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ALPHA FOUNDATION FOR THE IMPROVEMENT OF MINE SAFETY AND HEALTH

Final Technical Report

1. Cover Page

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2. Executive Summary

The objective of this research project was to develop and deploy an integrated safety system to help reduce equipment-related fatal and non-fatal injuries in US surface mining operations. Specific aims in this project were to (i) design a sensor network system geared towards surface mining safety; (ii) establish an infrastructure communication platform for real-time situational awareness; (iii) develop a non-distractive graphical user interface (GUI) for equipment operators/drivers; and (iv) educate and train a new generation of professionals who will be working on surface mining safety research (e.g., capacity building).

The following contributions were made.

I. Sensing systems

a. <u>*Proximity warning*</u>

(i) A zone-based proximity warning system was designed using low power IEEE 802.15.4 radios for detecting obstacles and vehicles at shorter distances (< 30ft), and marking them into zones around the vehicle.

(ii) For timely warning about approaching vehicles at long distances (30-600 ft), a GPS system was integrated with Wi-Fi (IEEE 802.11a/b/p) radios in an *ad-hoc* mode. The use of a *peer-to-peer ad-hoc mode* avoids the need for centralized network infrastructure such as cellular systems. Instead, information about approaching vehicles is communicated as soon as they come into communication range of each other.

b. <u>*Fatigue monitoring*</u>

(i) A novel fatigue monitoring system was designed using *lightweight, commercially available brain-sensing headbands* (specifically, MUSE).

II. Communication systems

(i) To support the Wi-Fi-based GPS warning system, a communication range test was performed in an operating surface mine to characterize the distances at which warning can be reliably received using each of the IEEE 802.11 family of radios.

(ii) A cloud-based logging framework (named **MapMyTruck**) was designed that can be used for *long-term data collection from GPS and other sensors*, thus recording and analyzing near misses in surface mines as well as facilitating better route planning.

III. Non-distractive Graphical user interface

(i) A **unified GUI** was developed for the integration and meaningful presentation of the information acquired from the different sensor network components.

(ii) The GUI was built with a **novel dynamic marker capability** that allows drivers to tag observed road conditions at run time on the GUI and then broadcast this to other drivers using an ad-hoc Wi-Fi network.

(iii) An **automated GUI evaluation tool** was developed using a camera-based, driver-activity-monitoring system that analyzes distractions experienced by a driver, especially with respect to usage of consoles and GUI during operation.

Much of the work for developing and testing these prototype systems was completed in collaboration with Red Hills Mine in Mississippi, in an actual surface mine setting. Some parts of the project were also tested and demonstrated at the Liberty Fuels Mine in Mississippi. Multiple graduate students received interdisciplinary education and hands-on training through this project.

The outcomes of the project are expected to have a positive impact on mine safety. The systems were designed to complement several existing products as opposed to reinventing them. Long-term deployment of these new systems in surface mines should provide a large amount of data related to collision avoidance and driver fatigue, benefiting planning and policy making. The outcomes of this project were presented at mining conferences in West Virginia and Pennsylvania, and to two Mississippi surface

mines, Red Hills Mine and Liberty Fuels Mine. One peer-reviewed journal paper has been published, one is under review, and two other are currently under submission.

3. Problem Statement and Objectives

This proposal addresses Alpha Foundation focus area 1, specifically Safety of Automated and Mechanized Equipment research area. Despite the record of progress achieved in reducing fatal and non-fatal mining injuries in the United States (U.S.), both the number and severity of mining injuries remain unacceptable. A persistent area of concern in mine safety continues to be related to mining equipment (powered haulage and hoisting). According to MSHA records [5, 28-29], a total of 643 fatal injuries between 1995 and 2011 in U.S. coal, metal, and non-metal mining have been attributed to mining equipment. This represents 68.8% of all mining fatalities in the US. The greatest proportion of fatalities is related to haul trucks (21.9%), belt conveyors (9.3%), front-end loaders (8.1%), dozers (6%), and miscellaneous equipment (36.5%). Further analyses of MSHA data indicate that 85.1% of truck-related fatalities, 80% of conveyor related fatalities, 84.6% of loader-related fatalities, and 87.1% of dozer-related fatalities occurred in surface mining.

During the past few decades, there have been many attempts to understand the fundamental causes of injuries related to the mining equipment. In order to reduce these injuries, the mining industry has applied numerous technological and engineering advances, behavioral principles, training programs, etc. Yet, challenges still remain as evidenced by the persistent recurrence of fatalities and the significant proportion of equipment-related fatalities as compared to all fatalities that occur in U.S. mining. Lack of research capacity in surface mining safety in U.S. mining schools presents additional problems.

The **objective of this research project** was to develop and deploy an integrated safety system to help reduce equipment-related fatal and non-fatal injuries in U.S. surface mining operations. Specific aims were to (i) design a sensor network system geared towards surface mining safety; (ii) establish infrastructure communication platform and information management system for real-time situational awareness; (iii) provide a non-distractive user interface for equipment operators/drivers; and (iv) educate and train a new generation of professionals who will be working on surface mining safety research (e.g. capacity building).

4. Research Approach

The mine partner for this project was the Red Hills Mine (Mississippi Lignite Mining Company) based in Ackerman, Mississippi. The mine has nine coal seams in total, with thicknesses ranging from 12 in. to 60 in. The top three seams are not minable because of low coal quality. The mine has a complex geology and a significant amount of annual rainfall (4.7 ft). The mine produces approximately 3.5 million tons of coal and about 40 million bank cubic yards of overburden per year. The operation utilizes diverse mining equipment, including Dragline Marion 8200, electric shovel P&H 2800, 15 Caterpillar end dump trucks CAT 785 and 789B (with payloads of 165 and 200 t, respectively), bulldozers CAT D11, D10, and D6; the Wirtgen surface-miner and various auxiliary equipment.

One of the first steps in this project was to visit Red Hills Mine in October 2013 and get a preliminary insight into specific sensing technologies that would improve mine safety. Vehicular collisions and near misses arising from inadequate collision warnings and driver fatigue and drowsiness were identified as two main areas of concern for the surface mine operations. This observation is consistent with recent studies by NIOSH researchers [30]. The huge size and sheer momentum of the haulage equipment coupled with poor visibility and hidden views make it essential to receive timely warnings about approaching vehicles, obstacles, and personnel [6]. Likewise, nighttime operations and long, strenuous operating hours make driver drowsiness a serious concern. Hence, sensing, communication, and user

interface systems are primarily focused on collision avoidance and driver drowsiness detection. The specific research tasks are described briefly in the following sections. The *corresponding accomplishments are described in Section 5*.

4.1 Task T1: Sensing subsystems

In this task, we focused on the design of three sensing subsystems: (i) RF-based proximity warning system based on low power IEEE 802.15.4 radios, (ii) a Wi-Fi-based collision warning system using communication of GPS data, and (iii) a fatigue sensing system using brain-sensing headbands that measure EEG signals.

4.1.1 RF-based proximity warning

The goal of this system is to provide a warning to a vehicle operator when another equipment or personnel comes close, and also to accurately determine the location as one of several zones around the vehicle. For areas that are closer to the equipment (< 30 ft), GPS data is not precise enough to provide a location indicator. Hence, we use an RF-based system. Specifically, we have utilized the Telos platform [20], which consists of a 2.4GHz IEEE 802.15.4 radio [23]. This is the same radio used by ZigBee devices, but we did not utilize the ZigBee communication protocol in this project. RF-based tagging systems have been previously used for proximity detection in surface mines, but existing systems are typically designed only to detect the presence of other vehicles or personnel in the nearby vicinity and not to pinpoint a location or direction. However, in this project *we showed how multiple low cost, low power, RF devices embedded on the truck along with the received radio signal strength indicator on the radios can be used to accurately identify the zone in which an obstacle is detected.*

System assembly and procedure

For our test deployment of the RF-based proximity system, we used 4 Telosb motes as our RF sensors and installed them on 4 sides of a CAT 769 haul truck. These were used as zone-marker motes. We divided the truck into 8 proximity zones as shown in Figure 1. The Telos platform consists of a Texas Instruments MSP430 microprocessor along with a 2.4GHz IEEE 802.15.4 radio (Figure 2). This is the same radio used by ZigBee devices, but we do not utilize the ZigBee protocol here. A photo taken in the Red Hills mine with one of the zone marker motes deployed on a CAT 769 haul truck is shown in Figure 3.

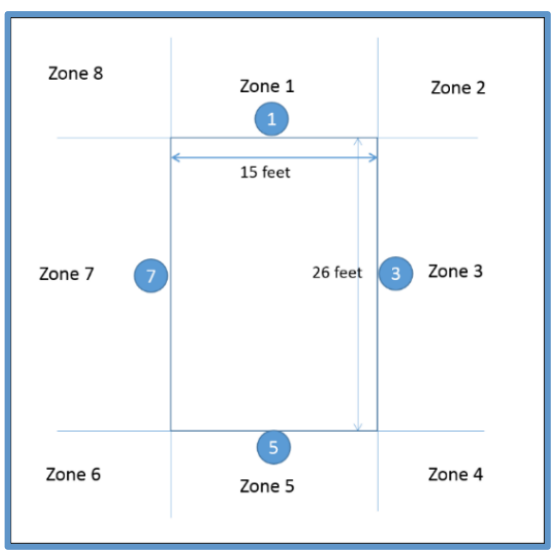


Figure 1: Schematics of mote deployment and zones surrounding a CAT 769 haul truck. The 4 blue circles indicate zone marking motes deployed in zones 1, 3, 5, and 7, respectively.

Figure 2: Telosb mote used for proximity sensing and zoning; it contains a TI MSP430 microcontroller along with an IEEE 802.15.4 radio

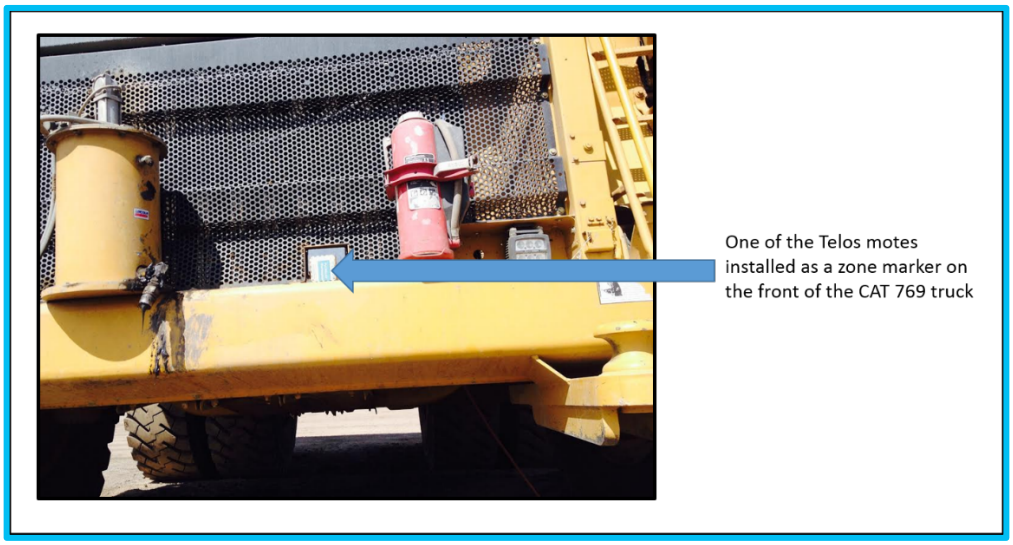


Figure 3: One of the Telos motes installed on the front of the CAT 769 truck as a zone marker mote during the testing of the proximity zoning system

A mobile mote (whose location is to be tracked) acts as a transmitter and sends out a beacon message once every 200ms, i.e., at 5 Hz. Note that the mobile mote is the unit carried by the object being tracked, e.g., this could be mine personnel, vehicles or even large stationary objects in the vicinity to which collision needs to be avoided. The 4 zone-marker motes act as receivers of beacon messages sent out by mobile motes. All the zone marker motes that receive this message record the received signal strength for the message (RSSI). The RSSI recorded by each zone marker is then transmitted wirelessly to a base station mote located inside the truck. The base station continuously sorts incoming messages based on their RSSI. The RSSI values from the motes are averaged over a moving window of 3 seconds. These RSSI values are used to classify the mobile object into one of the 8 zones around the vehicle.

