classified. Average loss takes into factor the cost of misclassification as well. In classification problems, the cost of misclassification errors, false positive and false negative, may not be equal. For example, in detecting oncoming trains the cost of false negative is much higher than the cost of falsely detecting the presence of a train. For this, we define a cost value L_{ij}, which is the cost of classifying the instance as class j when it is really class i.

For an observation, $X = x$ the classifier gives the probability $Pr(Y = y|X = x)$. Then, the loss function is

$$Loss(Y = j|X = x) = \Sigma_i L_{ij} Pr(Y = i|X = x) \tag{10.3}$$

The cross-entropy not only looks at the misclassifications, but also with what confidence level the instances were misclassified. This loss function for a model Q is defined as

$$L(data, Q) = -\frac{1}{n}\Sigma_{i=1}^{n} \log Q(Y = y_i|X = x_i) \tag{10.4}$$

where $Q(Y = y|X = x)$ is the conditional probability predicted by the model. If perfect classification were possible, $L = 0$. If there is some unavoidable uncertainty associated with the classifier, the best classifier will have $L = H(Y|X)$. Less suitable classifiers will have the loss larger than the conditional entropy.

10.2 Naïve Bayes Classifier

In a Naïve Bayes classification method it is assumed that the features are independent of each other for each class. Theoretically, the class conditional independence of feature points greatly simplifies the training step as the one-dimensional class-conditional density can be estimated individually for each feature point, instead of the n-dimensional density function (for a system with n feature points) if the feature points were not independent.

10.3 Support Vector Machines

Support vector machines can be used for classification purposes if we require to classify the samples in exactly two classes. It works by determining the best hyperplane that separates all training samples in one class from another. A hyperplane is regarded as best, if the margin between the two classes is as maximum as possible. The margin is defined as the width of the slab parallel to the hyperplane that does not contain any interior data points. In figure 10.2, we show the training samples being divided into two classes: Class '+' and Class '-'. The separating hyperplane is shown to clearly divide the two classes with a specific margin. The best classifier will have this margin as high as possible. The samples closest to the separating hyperplane are called the support vectors.

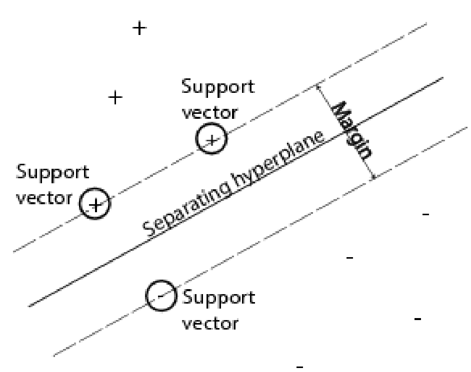


Figure 10.2 Illustration of support vector machine-based classification [18]

10.4 Discriminant Analysis

The discriminant analysis classification method assumes that different classes generate samples using different Gaussian distributions. It then attempts to learn the parameters of those distributions using the provided training samples. The classifier then predicts the class of a new test sample by choosing a class that minimizes the expected classification cost. The expected classification cost is the weighted average of the cost of misclassifying the sample point, averaged with respect to the posterior probability of the class for the observation being classified. The posterior probability is calculated from the estimated Gaussian probability and the probability distribution of the class and the observations using Bayes rule.

10.5 Ensemble Learning

Ensemble learning is a powerful tool that can combine the results from multiple weak learners for a much more reliable predictions. Figure 10.3 shows how ensemble learning works in MATLAB. It combines the information from training samples, type and number of weak classifiers and an ensemble method to form a more reliable ensemble classifier. A classification could be a possible weak learner that can be used.

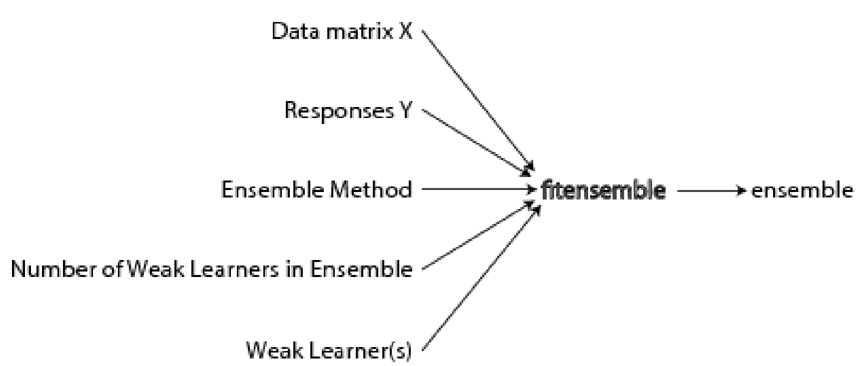


Figure 10.3 Illustration of ensemble classification framework [18]

In this project, we plan to investigate each of these algorithms to estimate the best possible classifier for our data sets. From initial observations, we see that classic SVM cannot be used since we have more than two classes. We are exploring the use of Multiclass SVM to address this issue. Also, we could observe that using a Naïve Bayes classifier does not represent an optimal approach, either, as the feature points being considered are not independent of each other. Since in this project the real-world classification is based on multiple if-else events, the best method right now seems to be using an ensemble of classification trees. However, MATLAB provides other powerful tools like feature selection and cross validation that will greatly help to reduce the misclassification rates with other algorithms as well, and we fully expect to be investigating these approaches much further.