When the mobile mote was inside one of the zones tagged by a zone marker mote (i.e., zones 1,3,5,7 in the Figure 1), the RSSI values from those motes were clearly dominant compared to RSSI values from other motes. We observed an *almost 100% accuracy when classifying motes into only one of these 4 zones.* When the motes were in the other zones, there was no clear dominant RSSI value from any given zone marker mote. We utilized this fact in classifying whether a mobile mote was in zone 1,3,5,7 or in zone 2,4,6,8. The RSSI data sent by the zone marker motes corresponding to each mobile mote beacon

are collected by the base station. This data is sorted based on the RSSI values. We computed the difference in the top two RSSI values at any instant and then took a moving average over the last 3 seconds. This difference is used to classify the zone of the object.

4.1.2 GPS+Wi-Fi based collision avoidance

GPS devices can provide location estimates with an accuracy of about 10 ft. Therefore, GPS devices, along with some form of wireless communication, are increasingly being used for detecting approaching vehicles and for collision avoidance [1-4, 19]. In this project, we used a GPS-based system for collision detection from longer distances (> 30ft). At very short distances, the GPS systems are not accurate enough to correctly estimate the direction in which a nearby obstacle has been detected, although they can estimate that there is an object nearby. Therefore, for shorter distances, we used an RF-based system as described in Section 4.1.1.

GPS-based proximity warning systems are increasingly being recommended for collision avoidance and vehicular safety, in the context of regular pick-up trucks as well as heavy mining trucks. The basic idea in these systems is to use a GPS receiver along with some form of wireless communication module on each vehicle to provide updates about its location to other vehicles. These updates can be provided in two ways: (i) a centralized cellular or long-range communication infrastructure can be used to communicate data from each vehicle to a processing center and then re-broadcast data from there to all the vehicles; (ii) GPS data can be communicated in a decentralized peer-to-peer manner only to vehicles that are close by. The former approach is more cumbersome and expensive, involving excessive setup costs inside surface mines as well as high cost for data usage. Therefore, in this project we employed the latter mechanism by utilizing IEEE 802.11 (Wi-Fi) radios in an ad-hoc mode (Figure 4). In this mode, two Wi-Fi radios can communicate with each other as soon as they come within range of each other.

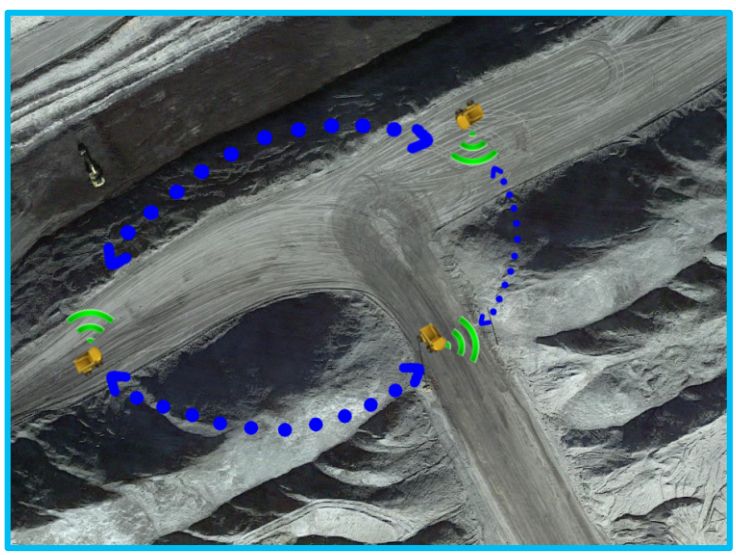


Figure 4: Trucks equipped with GPS and wi-fi form an ad-hoc network to warn each other

The system setup and software components are described below. Each vehicle contains a GPS unit attached to a microcontroller board and a Wi-Fi card and antenna. Each device is configured to belong to a Wi-Fi network in an ad-hoc mode with the same cell ID. This allows data communication without having to explicitly join a network when devices come into contact. The process of joining a network is time consuming (with a latency of several seconds) and will result in large delays. By setting up an ad-hoc mode this latency can be avoided. At the same time, we note that we do not rely on a central infrastructure for data communication. In terms of software, a GPS program periodically samples the GPS coordinates at 5 Hz and sends it to a microcontroller board using a socket program. Then a data broadcast and reception module on the microcontroller utilizes the underlying communication network to broadcast

the GPS data as well as receive GPS data from other transmitters within communication range. Each transmitted packet has a unique sequence number, vehicle ID and timestamp. The received data is plotted on the graphical user interface.

An often-overlooked aspect when designing a GP-based warning system is the quality of wireless communication and the effective distance range at which GPS locations of nearby vehicles can be received inside a surface mine. The topology of a surface mine is different than that of regular roads and contains multiple benches, deep pits, high obstacles such as berms, and sloped muddy roads, which cause a hidden line of sight for wireless radios, leading to poor reception. At the same time, some other conditions are more relaxed when compared with regular roads: (i) the number of vehicles per unit area is much lower thereby reducing channel contention, and (ii) the chances of interference from other devices such as Wi-Fi routers and Bluetooth devices are also lower. In this project, we systematically investigated packet reception characteristics and received radio signal strength at different source-destination distances for IEEE 802.11 a, b, and p radios at Red Hills Mine. By characterizing effective communication range for 802.11 radios in these settings, we were able to determine the effectiveness of such collision warning systems for operation in surface mines, and identify the appropriate 802.11 radio type to use. The system and method used to evaluate the communication aspects is described in Section 4.2.1.

4.1.3 Fatigue sensing system

Driver fatigue is a serious concern for surface mine operations. Work involving the use of mining equipment and pick-up trucks is usually done in two shifts, one daily and one overnight. These shifts are long and strenuous. Moreover, the margin of error is quite small and often a momentary lapse of attention while operating equipment can lead to severe consequences. Given the importance of fatigue monitoring, there have been technologies developed in the industry and academia to address these concerns. These products use a range of technologies such as monitoring of eyes and blink patterns using cameras [40-43], monitoring heart rate variations [46], monitoring yawns [47], monitoring head movements using accelerometers [49], and monitoring sleep patterns over past few days to predict fatigue [48]. Among these technologies, monitoring blink patterns and measuring percentage of eye closure has been the most predominantly used one for fatigue monitoring.

Fatigue assessment using PERCLOS

PERCLOS or percentage eye closure is a commonly used metric for detecting drowsiness. The basic idea here is to observe the blinking patterns of a subject and compute the percentage of time that the eyes are more than 80% closed. Typically, values of PERCLOS less than 0.009 are considered not drowsy while values above 0.012 are considered drowsy (values in between fall into an uncertain category) [44].

Measuring PERCLOS using IR cameras

Vision-based systems are most commonly used for determining PERCLOS. A camera is focused on the subject's face, and computer vision algorithms are used to extract the eye region and determine eye closure. Some such systems have recently been introduced in the market. They are often supported with IR cameras so that the system can work in the dark. One of the subtasks that we undertook related to this topic is to evaluate the effectiveness of IR camera-based systems for fatigue monitoring. We installed two trucks with a camera-based system for monitoring the driver's face region. We observed that such a system could measure PERCLOS reasonably well when a subject stays in proper view of the camera. However, the system is unable to do so under several scenarios that are highlighted in Figures 5 and 6.

Camera-based systems are hard to position inside a truck in such a way that it works for all drivers. Occlusions such as a cap and the steering wheel often obstruct the view of the eyes. The system also fares poorly when there is a lot of glare in the subject's eyes either under too much sunlight or in the presence of bright road lights. When the driver wears glasses, the impact of glare is more pronounced. Our evaluations are quantified in Section 5.1.3.

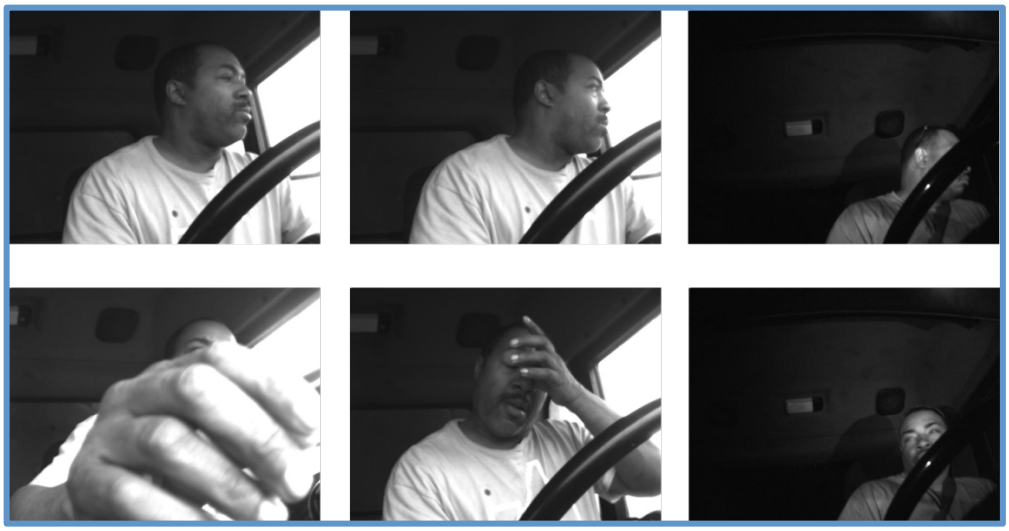


Figure 5: Scenarios where IR camera-based fatigue detection systems fail due to occluded views of the eye region

Figure 6: Scenarios where IR camera-based fatigue detection systems fail due to glare caused by reflection on glasses

Novel drowsiness detection technique using lightweight brain sensing headbands

To address the issues faced by camera-based systems, we designed a novel system that uses lightweight, brain-sensing headbands for drowsiness detection. Specifically, we used a device called MUSE manufactured by Interaxon Inc [45]. MUSE is extremely lightweight, weighing just 61 grams. The system is battery operated and equipped with Bluetooth for data collection The EEG signal is recorded through forehead sensors, and the device does not require use of gels for proper contact. These factors make MUSE convenient to use in the occupational settings. The original purpose of the device is to measure brain activity using EEG signals and aid in meditation. In this project, we have utilized this headband to aid in drowsiness detection by accurately determining blinks and blink durations. We have also explored the use of the headband for drowsiness detection using spectral analysis of neurological EEG signals obtained from the headband.

Figure 7: (left) The MUSE EEG-sensing headband that we used for drowsiness detection; (right) a subject wearing MUSE headband and operating a driving simulator

Medical studies have been done on the use of EEG signals for drowsiness evaluation in the past. However, these are typically done with hospital EEG sensors that are bulky, with several dangling probes. The use of portable, brain-sensing headbands for drowsiness detection has not been explored before to the best of our knowledge. We have systematically evaluated the use of this device on several subjects in both a fresh and drowsy state. The effectiveness of this system for drowsiness detection, along with results obtained in our study, are described in Section 5.1.3.

4.2 Task T2: Communication systems

In this section, we describe the research tasks related to design and testing of the communication subsystems that supported the mine sensing and data collection systems in this study.

4.2.1 Ad-hoc Wi-Fi network for GPS communication

In Section 4.1.2, we described a GPS-based collision avoidance system that uses the IEEE 802.11 Wi-Fi in an ad-hoc mode to receive GPS data. For this task, we carried out a systematic evaluation of the various IEEE 802.11 radios inside surface mine topologies to understand the reception characteristics of the data and to facilitate the selection of an appropriate radio that maximizes the distance from which warnings can be reliably received.

IEEE 802.11 and Wi-Fi overview

The Wi-Fi Alliance defines Wi-Fi as a wireless local area network (WLAN) product based on IEEE 802.11 standards. **IEEE 802.11** is a set of media access control (MAC) and physical layer (PHY) specifications for implementing wireless computer communication in the 2.4, 5, and 60GHz frequency bands. The IEEE 802.11 family consists of a series of standards that use different modulation techniques and frequency bands, but use the same underlying communication protocol. In this research project, we specifically considered the IEEE 802.11 a, b, and p series for evaluation.

The 802.11a specification is an amendment to the IEEE 802.11 family that uses the same frame format and link layer protocol as the original 802.11 specification, but operates in the 5.8 GHz band and uses the orthogonal frequency division multiplexing (OFDM) technique for signal modulation. It can achieve a net data rate of 54 Mbps including error correction codes, which effectively results in throughputs of about 20 Mbps. The advantage of 802.11a is the use of the 5 GHz frequency instead of the crowded 2.4 GHz ISM band, where interference from other devices often can be found.

802.11b is an amendment of IEEE 802.11 that uses the direct-sequence spread spectrum (DSSS) with data rates of 5.5 and 11 Mbps in the 2.4 GHz range. One disadvantage is the use of the 2.4 GHz frequency where many other devices operate such as Bluetooth devices and Wi-Fi routers that may cause wireless channel interference. However, in surface mining environments, we do not expect this interference.

The 802.11p supports wireless access in vehicular environments (WAVE) and contains enhancements required to support Intelligent Transportation Systems applications [21]. The standard uses the 5.9 GHz ISM band and enables car-to-car or vehicle-to-vehicle communication. Available data rates for this standard are 3, 4.5, 6, 9, 12, 18, 24, and 27 Mbps. Similar to IEEE 802.11a, 802.11p radio is based on matured orthogonal frequency-division multiplexing (OFDM) technology. The medium access control (MAC) layer functionality is slightly modified to include provision for rapid communication of DSRC devices with no need for authentication or authorization processes as in the original 802.11 standard.

Communication range tests

The topology of a surface mine consists of multiple benches, sloped terrains with mud, and rocks/soil piled at the edge of vehicular pathways. As mentioned before, this causes several hidden-line-of-sight scenarios at intersections for both drivers, as well as the propagation of 802.11 radio waves. In many of these cases, the pathways are sloped with hairpin-bend intersections where vehicles are unable to see each other and must rely on location warnings with adequate response time. To characterize the performance of IEEE 802.11 inside a surface mine, we conducted range tests using a sender-receiver pair of the above system under the following different topological conditions: (i) Line of sight, (ii) Non line of sight, (iii) On an inclined hairpin-bend with receiver at the bottom, and (iv) On an inclination with receiver at the top. Sender and receiver were separated by distances in steps of 30ft. Sender transmission rate was fixed at 5Hz with each packet about 100 bytes. The results of our evaluation are described in Section 5.2.1.

4.2.2 Cloud-based logging system for data collection and long-term analysis

The network setup in Section 4.2.1 is used for instantaneous warning generation. But there is a need for long-term data collection from GPS and other sensors that may be deployed on every truck. To facilitate this, we designed a cloud-based logging framework.

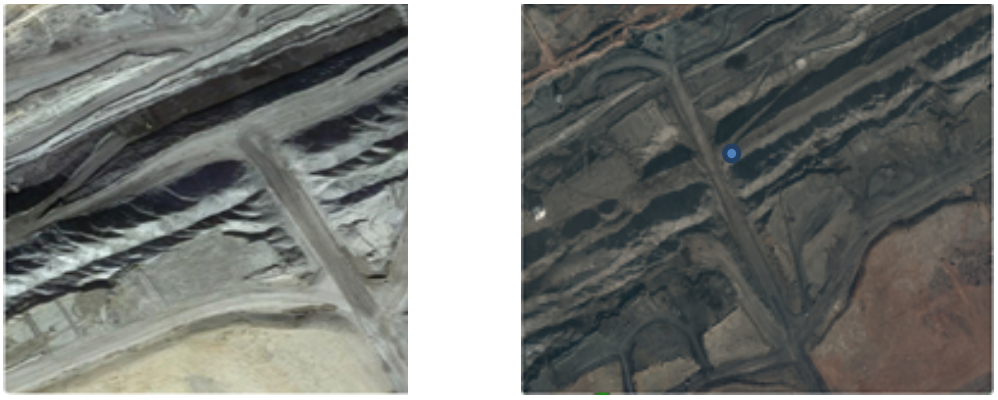
The surface mine where we did our testing (Red Hills Mine) has a Verizon private wireless network through which individual trucks could have access to the Internet. However, the connection was intermittent and slow speed. Also, the cost was based on data sent, and logging every piece of information from the sensors would be expensive and create a lot of data traffic. The cloud-based logging system that we designed is aimed at addressing this challenge. Description of the system and sample GPS data logged with this system is shown in Section 5.2.2.

4.3 T3: Graphical User Interface (GUI) Design and Evaluation

Appropriate design of the user interface is important to ensure effective communication of warnings to equipment operators and appropriate response selection. Typically, individual monitoring systems such as those for proximity warning are equipped with their own user interface and interaction console. However, this leads to distraction and confusion. In this task we have designed a unified interface for RF based proximity warning, GPS based collision avoidance system and the fatigue monitoring system. We have also developed an automated evaluation tool that can determine the effectiveness of a GUI system by measuring user distraction levels when operating the console.

4.3.1 GUI Development

GUIs with the ability to integrate realistic earth view maps with GPS sensor data could have the potential to enhance users' situation awareness, and therefore such GPS-based systems could very well serve as navigation systems that help in improving drivers' safety. However, there are several challenges associated with developing a navigation system that incorporates accurate earth-view maps. The first challenge is related to limited data sources. Google Earth maps and Bing maps are not updated frequently. The maps provided by Google or Bing are updated every 1 to 3 years. For a typical surface mine maps change on a regular basis depending upon the excavation plan (Figure 8). Therefore, there is a need to incorporate custom mine-specific maps while retaining the ability to zoom and rotate.



(a) (b)

Figure 8: Challenges associated with implementing earth-view maps in the GUI: (a) map obtained from Google earth map data source; (b) map of the same region as (a) obtained using custom aerial imagery

Second, the mine environment also exhibits conditions that often change quite frequently, even several times a day. For example, there may be paths that have become temporarily inaccessible or a road that has become slippery and hazardous. Currently, there is a problem with operators including these indications into the map GUI and thus providing safety warnings. Finally, there is a need to include non-GPS data such as location data obtained from RF sensors, cameras, or LIDARs into the same navigation interface because it is hard for operators to switch between multiple screens to look for hazard warnings. In this task, we have addressed all three challenges.

4.3.2 GUI Evaluation

Once a GUI has been designed for vehicles, testing and evaluation is typically carried out in a subjective manner. The system is installed in the truck for a few days and drivers are then interviewed about aspects of the GUI such as the ease of use, distraction levels, etc. This approach is often not very effective because it does not quantitatively evaluate the performance of a GUI design. To address this issue, in this task we have designed an automated tool based on Computer Vision techniques that can measure the distraction associated with usage of a GUI system.

Specifically, we designed a camera-based activity recognition system that classifies a driver's activities into one of several classes such as driving, looking sideways, changing gear, changing controls, or viewing the GUI, talking on the radio, etc. By doing so, several metrics related to the time spent by a driver on GUI and control-related activities can be computed. This can provide valuable insights into the effectiveness of the GUI system as it can show the time it takes for each GUI-related interaction such as just viewing a map or interacting with the GUI by pressing buttons, switching screens, etc.

The activity recognition system, designed using deep learning techniques and convolutional neural networks, was shown to have high accuracy in recognizing driver activity as presented in Section 5.3.3. Note that this system does not have to be permanently mounted on a truck, i.e., it can be utilized only during evaluation of new user interface systems.

4.4 Task T4: Data analysis and validation

The task of data analysis and validation was folded into individual sensing systems, communication systems and graphical user interface systems designed in this project. Much of this validation was carried out using data collected in Red Hills Mine. Individual data validation and analysis activities are summarized below.

1. Preliminary data for the RF proximity warning system was first collected and analyzed for designing zone detection algorithms. Once these were designed, the system was demonstrated at the Red Hills Mine in October 2015.
2. Data was collected in October 2014 and March 2015 to characterize IEEE 802.11 communication characteristics inside a surface mine. This analysis was used to design the Wi-Fi-based collision avoidance system that was demonstrated in October 2015.
3. IR camera data was collected in October 2014 to understand and characterize the limitations of camera-based approaches for blink detection and fatigue analysis. To counter these drawbacks, an EEG-based system was designed for characterizing blinks and blink durations. This system was analyzed and demonstrated in October 2015.
4. The cloud-based data logging system was installed in 3 trucks inside Red Hills Mine and the ability to upload data was demonstrated in October 2015. It was also shown that the system could compress data based on vehicle speed and also tolerate intermittent Internet connection.
5. The integrated GUI was qualitatively demonstrated during the testing and validation of the RF proximity warning and GPS collision avoidance system October 2015. In addition, a quantitative tool for characterizing distraction levels of users was designed.
6. Camera data was collected in March 2014 on three different trucks to characterize a driver's activities, especially those related to operation of consoles and talking on radios. This data was used to train and test the driver activity recognition system used for computing distraction levels caused by graphical user interface, radio, and other consoles in the vehicle.

With the prototype systems that we developed and tested in this project, it will be possible to collect data over a longer term and use data mining techniques to analyze this data and use it to enhance mine safety. We point out some specific examples here:

(i) With our fatigue monitoring system, long-term data collected from multiple drivers and shifts can be used to track attentiveness and freshness levels using blink rates and potentially EEG signals. This can be used by mine safety operators to design optimal shift hours and duration. Drowsiness data can also be used to develop personalized work shifts for drivers based on their specific pattern of drowsiness. Real-time warning systems can also be developed that use a combination of blink analysis and spectral data for more accurate and timely warnings.

(ii) Data collected by our portable camera system can point out deficiencies in user interface designs and can be used to optimize placement of instruments, gauges, and radios.

(iii) Long-term data collected from our GPS system can be used to analyze vehicle trajectories in the mine and assess near misses, hazardous routes, etc.

4.5 Task T5: Capacity Building

In this project, we conducted interdisciplinary education and training of computer science and electrical engineering, mining engineering, and industrial engineering graduate students. Graduate students in these fields were involved in developing hardware components and writing software, were exposed to the safety challenges in surface mines, and received hands-on experience with the operations in actual surface mines. A graduate student trained in mining engineering provided insights about specific challenges and focus areas in surface mines, and in turn was trained in computing technologies that can be applied towards surface mine safety. All these students spent time working on data collection and testing in an operating surface coal mine.

5. Summary of Accomplishments

In this section, we summarize our research accomplishments by classifying them into the following 4 categories: (i) sensing systems, (ii) communication and networking, (iii) user interface design and testing, and (iv) workforce training.