Chapter 11 Overall System Design Integration and Evaluation

11.1 System Level Overview

Figure 11.1 shows a system level representation of the functional block diagram of the proposed detection-alert system. In this section, we shall revisit how the system works in order to provide some context to the later sections and also integrate the discussions with the earlier sections.

On a physical level, the system is implemented as multiple different units, deployed at different locations. The planned system units are:

- The train detection unit: deployed next to the track several miles away from the work site at each track leading into the work area.
- The relay units: deployed between the detection unit location and the work site to relay the wireless signal from the detection units.
- The worksite units: deployed at the work site, providing audio-visual alerting of an approaching train and signaling when it is safe to resume work after all trains have been detected leaving the protected area.

The train detection system is deployed at the observation point. The sensors monitor the physical variables and acquire them as analog signals. The analog signals are then digitized and sent to the processing unit. The processing unit conditions the acquired signal and runs a complex machine learning-based data processing algorithm to determine if an oncoming train is present on the track. In our prototype design, we have used a DAQ for signal acquisition and digitization. However, the choice of this unit is not limited to a particular hardware. The signal conditioning algorithms are specific to particular sensors and have been explained accordingly in earlier sections.

We have used a classification tree as the machine learning tool for decision making. The details of the data processing algorithm are presented in later sections. After making a decision, the message is transmitted to the worksite using a wireless communication link. At the worksite unit, the wireless message is decoded and mapped to one of the pre-defined sets of events (such as train approaching, train departing the area, no trains detected, etc.). The processing unit at the worksite then uses appropriate control logic to switch on the alarm systems to alert the workers of trains detected in the area.

In addition to the alarm system for alerting workers about the oncoming train, we highly recommend using an indicator that represents the system is working properly and the rail workers not to enter the worksite unless they can clearly see this indicator. There are two main reasons of doing this—hardware failure and human error. Hardware failure may surface in the form of disconnected wires and sensors, faulty hardware, undetected power failure, etc. Typical human errors include forgetting to switch on equipment, improperly connecting wires and equipment, etc. For the sake of their own safety it is recommended that whenever the indicator is not lit, this is viewed as an approaching train.

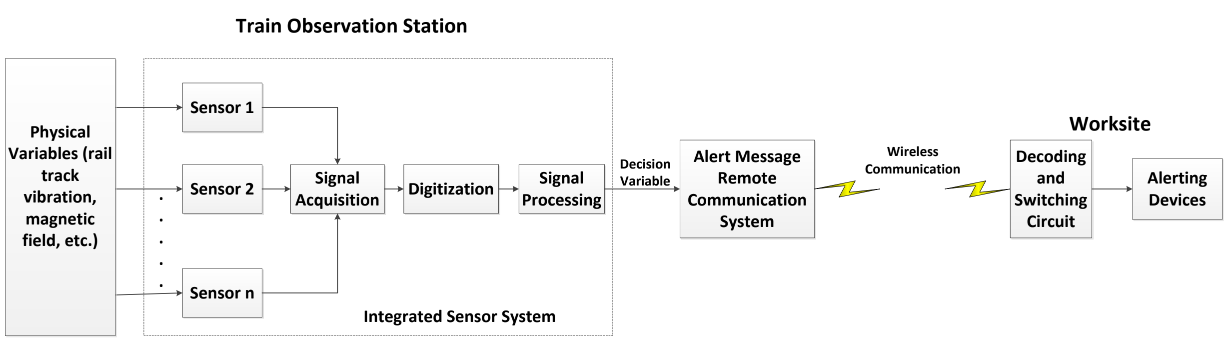


Figure 11.1 Block diagram representation of detection and notification system

11.2 The Communication Link

To transmit the alert messages from the detection location to the worksite, we recommend the integration of WiFi mesh capabilities into the system units. This can most easily be achieved by integrating commercial off-the-shelf WiFi routers. Typical open-mesh commercial wireless products are best suited for this purpose. These routers are sold with built-in mesh capabilities. If other routers are chosen that do not support such functionalities, it might be necessary to overwrite the factory system firmware of the router by using one of the common open source firmware packages freely available online. We recommend using one of the most popular such firmware releases — DD-WRT. Following the selection and acquisition of such a platform, one of the ad-hoc mesh routing protocols like OLSR (Optimized Link State Routing) needs to be configured on the routers. The operation of the system is best explained with the aid of the scenarios shown in figures 11.2 and 11.3 below.