5.1 Sensing systems

Three different sensing systems were designed and tested in this project: (i) RF-based proximity warning, (ii) GPS and Wi-Fi-based collision avoidance, and (iii) wearable EEG-based fatigue monitoring. These are described below.

5.1.1 RF-based proximity warning

We have designed and tested an RF-based proximity warning system that uses IEEE 802.15.4 radio operating at 2.4GHz frequency. We show how multiple RF devices embedded on the truck along with the received radio signal strength indicator on the radios can be used to accurately identify the zone surrounding the vehicle in which an obstacle is detected. *Unlike ultrasonic sensors and camera-based solutions [12-17], this approach does not have line-of-sight restrictions or blind spots.* The system described in Section 4.1.1 was validated and demonstrated at Red Hills Mine. The classification accuracy obtained using this scheme is shown in Figure 9 for distances of 10, 20, and 30 feet from the truck. As observed in Figure 9, we get almost 90% accurate zoning and about 10% of the time, the zones are classified as the directly adjacent zone.

Figure 10 shows an object being tracked using this system during a demonstration at the mine. A person carrying an RF sensor was asked to walk around a CAT 769 truck at a distance of about 10 feet from the truck. The motion of the person was tracked using a visualizer. In Figure 10 (left), we show a person carrying the RF sensor in proximity of the truck. The red dot in Figure 10 (right), indicates the tracked position of the object on the visualizer.

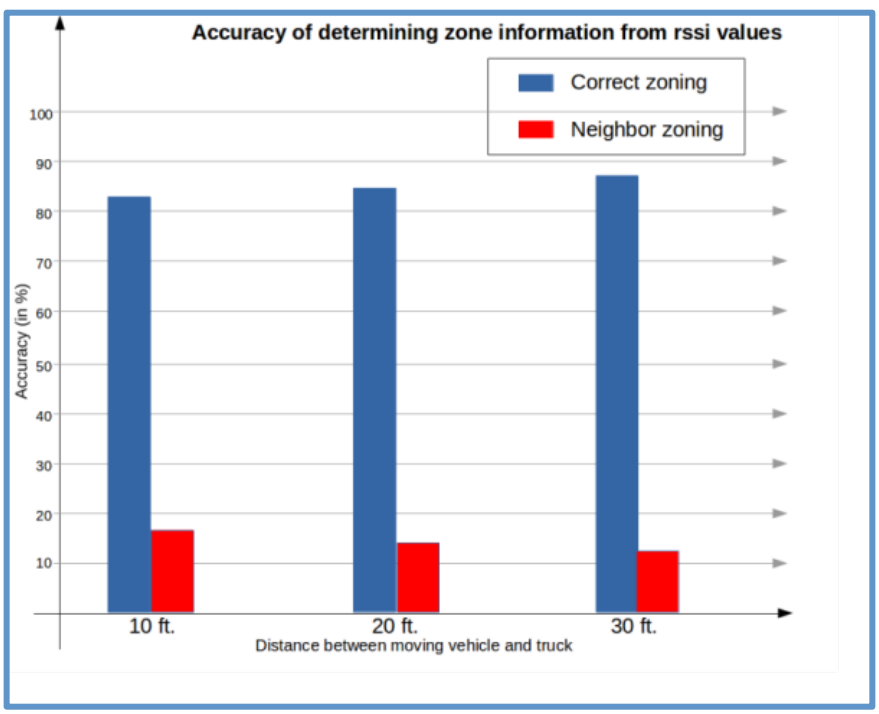


Figure 9: Accuracy of determining zone information based on RSSI values

Figure 10: (Top left) Subject standing 10 ft in front of CAT 769 truck (Top right) Red dot indicates subject shown in front of truck on GUI (Bottom left) Subject standing 5 ft in back of CAT 769 truck (Bottom right) Red dot indicates subject shown in back of truck on GUI

5.1.2 Wi-Fi-based GPS collision avoidance system

As described in Section 4.1.2, we developed a collision avoidance system that communicates GPS data of approaching vehicles in a timely manner. The use of an *ad-hoc* mode for Wi-Fi networks avoids the need for a cellular or long-range multi-hop network in which GPS data would first be transmitted to a central processing unit and the vehicle locations would be then broadcast from that central system. Instead, in the proposed approach, information about approaching vehicles is known as soon as they come into communication range of each other. This also keeps the display for equipment operators free of clutter, as only information about nearby vehicles is displayed. The system was tested and demonstrated Red Hills Mine. A demonstration of the technology was carried out in which approaching vehicles were tracked on a graphical user interface. The ability of the system to provide timely warning was validated using this demonstration.

In Figure 11, we show one of the results of this experiment at a 5-path intersection of the mine. The intersection is obstructed by tall piles of extracted overburden and therefore there is no direct visibility of approaching vehicles. In Figure 11, the yellow rectangle indicates the tall obstacles. X is the location of the receiver node. The thick blue lines are the track of the vehicle, which is driven along different sides of the intersection. The pink dots show the received GPS location from the mobile mote. Points A, B, C, and D show the maximum range at which GPS locations can be obtained at a steady rate along the different sides of the intersection. It can be seen that the range from X to C is about 490 ft (151m) but in the presence of obstacles this range decreases. The distances to X from A and D is about 270 ft (82m) and 255 ft (84m), respectively. The direct geometric distance from B is 134 ft (41m), however along the path of the vehicle, the distance is much larger.

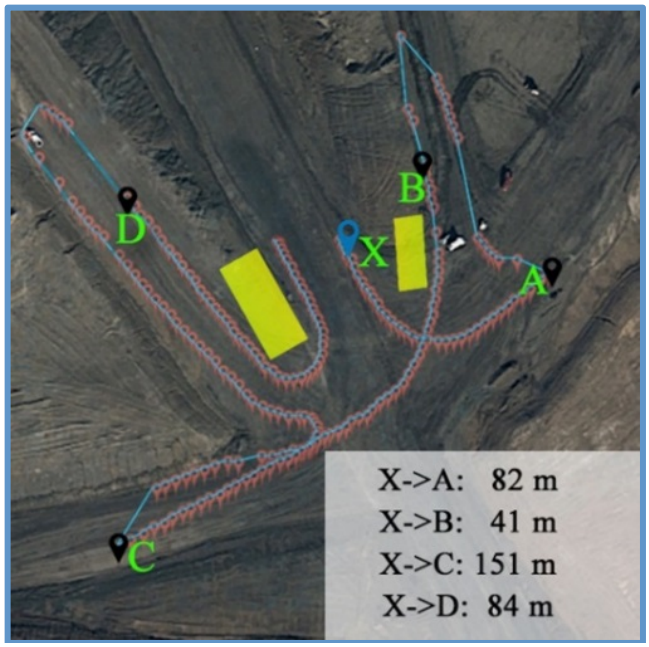


Figure 11: GPS tracking range with 802.11b radio on a 5-path intersection with obstacles. The yellow rectangles represent the tall obstacles. X represents the position of the receiver.

5.1.3 Fatigue sensing system

As described in Section 4.1.3, we have designed a novel fatigue monitoring system using brain sensing headbands. In this section, we quantify the performance in terms of blink detection accuracy and compare that with camera-based systems. We also show the blink duration measurements made for fresh and drowsy subjects using the MUSE EEG sensor. Finally, we also describe the results from spectral analysis of the EEG signal and highlight its ability to detect the onset of drowsiness as well.

Effective blink detection using EEG signals

When the MUSE headband is attached to the forehead, we observe a clear distinguishable pattern in the EEG signal corresponding to a blink. This is illustrated in Figure 12.

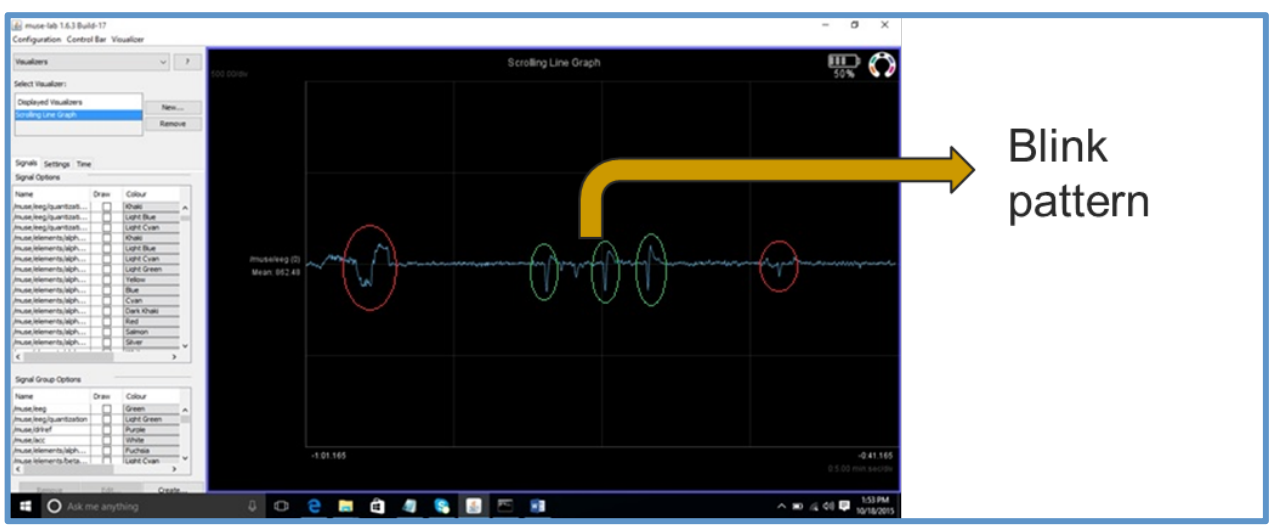


Figure 12: Blinks detected using EEG; the green circles show the pattern of blink; the red circles are not blink – they are caused by head movements

This makes it more reliable to detect blinks and compute blink durations using EEG signals obtained from the headband, even under conditions such as poor lighting, glares, usage of glasses, or improper camera view. We developed a software program to detect blinks and compute blink durations based on the EEG data obtained from the headband.

Figure 13 (right) illustrates the difficulty of capturing blinks when light is shining on the eye region when using IR cameras and the subject is wearing glasses. As a result the IR based system is not able to detect blinks, while the EEG-based approach can clearly distinguish blinks as shown in Figure 13 (left).

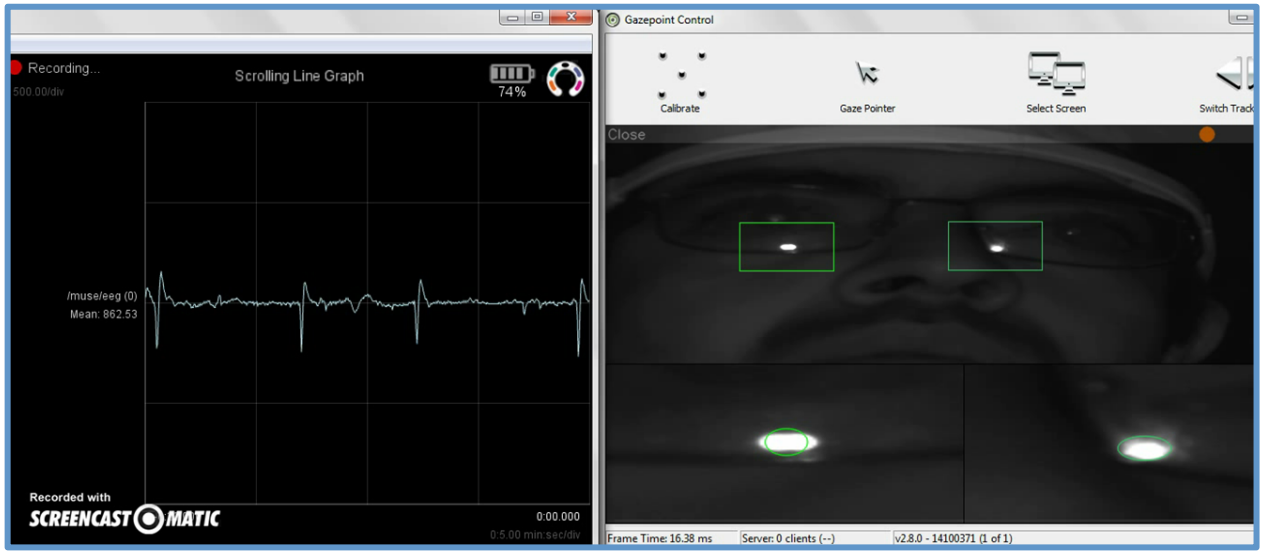


Figure 13 (left) Blinks detected using signals from EEG headband. (right) Glare in the eye region causes difficulty for IR camera based system to detect blinks accurately.

Table 1 shows the blink detection accuracy using the headband for data collected with 3 subjects for 1 hour each. As can be seen, the accuracy of detection is quite high. An IR camera-based approach can obtain comparable performance to that of Table 1, provided the subject is looking straight and the camera is able to capture proper view of the eye region. However, the performance deteriorates under adverse conditions such as wearing glasses or improper camera views.

Table 2 compares the blink detection accuracy for a person wearing glasses when the IR illumination causes glares around the eye region. As seen in the table, the IR-based approach has a lot of false negatives.

Note that in the presence of head motion, EEG signals can occasionally detect false positives for blinks because of spikes in the signal. However, we can potentially filter these false blinks by correlating with accelerator data which records head motion and is included in the headband.

	Blinks	Percentage
True positives	3586	97
False Positives	74	2
False Negatives	107	3

Table 1: Blink detection accuracy using EEG headband

	EEG	IR
True positives	98%	14%
False negatives	2%	86%

Table 2: Blink detection accuracy for EEG-based approach and IR camera-based approach when subject is wearing glasses and the IR illuminator causes glare in the eye region. The IR camera solution causes false negatives because most of the time, the camera is unable to record the blinking motion.

Blink duration comparison for fresh and drowsy subjects using EEG signals

To compare the blink characteristics of fresh versus drowsy subjects, we collected the EEG data for 5 subjects in fresh as well as drowsy conditions, for one hour each, in an indoor driving simulator. 'Fresh' data was collected in the morning (sometime between 8 and 11 am) after each of the subjects had adequate 6 to 8 hours of sleep. The data was collected at a time that they individually rated as being fresh. For collecting 'drowsy' data, the subjects were asked to be awake for 18 hours since they woke up in the morning and were instructed to not have any caffeine throughout the day. During data collection, the room was dark except for a dim light in one corner of the room, to simulate night-time driving conditions.

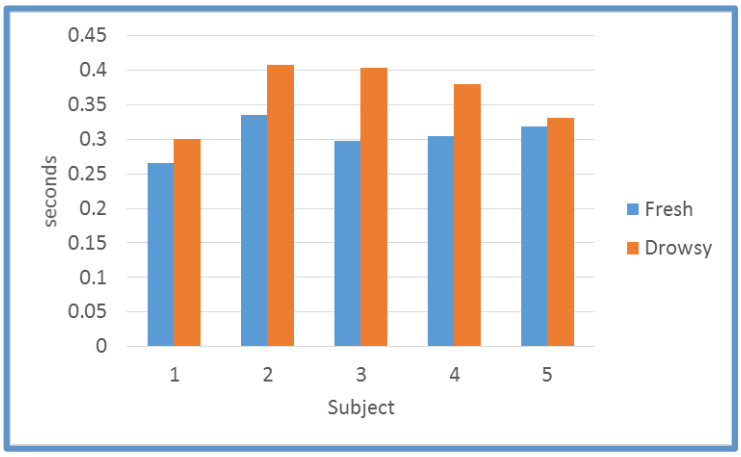


Figure 14: Comparison of average blink duration for 5 subjects in fresh and drowsy states

Figure 14 compares average blink durations obtained using the EEG data for fresh and drowsy subjects. For individual subjects, the average blink duration was higher in the drowsy state compared to the fresh state. Note that the blinking patterns vary across subjects, so it is not feasible to obtain one common threshold for detecting drowsiness. Progressively increasing blink duration can potentially be used to detect onset of drowsiness.

Spectral analysis of EEG for drowsiness detection

In addition to the blink pattern obtained using EEG signals, we believe that spectral analysis of EEG signals can yield further information about onset of drowsiness. EEG signals are typically classified into several frequency bands: alpha (8-15Hz), beta (16-31 Hz), theta (4-7 Hz), and delta (<4 Hz). Each of these bands is associated with a certain type of brain activity. For instance, beta waveforms are associated with high thinking and focus, alpha waveforms are associated with relaxation and theta/delta waveforms are associated with drowsiness and slow wave sleep.

We have done a preliminary analysis on the spectral information for the EEG signals corresponding to the 5 subjects in fresh and drowsy state. Specifically we compared the power spectral density in the 2-4Hz range (which corresponds to the high delta and low theta band) for fresh as well as drowsy states. The average spectral density over a 60-70 minute duration is shown in Figure 15. The figure shows that the 2-

5Hz band is more active in the drowsy state than the fresh state. Here also, we observed that the actual values differ for different subjects, while relatively the mean power spectral density was higher in the 2-4Hz range in the drowsy state. Note that the data in Figure 15 corresponds to an aggregated average over 60-70 minute duration. We also observed instantaneous spikes in the spectral power for the 2-4 Hz range that are more prominent in the drowsy states. This is shown in Figure 16 for one of the subjects.

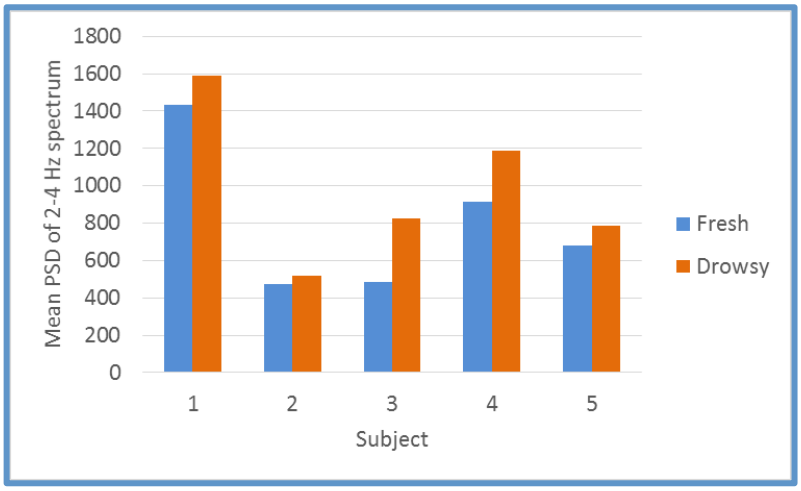


Figure 15: Comparison of average spectral power in the 2-4Hz range for 5 subjects in fresh and drowsy states over 60 minutes each.

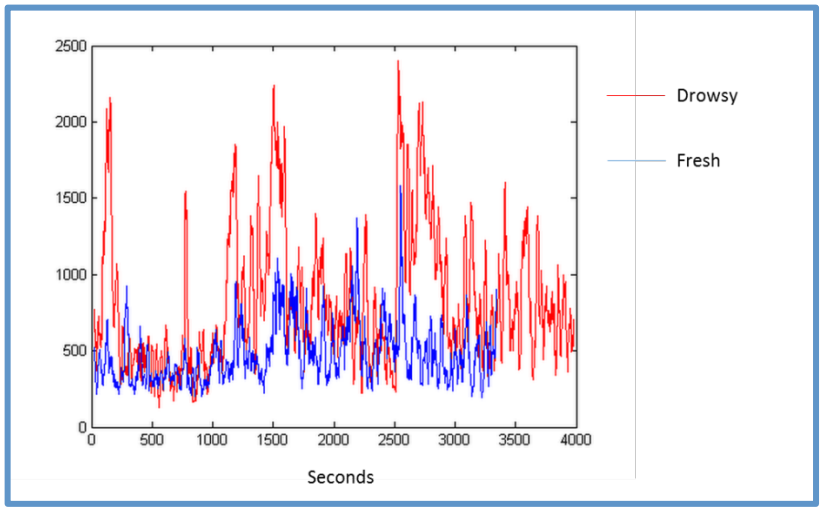


Figure 16: Moving average of spectral power in the 2-4 Hz for one of the five subjects

Summary for EEG-based drowsiness detection

In summary, we contributed a new approach for fatigue monitoring and driver drowsiness detection using off the shelf, lightweight, wearable EEG headbands. We developed a tool for detecting blinks and analyzing blink durations. We showed that use of EEG headbands for blink analysis is more robust than camera-based approaches, especially in some adverse lighting conditions. We have done a preliminary analysis using data from 5 subjects that show that both blink patterns as well as spectral data obtained from wearable EEGs can be used towards detection of drowsiness.

Moving forward, we would like to collect additional data on more subjects, perform more rigorous statistical analysis, and use these results to design real-time algorithms that use either blink data or spectral analysis of EEG data or both for detecting onset of drowsiness. We would also like to see *how*

soon drowsiness can be detected based on changes in spectral data and blink duration patterns, while maintaining high accuracy.

5.2 Communication systems

In this section, we describe our accomplishments and results related to communication systems development.

5.2.1 Range tests on Ad-hoc WiFi network for GPS communication

To support the collision warning system using GPS data, we have used a WiFi network. It is necessary to evaluate the feasible range at which warnings about approaching vehicles can be adequately received. To characterize the performance of IEEE 802.11 inside a surface mine, we conducted range tests using a sender-receiver pair of the above system under the following different topological conditions: (i) Line of sight, (ii) Non line of sight, (iii) On an inclined hairpin bend with receiver at the bottom, and (iv) On an inclination with receiver at the top. Sender and receiver were separated by distances in steps of 30 ft. Sender transmission rate was fixed at 5Hz with each packet about 100 bytes. The results of our evaluation are described below.

The system that was assembled for testing consisted of the following hardware and software components:

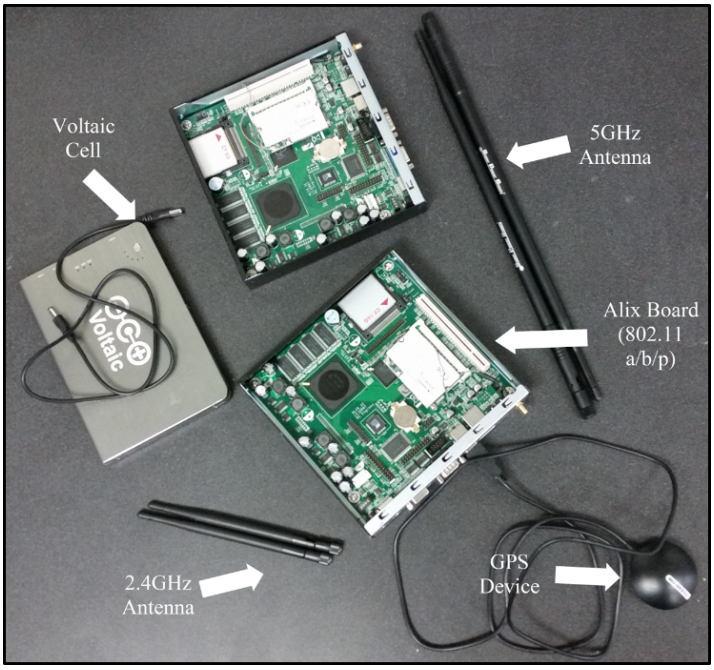


Figure 17: Components of Wi-Fi range test inside a surface mine: GlobalSat BU-353 GPS device, Alix single board computers, dual band antennae, Unex 802.11 wireless cards and Voltaic cells to power the system

Hardware (Figure 17):

(i) GPS sensor: The Globalsat BU-353 was used as the GPS module for the system [26].
(ii) Processing: Each GPS device was attached to an Alix 1e [22] single board computer that has a 500MHz AMD Geode CPU and 256 MB SDRAM. This board has a mini-pci slot for inserting the wireless card.
(iii) Wi-Fi module: The *UNEX CM9-GP* mini-pci wireless card [24] was used as the Wi-Fi module that has support for IEEE 802.11 a, b, g, and p standards.
(iv) Antenna: A 9dBi dual band 2.4 GHz / 5 GHz antenna was attached to the wireless card for communication.