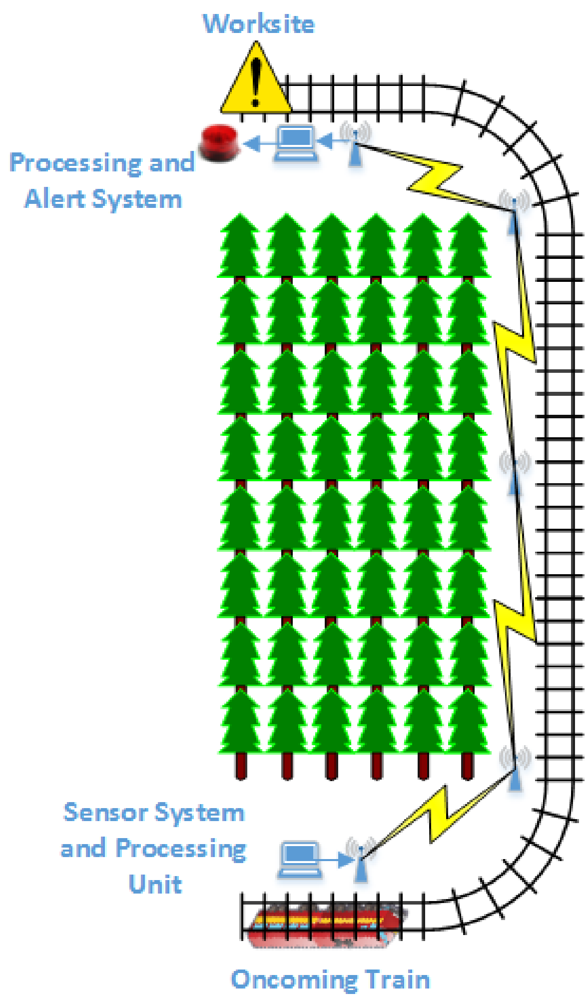


Figure 11.2 Scenario depicting lack of line of sight between oncoming train and worksite

In figure 11.2, we demonstrate how the communication link functions in one of the worst possible scenarios from the point of view of wireless communications. The rail track includes one or more curves and a train is approaching from beyond one of the curves. There are obstructions between the worksite and the train, which removes the possibility of line-of-sight. This means that neither a direct communication link between the two points of interest is possible, nor are the workers physically able to visually detect the train. The obstructions could be a forest area or trees as shown in the figure, or even hills or building structures.

The sensors report their readings to the train detection unit for processing. The processor runs the detection algorithms and makes a decision whether to alert the worksite. If the algorithm detects a train, it sends data packets destined to the worksite unit. On the sender side, the processor needs to have interfaces to connect to a digital acquisition unit or the sensors themselves. It needs to connect to the router either via a WiFi card or an Ethernet port. There is no restrictions on the type of hardware used. Anything from a simple microcontroller-based system to a laptop could be used.

The data packet is routed via multiple relay units to the worksite unit. The system at the worksite decodes the information from the received messages. If the decoded message maps to one of the pre-assigned alert codes, it triggers the corresponding switches, and the workers are alerted.

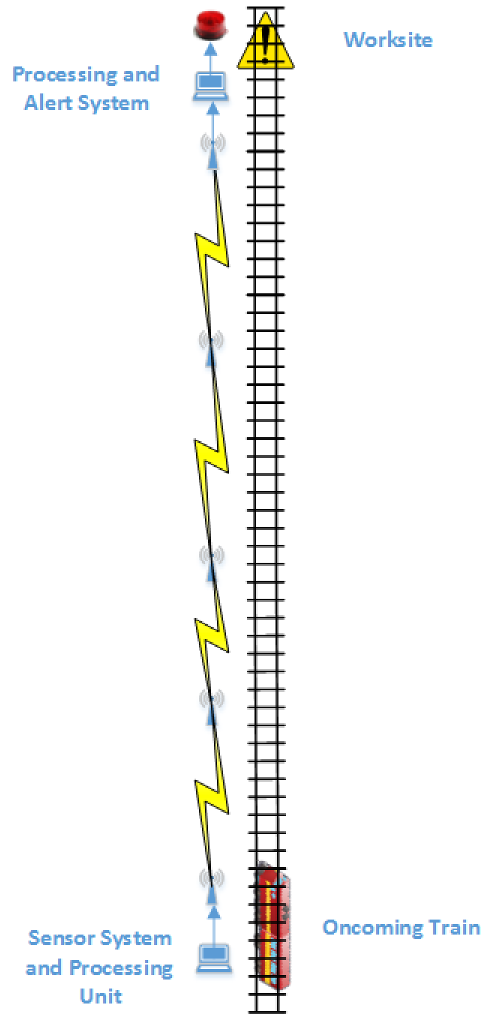


Figure 11.3 Scenario depicting line of sight between oncoming train and worksite

In Figure 11.3 we demonstrate a much simpler scenario where there is a possibility of direct line of sight between the detection site and the work site. The system can be similarly deployed in this case. The performance and reliability of the system will improve due to better operating conditions.

In our tests, we have observed that standard WiFi routers can provide a communication range of approximately 0.5 miles. To provide the workers a minimum of 5 minutes to leave the work site and remove their equipment, and assuming that the train is traveling at a rate of 60 miles an hour, it is advisable that the difference between the detection unit and the worksite be about 5 miles. It must be noted these are very conservative estimates, and under typical scenarios the workers will get more than 5 minutes to leave the worksite with the equipment. To cover the range of 5 miles, at least 10 relay units need to be deployed for a reliable end-to-end delivery. However, to take advantage of all the benefits of the mesh network, it is recommended that more units are deployed in order to avoid a chain like topology in which each relay unit is also a single point of failure. Due to closer spacing between the routers, the routing protocol will be able to self-heal and skip non-responsive relays in order to reliably deliver the message. Communication failure is detected by the worksite unit and is alerted to the workers in the area immediately.

It is interesting to point out that there are other contending wireless standards that are candidates for integration with our system. These include WiMAX, cellular services or a custom radios operating on licenses frequency bands. WiMAX, though a suitable solution, requires very costly equipment, whereas our proposed solution WiFi deploys cheap off the shelf equipment. WiMAX also often requires a license to utilize the frequency bands it operates on. Cellular services may not reliable in remote areas. These areas are the primary work sites, however, and thus this is not a desirable solution. Similarly, developing a proprietary communication solution requires time and resources and thus we felt it was not a suitable option. Furthermore, we did not want the system to have hard limitations on required hardware. Using an open standard like WiFi will permit the railroads to pick and choose any suitable product from a vendor of their choice. Also, using a particular frequency may require licensing from FCC, which will significantly increase the cost of deployment.

We can summarize the advantages of using our recommended communication technology as follows:

- Operates using an open standardized technology
- Operates on license-free ISM band
- Inexpensive to deploy
- Built-in security via node authentication mechanism and encryption
- No single point of failure due to mesh capabilities
- Self-healing network architecture due to mesh capabilities

This solution can easily be integrated into the final system architecture, for all the different system units such as train detector units, relay units, and worksite units.

11.3 Tests at Union Pacific Rail Yard

On May 14, 2014, we visited the Union Pacific Rail Yard at Council Bluffs, IA to test our sensors in real world settings. Figure 11.4 shows a sample scenario of the rail yard we used as our test bed and an oncoming train that we are trying to detect.

Figure 11.4 A representative scenario of an approaching train on a live track in the Union Pacific rail yard in Council Bluffs, IA

We positioned ourselves and the sensor equipment next to one of the tracks. The entire test setup was also highly portable, allowing us to move from one track to the next with minimal effort, depending on which track exhibited the most activity. The setup consisted of a non-metallic enclosure that houses the AMR sensor board, the DAQ, and a 6V rechargeable battery for powering up the PCB. The train detection unit is completed by connecting the DAQ to a laptop via a USB interface. The laptop, in this prototype design, is the system's data processor, responsible for signal analysis and train detection classification. This particular field test focused on the evaluation of the AMR sensors. For the other system sensors, we have conducted similar field tests and presented their results in earlier sections.

To maintain an acceptable distance between the rail tracks and us, a USB extension cable was used. The setup of the sensor and other system components while measuring the impact of a passing train is shown in figure 11.5. A USB-based web camera was stationed on a tripod stand and kept in alignment with the sensor board, looking straight across the track and the passing train. The purpose of the camera was to record a time-stamped video of all the activities taking place in the vicinity. The observations recorded from the sensors are also time-stamped as well as time synchronized with the video. This makes post processing easier as we can attribute a specific recording from the sensor with a corresponding activity on the tracks by matching the time stamps. Also, a video recording can be used as a verification tool of an actual observation and not just false triggers or measurement errors.

Figure 11.5 Set-up of the sensor and the accessories while measuring the passage of a train

The actual measurement process was straightforward. A software application written by us configures the DAQ to sample the AMR sensor at a rate of 24 kSamples per second. As explained in earlier sections, the AMR sensor basically reports the variation in the magnetic field across two orthogonal axes. We have positioned the sensor board parallel with the side of the passing train. Therefore, the reported variations in the magnetic field correspond to the changes in the magnetic field across the side of the train (vertical component of the magnetic field) and across the track while the magnetic component along the rail track is not measured. Two input analog ports of the DAQ are configured to receive the two outputs from the sensor board. The controlling software maintains a log file of the time-stamped observations of the AMR sensor.

We collected data from scenarios that comprised of trains passing the track adjacent to the sensor, the tracks further away from the sensor, the same train passing the sensor multiple times, impact of different types of railcars, and impact of locomotives. We then post-processed the data using MATLAB. As explained earlier for our parking lot tests, the signal was buried in high frequency noise and hence filtering techniques were needed to improve the reliability of operations. Figures 11.6 (a) and 11.6 (b) show the observed amplitude across the two orthogonal axes, while figures 11.6 (c) and 11.6 (d) show their corresponding filtered version.