Summary of findings

In Figures 18-21, we show the packet reception rate for IEEE 802.11 a, b, and p radios under different conditions and the corresponding RSSI values that indicate the strength of radio reception. The data shown is derived from several trials by systematically sending and receiving data from different distances. The points shown are medians over these trials. Approximate trend lines have been fit to better understand the pattern in this data.

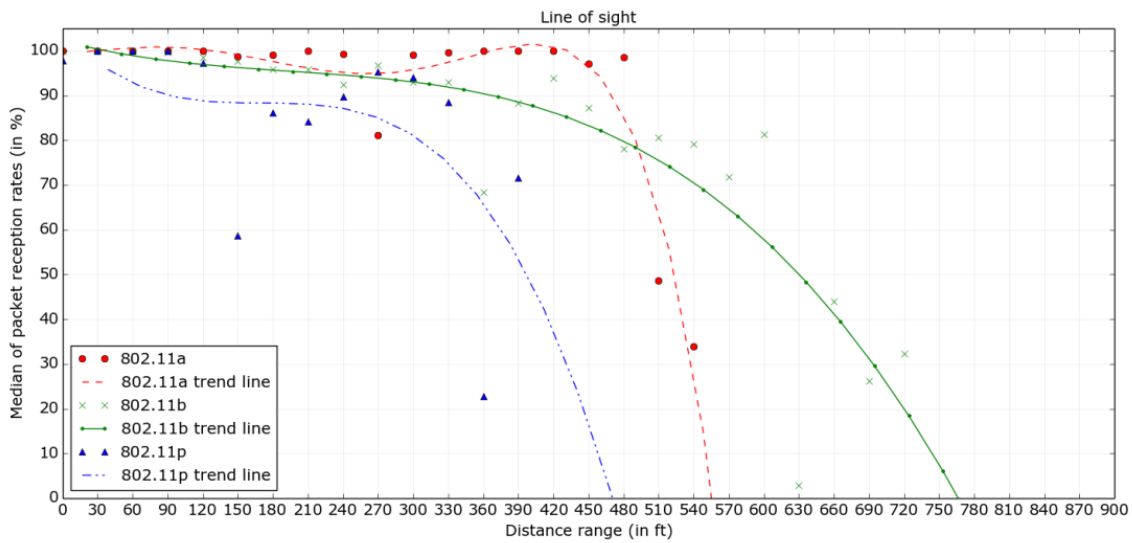


Figure 18a: Median packet reception rate as a function of source receiver distance (direct line of sight)

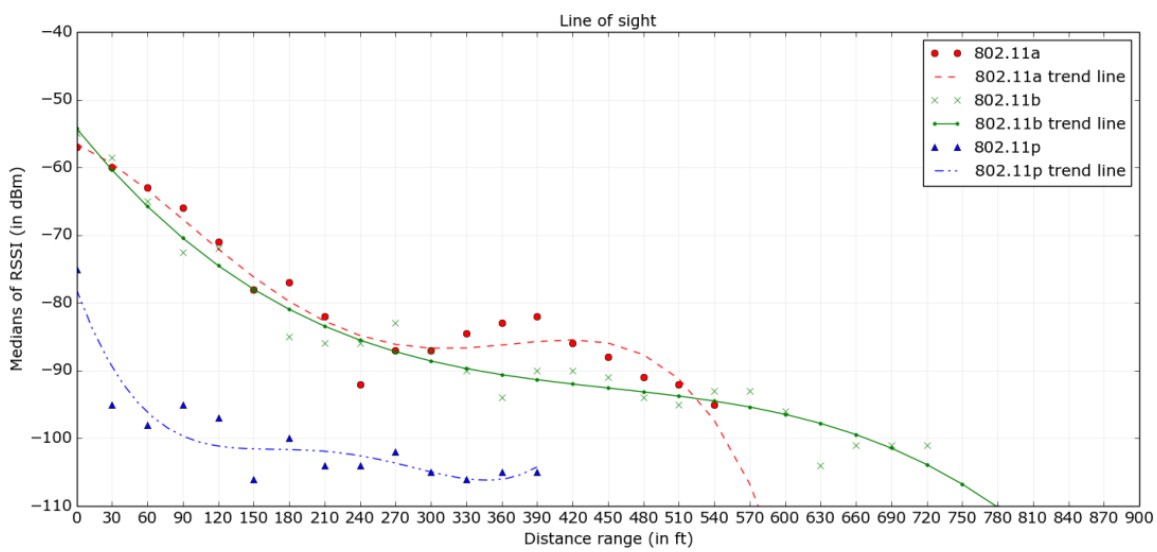


Figure 18b:RSSI trend as a function of receiver distance (direct line of sight)

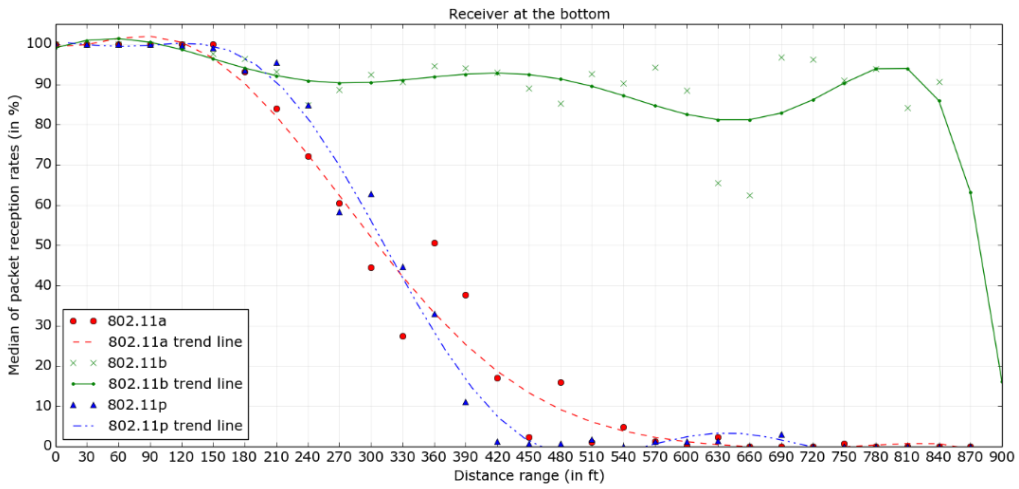


Figure 19a: Median packet reception rate as a function of source distance (receiver at bottom)

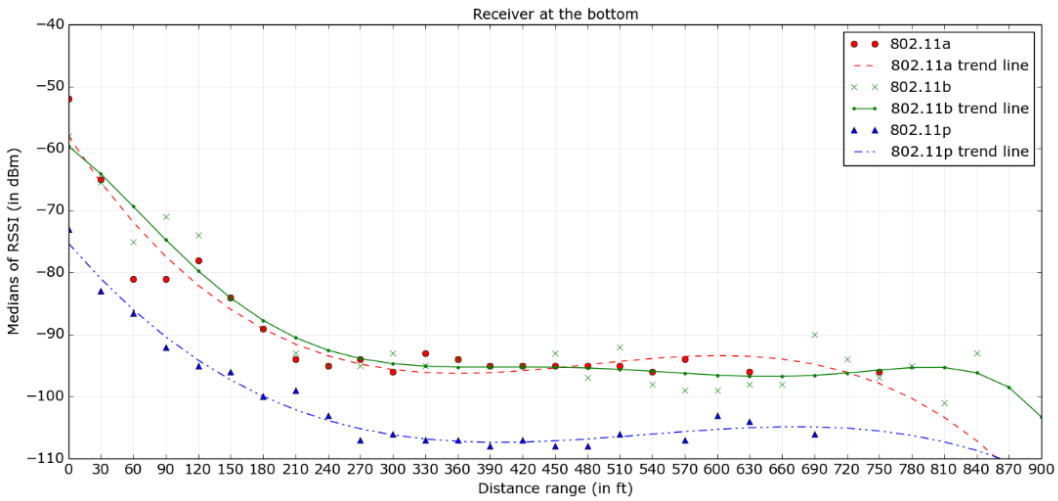


Figure 19b:RSSI trend as a function of receiver distance (receiver at the bottom of an incline)

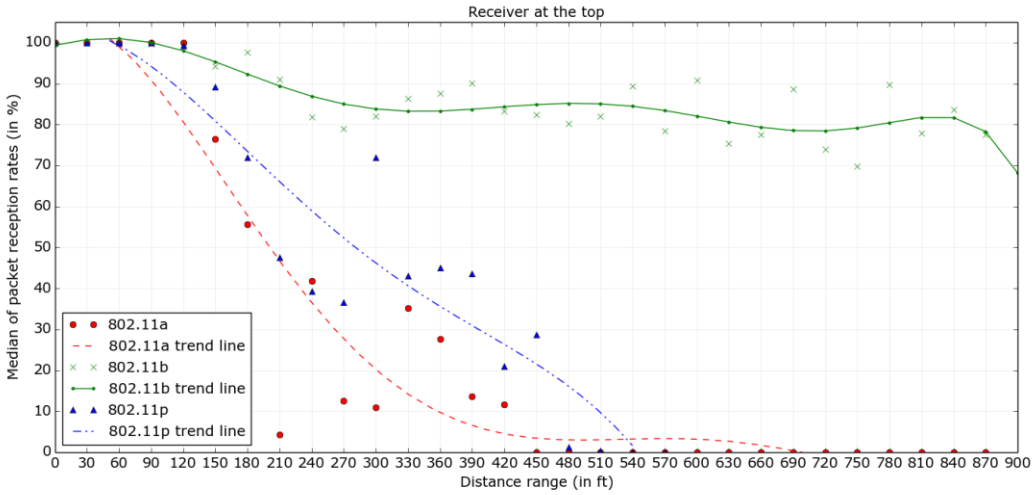


Figure 20a: Median packet reception rate as a function of source receiver distance (receiver at the top)