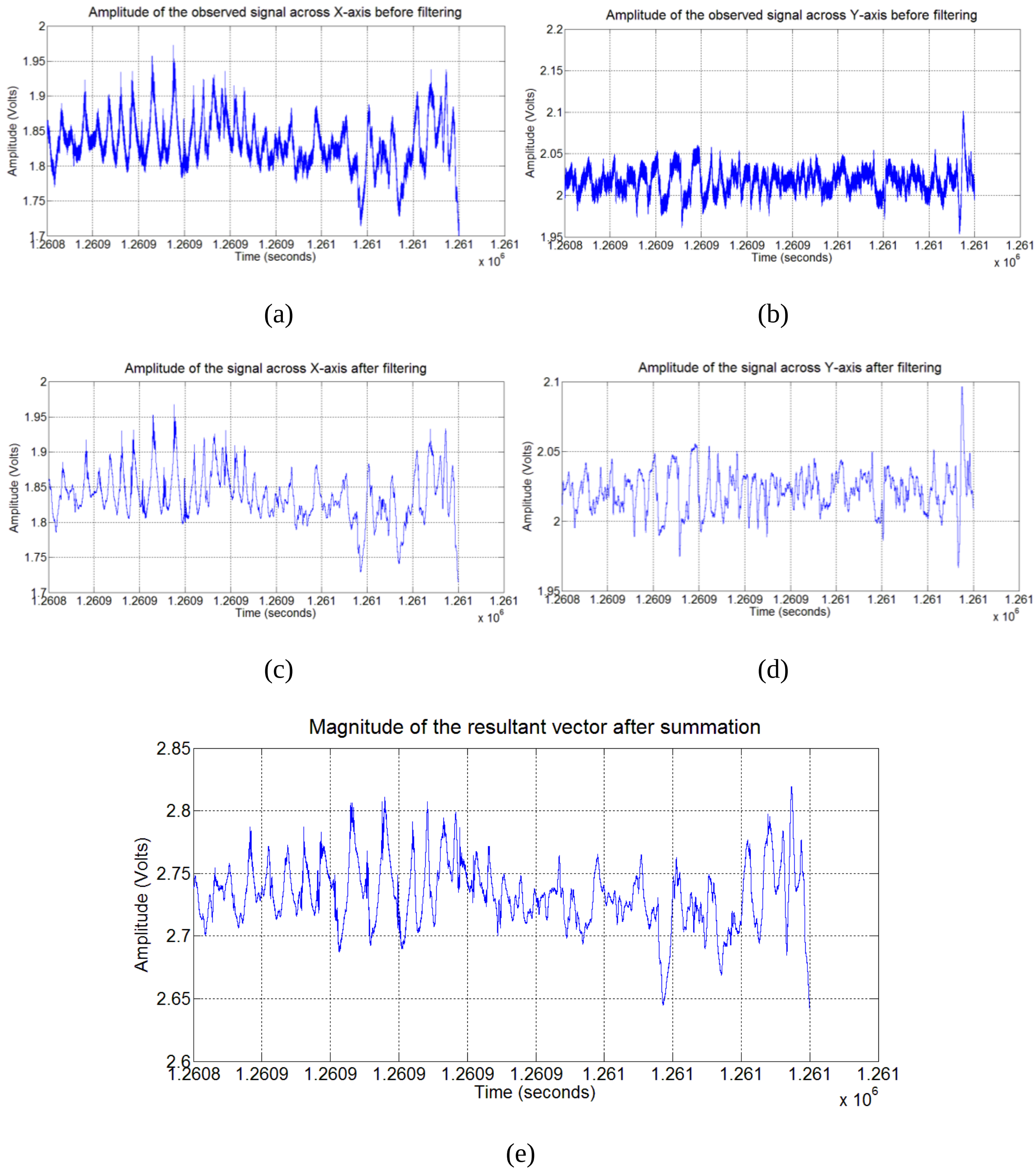


Figure 11.6 (a), (b) observed amplitude of the signal at the two orthogonal axes before filtering; (c), (d) amplitude of the signals in (a) and (b) after filtering; (e) magnitude of the signal after vector summation of the signals in (c) and (d)

Any form of low pass filter with suitable cutoff frequency can be used for removing the high-frequency noise. However, in our case we decided to use a moving average filter with a memory of 100 samples. The peaks in the amplitude are the result of sampling the passing of the wheels and axles of the train by the sensor system.With the objective of using a single value to represent the impact, we calculated the joint vector created from both orthogonal axes and then calculated its magnitude. This resulting magnitude is shown in figure 11.6 (e). The time axes in figures 11.6 (a)-11.6 (e) represent the time in seconds, i.e., the standard date and time vector including day, hour, minute, and seconds have been converted to number of seconds. Also, it should be noted the designation of a particular axis as X or Y is arbitrary.

11.4 The Data Processing Methodology

In this section, we describe how we used the collected data from the three different sensors and integrated them using signal processing and advanced machine learning. We also include the results of data processing here.

Any machine learning requires two sets of data—a training set and a test set. To achieve the test set, we broke the data observed from the sensors into continuous chunks of 100,000 samples. In real time, at sampling frequency of 24 KHz, it will take 4.17 seconds for the system to collect 100,000 samples. Even by accounting for any possible processing and propagation delay, the time duration to collect the samples and alert the workers will still be much less than 5 seconds. At a speed of 60 mph, the train would have traveled at most 440 ft after crossing the sensors. Since the sensor system is around 5 miles away from the workers, the delay of 5 seconds in decision-making poses absolutely no risk for the workers at the work site. The samples were observed from different sets of observation to prevent any possible bias towards a particular data set. A random set of 2,000 samples were taken from all the chunks to get the training set.

The machine learning process also requires extraction of some features from these samples that determine whether a train is present on the track or not. For the proximity sensor, the average amplitude and the variance of amplitude were calculated for each sample. As explained in previous reports, the proximity sensor reports the distance of the object from the sensor if the object is closer than 10 ft, otherwise it just reports 10 ft, which then is interpreted as an open field of view. Therefore, the amplitude clearly is a significant parameter that describes the presence of the train on the track. Similarly, in the absence of any object, the sensor will repeat a constant 10 ft observation and hence the variance would be very low. However, a train will cause fluctuations as the sensor will often sample the space between two railcars.

For the accelerometer and the anisometric magnetometer sensor, we used the average and the variance of the amplitude for the same reasons. The only difference is that in the case of these two sensors, we used the absolute value to compute the average since they also have negative valued observations. Also, the magnetometer sensor reported two orthogonal readings (labeled as X and Y axes). Therefore, we calculated the resultant magnitude to account for the contribution of both orthogonal vectors.

Apart from the amplitude mean and variance, we also looked at the frequency profile of the accelerometer and magnetometer sensors. For the accelerometer, we observed that a significant amount of power is concentrated in the low frequency domain, particularly below 4 KHz. Therefore, by Fourier analysis, the energy/power content of the signal under 4 KHz and the entire frequency profile was evaluated. Furthermore, the ratio of the two parameters was also used as an additional parameter. For the magnetometer, most of the signal was concentrated in the low frequency domain as well. However, in case of the magnetometer sensor, this primarily comes from the sensor sampling the wheel and axle system of the railcars. Therefore, this signal power resides in a much lower band. We used the energy under 100 Hz as a feature vector for our system. Similarly, we also calculated the energy across the full frequency profile and the ratio as in the case of the accelerometer for additional feature parameters. To calculate the frequency domain parameters, the DC power was suppressed for both the accelerometers and the magnetometers. This was done to remove the DC bias coming from the sensor and peripherals, which might be different even for different instances of the same sensor.

The classifier was trained for the following scenarios:

i) When a train actually crosses a sensor system

ii) When the proximity sensor is false triggered, e.g. when a deer crosses the sensor

iii) When the accelerometer is false triggered, e.g. nearby drilling operations

iv) When the magnetometer is false triggered, e.g. passage of a ferrous material near the sensor

v) Two of the three sensors get false triggered

vi) All three sensors get false triggered

vii) When nothing happens

The classifier was trained with 2,000 samples of each feature point. A binary classification tree was used as the classifier using MATLAB. The first scenario was classified as class 1 representing the presence of the train, while the remaining scenarios were classified as class 0 representing the absence of the train. It is possible to determine how well a particular classifier has been trained by calculating cross-validation error. For this purpose, MATLAB reserves a section of the training data for testing purposes. The cross-validation error was observed to be 0.0059.

It is interesting to discuss how to train the classifier when all three sensors are falsely triggered. If we train the classifier to recognize these false triggering as absence of train event, then there is a possibility that when a train is actually present, the classifier predicts this as a non-train event. This is because of the very short training interval and the resulting possibility that the signal registered from false triggering and an actual train are very similar. This makes the system unreliable and dangerous as well. However, if we train the classifier to recognize the simultaneous triggering of all three sensors as the presence of train event, the possibility of not reporting a train when it is actually present is eliminated. This does increase the possibility of false triggering when all three sensors report activities in the absence of a train, but this probability of this scenario occurring is very small. Taking into account the very low probability of simultaneous false triggering and imminent risk to workers due to possible false negative detection, we have gone with the latter approach. The system thus has been biased towards never not reporting a train, even if it is not sure.

We also trained the classifier on a reduced set of only 10,000 samples of data. This was done to determine if it would be feasible to reduce the decision time without sacrificing accuracy. However, it turns out that even though using sets of 10,000 samples lets us alert the workers in under half a second, the system becomes more error prone. The cross-validation error in this case was observed to be 0.0071. These are all false alert triggers, never missed trains.

Since, the delay of 5 seconds is well within the safety limits, we recommend not reducing the sample size to too small a value. However, this also shows the trade-off between delay and error performance of the system.

The classification trees of training using both 100,000 and 10,000 samples long data chunks are shown in figures 11.7 and 11.8, respectively. In the figures, the each node represents a feature point whose value determines which of the two branches the decision process will take. Since we are dealing with a binary tree with only two possible outcomes, either presence or absence of train, each node has two branches. Upon traversing through a particular set of branches, the last branch terminates either at a ‘0’ or a ‘1,’ indicating absence or presence of train, respectively. The depth of the tree shows how many feature points were considered before a decision was made. As shown in the figure, multiple sources of information were taken from all sensors to make a decision, which validates our multi-sensor based approach.