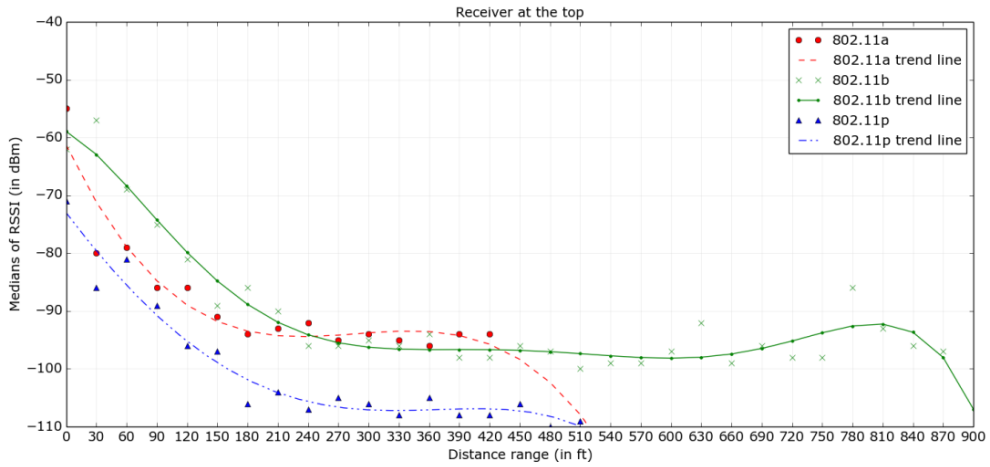


Figure 20b:RSSI trend as a function of receiver distance (receiver at the top of an incline)

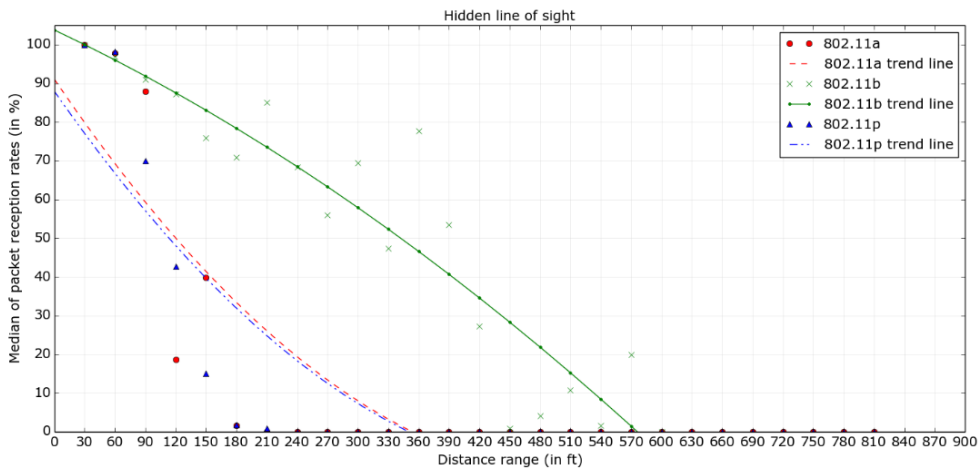


Figure 21a: Median packet reception rate as a function of source receiver distance (hidden line of sight; sender and receiver are separated by a large mound of dirt and rock)

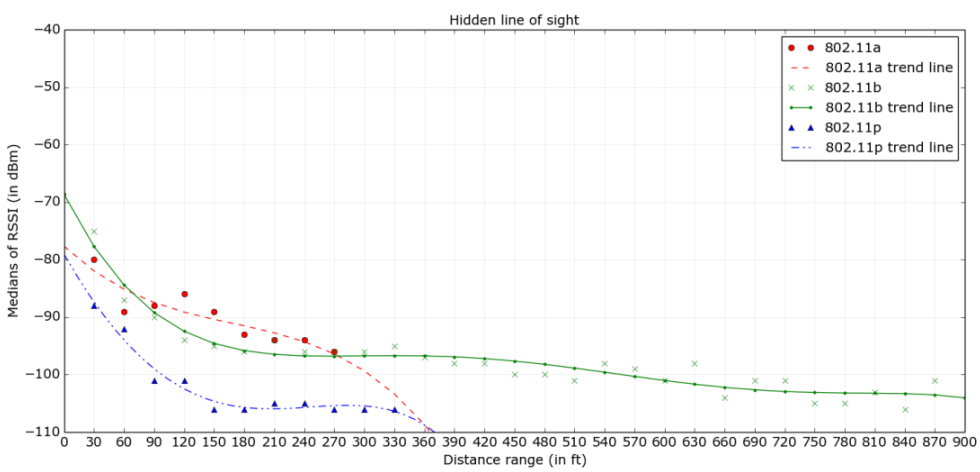


Figure 21b: RSSI trends as a function of source receiver distance (hidden line of sight; sender and receiver are separated by a large mound of dirt and rock)

In Figures 18a and 18b, we show the packet reception percentage and RSSI, respectively, for the line-of-sight scenario. Under the line-of-sight scenario, the graphs show a steady deterioration in signal quality and packet reception for all three radios. But we see that 802.11b and 802.11a have a much greater reception range than 802.11p under these conditions. Also, we note that RSSI and packet reception rate drop off steeply for 802.11a radios after a certain distance, but 802.11b is able to get weak signals at much greater distances.

In Figure 19a and 19b, we show the packet reception percentage and RSSI, respectively, for the sloped terrain scenario where the receiver is at the bottom of an inclined pathway. In Figure 20a and 20b, we show the packet reception percentage and RSSI, respectively, for the sloped terrain scenario where the receiver is at the top of an incline. In sloped terrains, 802.11b is observed to have a much larger packet reception range compared to the other two radios. Both 802.11a and 802.11p have similar characteristics with lower packet reception range. Also, we observe that RSSI values are relatively stronger when the receiver is at the bottom.

In Figure 21a and 21b, we show the packet reception percentage and RSSI, respectively, for the hidden line-of-sight scenario In hidden line of sight, when the sender and receiver are blocked by a high overburden piles, all three radios seem to be affected with lower packet reception range. The RSSI values are relatively weaker. However, in this scenario also, 802.11b significantly outperforms the other two radios in terms of communication range.

In Table 3, we list the approximate reception range at which more than 75% of the packets are received on average for each of the scenarios. We observed that with IEEE 802.11b, even in the worst condition (hidden line of sight), packets can be received at a distance of 240 feet from each other, giving adequate reaction time for the drivers (at a speed of 20 mph, this gives drivers about 9 seconds of reaction time.)

	802.11 b	802.11 a	802.11 p
Direct line of sight	500 feet	500 feet	320 feet
Receiver at top	600 feet	250 feet	250 feet
Receiver at bottom	600 feet	300 feet	250 feet
Hidden line of sight	240 feet	120 feet	120 feet

Table 3: Average distance at which more than 75% of packets are received under different topological conditions in surface mines for each of the three radios

Our findings show that although IEEE 802.11p (DSRC) radios are recommended for vehicular networks and intelligent transportation systems, the higher frequency (5.9 GHz) of these signals make them less suitable for use in surface mine conditions. IEEE 802.11b are better suited. The concern of potential interference in the 2.4GHz range with IEEE 802.11b is unlikely to be of concern in surface mines with much lower traffic and external interference.

5.2.2 Cloud-based logging framework for long-term data collection

As described in Section 4.2.2, we designed a cloud-based data logging system to facilitate long-term data collection from sensors in the mine (Figure 22).

This system could potentially be used to collect data from any sensor installed on the truck, but we have only integrated this with a GPS that tracks the location of trucks. We have named this software as **MapMyTruck**, since this feature of logging GPS data has several potential applications related to mine safety.

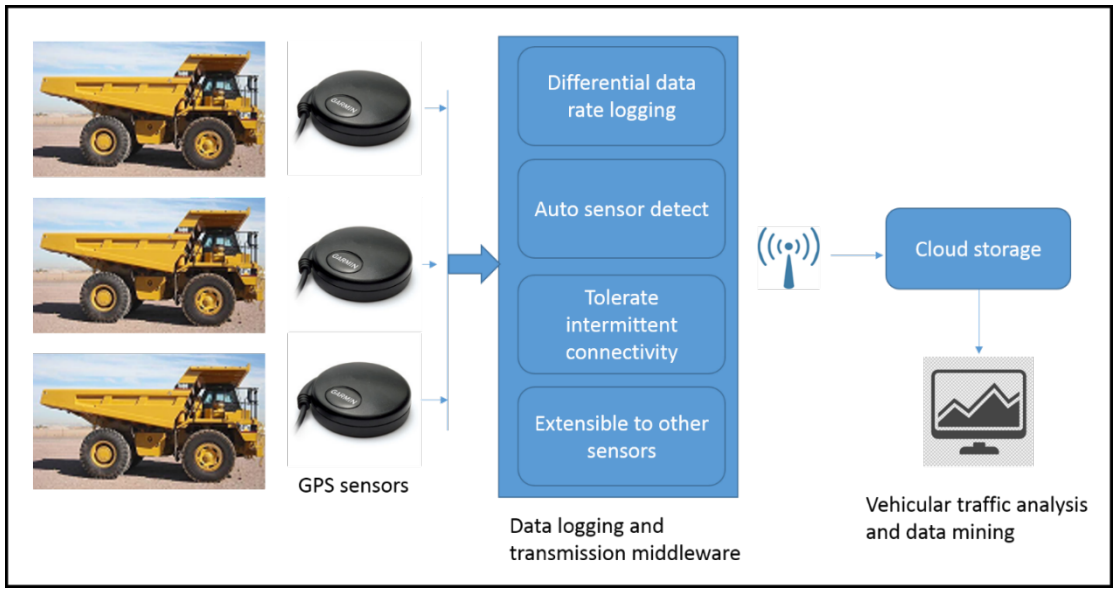


Figure 22: Cloud-based logging framework for long- term data collection and traffic analysis inside surface mines

For this purpose, we have used a Garmin GPS device attached to a Windows Tablet running the .NET framework. Upon installation, the GPS would log location coordinates locally as well as establish a remote connection to an FTP server and upload the data. Some of the features of this system are as follows:

a. **Speed-based logging rate**: Logging all the data periodically (even at a 10 second interval) would generate a huge amount of data which is not cost effective (Internet Service Providers and cloud services charge based on data transferred). For example, if each log is 100 bytes long, logging at 1 Hz would generate 360 Kbytes per truck per day. On the other hand, decreasing the logging frequency will prevent the data from being useful when vehicles come closer. Hence we designed a speed-based differential logging service that logs and transmits data proportional to the speed. No data is transferred when the vehicle is idle; the data rate is progressively increased with speed and is transferred at 1 Hz at speeds of 25 mph and above. This results in effective data usage and on a normal working day, in about 50 Kbytes of data per truck.
b. **Tolerates intermittent connection:** It is not feasible to assume that network connection is always available in a mine. Therefore, our service logs data locally and whenever connection is available, it uploads the data.
c. **Auto package installer and auto sensor detect**: The service can be installed with an easy-to-use package installer and starts itself automatically when a GPS device is detected.

GPS Location data collected from all the trucks and pick-up trucks over several months will enable a detailed traffic analysis that can be used to understand near-misses that were not caught by the real-time system. It will also point out traffic distribution in the mines along with median speeds in various areas. Such an analysis can lead to better and safer route planning.

Table 4 highlights the reduction in data gathered by logging based on speed as opposed to continuously logging the data. The precision in the table below indicates the maximum distance that can be traveled by a truck without logging an update. As an example, assume that each log (GPS + timestamp) is 100 Bytes. For a sample work day that consists of 12 hours at 5 mph, 2 hours at 10 mph, and idle the rest of the day, total logged data is 1.16MB as opposed to 8 MB if data was constantly transmitted at 1 Hz.

Figure 23: Sample track collected from the MapMyTruck Cloud based logging system for one of the trucks in Red Hills Mine

Speed (miles per hour)	Speed (meters per second)	Update rate (s)	Precision (feet)
< 0.05	0.02572	600	50.62
0.05 – 2.3	1.0288	20	67.50
2.3 – 4.6	2.0576	10	67.50
4.6- 9.2	4.1152	5	67.50
9.2 – 18.4	8.2304	2.5	67.50
18.4 – 36.8	16.4608	1	54.8
36.8 – 73.6	32.9216	0.5	54.8

Table 4: Logging rate as a function of vehicle speed and the corresponding precision in track accuracy; the precision denotes the maximum distance that can be traveled by a truck without logging any update.