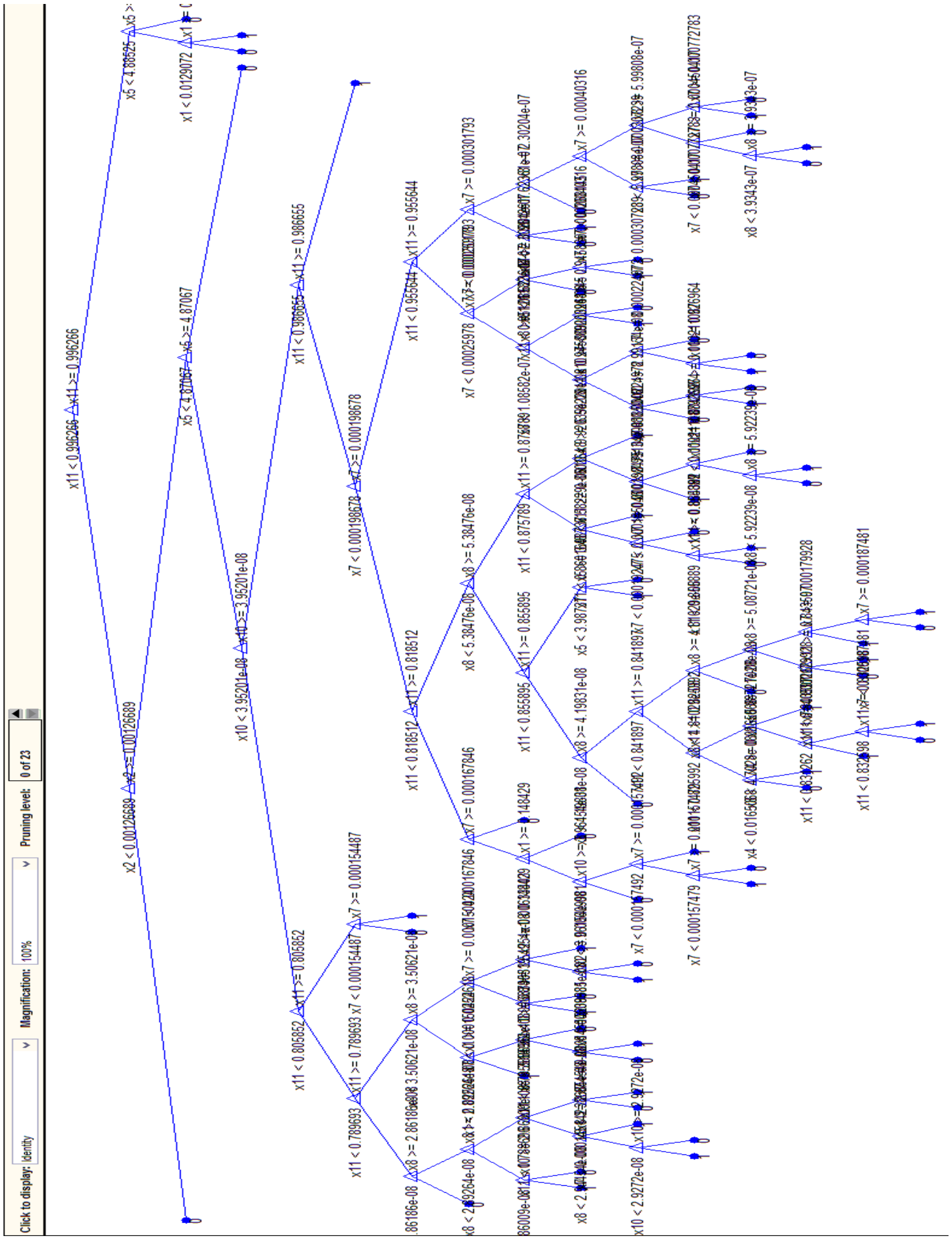


Figure 11.7 Classification tree diagram using 100,000 samples per observation

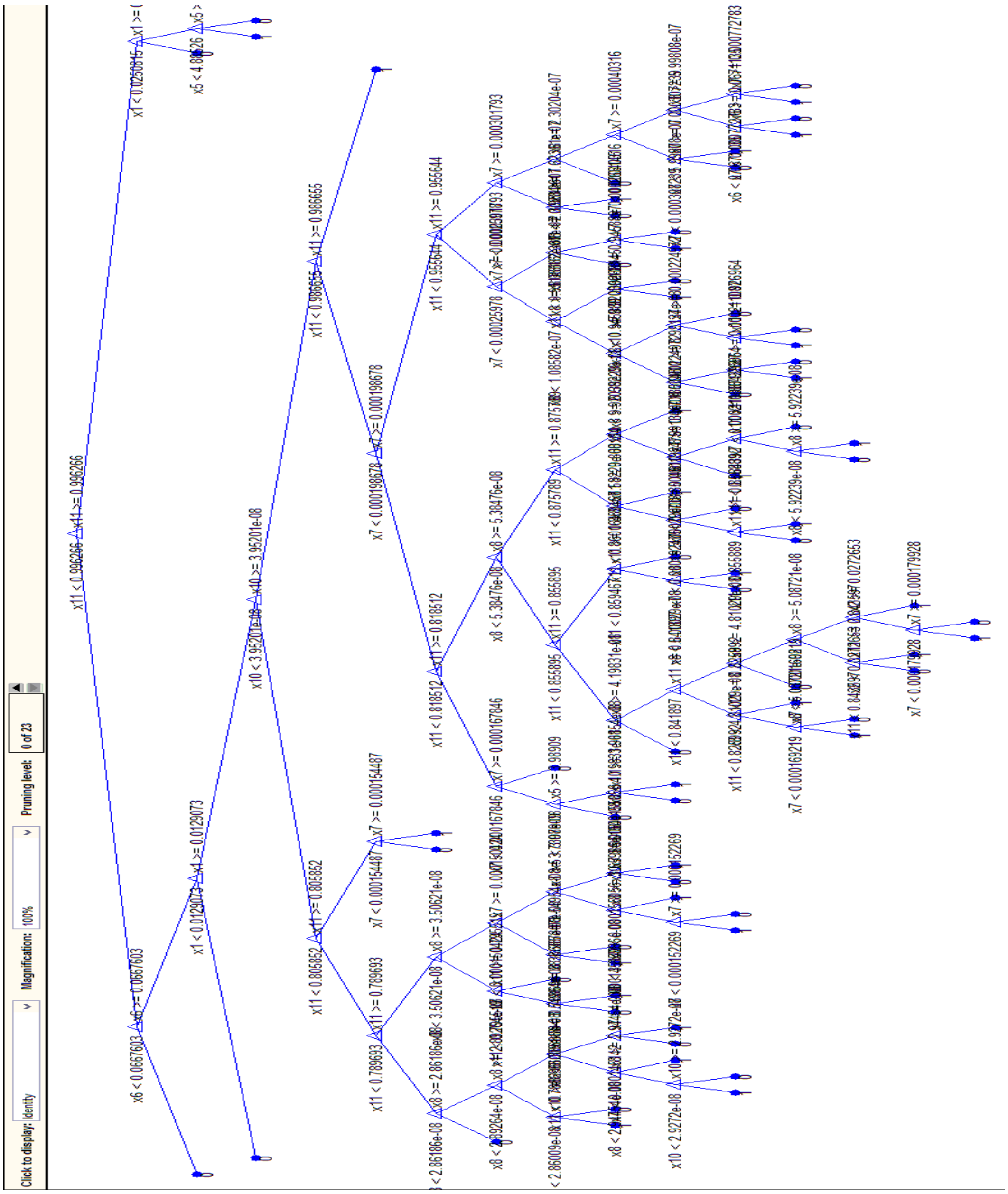


Figure 11.8 Classification tree diagram by using 10,000 samples per observation

Next, we have tested the classifier on independent test data to express the performance of the system using a confusion matrix, which is the most easily understood format for interpreting classification results. For this purpose, we again extracted 2,000 sets for scenario (i), representing the presence of the train and 200 sets each from the rest of the four scenarios representing the absence of the train. For the earlier specified training data, we obtain the following classification confusion matrix shown in table 11.1.

Table 11.1 Confusion matrix for approaching train detection using 100,000 samples

	Classified as Train Absent	**Classified as Train Present**
Actual Train is Absent	1404	196
Actual Train is Present	0	2000

The classifier did not misclassify any samples when a train was present. Therefore, there are no false negatives, which guarantees the security of the workers. Out of 1600 samples, when a train was absent, 196 samples were misclassified and would trigger the alarm system. But it should be noted that out these 1600 samples, 200 samples belong to the scenario when all three sensors are false triggered. As explained earlier, due to the very small probability of this occurring, there will be very few instances of the alarm system switching on unnecessarily. This shows the reliability and accuracy of our multi-sensor train detection system.

Chapter 12 Summary

This project set out to develop a fully automated, fully reliable platform for train approach detection. This research project is of high importance to the railroad industry because of the continued accidents and loss of life involved with railroad ground crews working on or near railroad tracks and trains passing through the work area. Currently, the railroads utilize personnel from their ground crews acting as lookouts for approaching trains. This approach is unreliable and risky, for reasons such as the attention of the lookout slipping, distractions, etc. that lead to late or missed alerts delivered to the ground crews. This also could lead to loss in productivity associated with having to position ground crew personnel as dedicated lookouts instead of being able to participate in the maintenance task at hand.

Multiple vendors have since developed commercial products touted as solutions to this problem. However, none of them have been adopted by the railroad industry. The reasons for this are clear: they are not reliable due to their reliance on a single detection method and the associated failure rates, and often require destructive and semi-permanent installation of equipment on railroad track. This makes them infeasible for this task.

To remedy this problem we investigated a highly portable multi-sensory approach. In our system, multiple different sensors and sensor system all observe the track and attempt to discover approaching trains. Their data is then processed by our system using advanced machine learning approaches that we have shown will eliminate the possibility of the system missing an approaching train. The system has a zero false negative detection rate, which makes it highly reliable in contrast to all other available systems. The system is also modular, expandable, and highly portable. It can be deployed in minutes and does not require destructive installation methods.

To summarize, our system addresses the need expressed by the railroad industry. We are grateful for the support provided by MATC, TTCI and Union Pacific to deliver a meaningful and impactful contribution to the railroad industry's efforts in protecting the health and lives of their employees and to make surface transportation safer and more efficient.

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