5.3 GUI Design and evaluation tool

In this section, we describe the design of our integrated GUI system and an automated evaluation tool that can measure the distraction caused by GUI systems.

5.3.1 Integrated GUI for collision avoidance

With respect to displaying GPS locations of approaching vehicles, one of the key challenges was that surface mine maps change on a regular basis depending upon the excavation plan. Therefore, there is a need to incorporate custom mine-specific maps while retaining the ability to zoom and rotate.

To do this, we developed a map pre-processing tool that can covert a custom mine map provided as an AutoCAD image into a hierarchy of tiles that represent the underlying map at different zoom levels. This is referred to as a geo-tile library. A geo-tile library stores the map as blocks of images typically of 256 x 256 pixel dimensions. The tiles represent a geo surface when affixed to a grid. These tiles have the latitude and longitude information embedded in them for seamless integration with the data provided by the GPS sensor. The tiles are created in the Mercator EPSG 3857 projection standard. This projection standard employs an elliptical projection scheme and ensures that the latitude and longitude of the locations are between -20,037,508.34 and 20,037,508.34. When acquired from the tile server, the tiles

follow a streamlined local file structure: first parameter in the file path refers to the zoom level and the next two parameters indicate the subdirectories for the x and y indices of the grid, respectively (Figure 24).

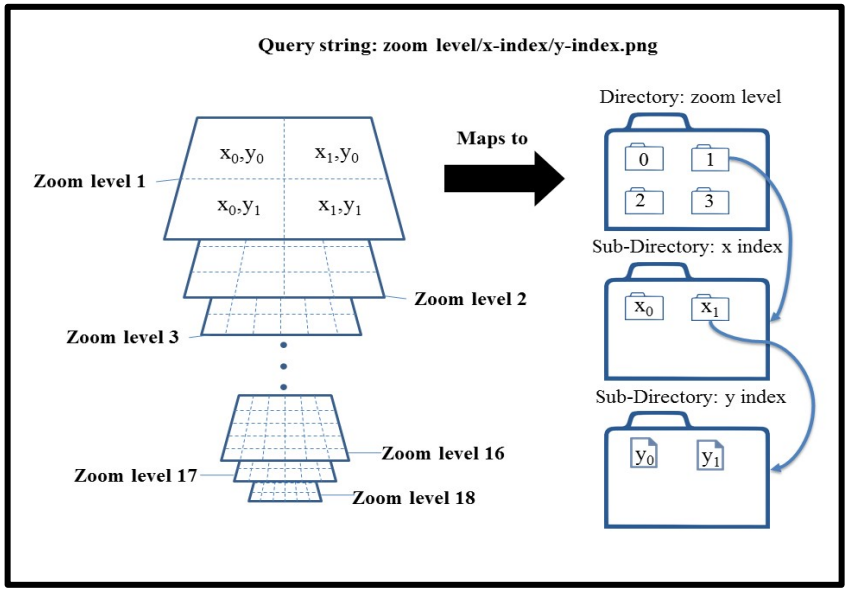


Figure 24: Graphical representation of the file structure for the tiles obtained from a tile server

This local file structure facilitates an efficient encoding mechanism for indexing of the map tiles when queried for displaying in the GUI. The following equations (i.e., (1) and (2)) represent the relationship between the latitude and longitude data provided by the GPS sensor and the tile and zoom levels used by the local file structure:

For n = 2 ^ zoom

$$Xtile = n * ((lon\_deg + 180) / 360) \quad (1)$$

$$Ytile = n * (1 - (\log (\tan (lat\_rad) + \sec (lat\_rad)) / \pi)) / 2 \quad (2)$$

where n is two power of zooming value, Xtile is x tile index in the grid after rounding, Ytile is y tile index in the grid after rounding, lon_deg is longitude value in degree obtained from the GPS sensor, and lat_rad is latitude value in radians obtained from the GPS sensor.

For our project, Red Hills Mine provided us with a map obtained via an aerial survey at high resolution. This image was then mapped to the geo tile library. The calibration of the earth-view map with the geo-tile library is a crucial step. Any error at this point may result in inaccurate presentation of GPS data within the GUI panel. To minimize such error, the boundaries of the custom earth-view map were matched in AutoCAD using the exact latitude and longitude values. Additionally, pointers (~ 45) were created to accurately orient and align the earth view map with the geo-tile map.

A unified GUI was developed for the integration and meaningful presentation of the information acquired from the GPS, Ad-Hoc network, and the RF system. The basic GUI was designed to make it similar in appearance and functionality with the typical GUI used in the commercially available navigation system. Based on JMapViewer, Java programming language was used to achieve the GUI functionalities such as zooming, translation, and rotation of the map. These functionalities maintain a fixed and centrally located position of the primary vehicle (driven by the system user who is the truck driver). The primary vehicle always moves forward (upwards) with respect to the environment (map, other vehicles, etc.) (Figure 25 (a)). Other vehicles/people/objects position obtained through Ad-Hoc network and RF sensor system are depicted using markers/symbols in the same GUI (Figure 25 (b), Figure 25 (c)). The GUI also provides zone based warning when an obstacle a remote object is in the close proximity of the primary vehicle (Figure 25 (d)).

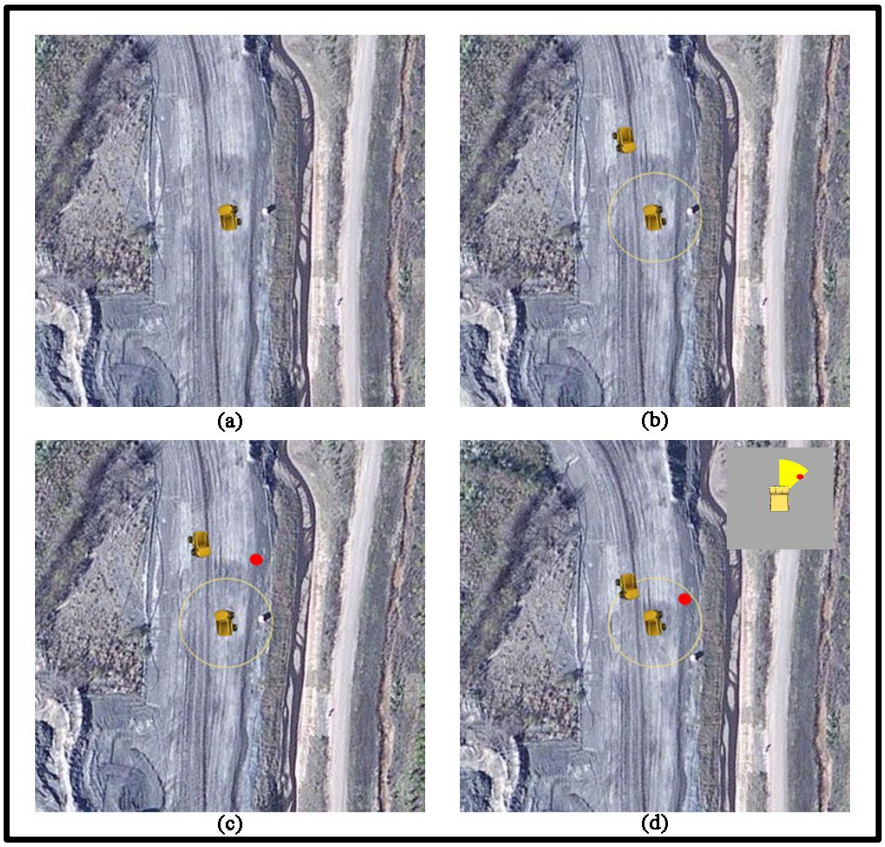


Figure 25: GUI: (a) Current vehicle location on an earth-view map; (b) other vehicle location obtained through Ad-Hoc network on a earth view map; (c) location of object of interest obtained through RF-based proximity system (d) GUI with proximity warning when the object comes within a distance of 20 ft.

The GUI is also capable of presenting information and warnings based on the data recorded from other auxiliary systems. The unified GUI presents information about several environmental factors such as temperature, air condition, wind speed, and humidity. The GUI also present cautionary and imminent warnings based on the information generated by the fatigue monitoring system. Cautionary warning is presented when first instance of drowsiness is detected. For the re-occurrence of drowsiness, an attention demanding, imminent warning is presented.

The signal dimensions used for the cautionary and imminent warnings are summarized in Table 5. The cautionary warnings are presented using audio and visual signals. The audio signal is 2500 ms long with a pulse duration of 200 ms and pulse-to-pulse duration of 385 ms. The frequency and intensity of the audio signal are set at 300 Hz, 80 dB, respectively [39]. The visual part of the cautionary warning consists of flashing of the GUI, i.e., the background color of the GUI changes between the default color and red (Table 5). The frequency of flashing is matched with the frequency of the audio signal. For imminent warnings, looming signal dimensions is used. To generate the looming warning, pulse duration is kept the same as the cautionary warning (200 ms) and the pulse-to-pulse duration is reduced from 385ms to 200ms over a duration of 4380ms. For the visual part of the imminent warning, flashing GUI with looming frequency (same as the audio signal) is used.

The functionality of the GUI was tested at Red Hills Mine and the Liberty Fuels Mine. Figure 26 shows the real-time position of an incoming truck B on the GUI with respect to the primary truck A. Please note that the primary truck is not visible in Figure 26(a). Result of this testing showed that the GUI was able to accurately show the position of the vehicles acquired using the GPS on the earth-view map developed using our map pre-processing method.

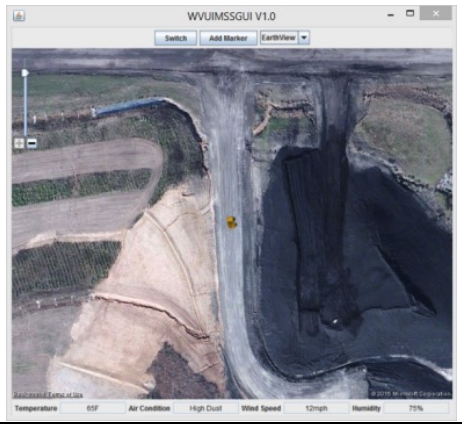
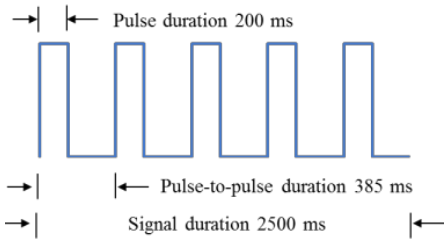
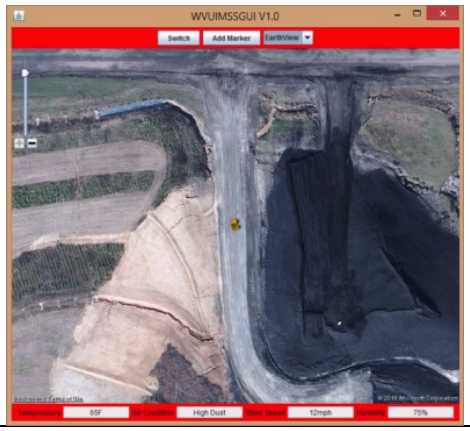
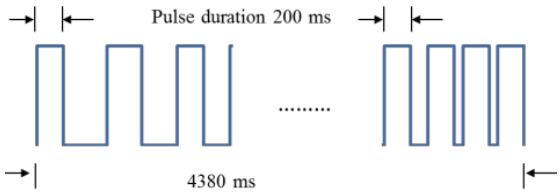
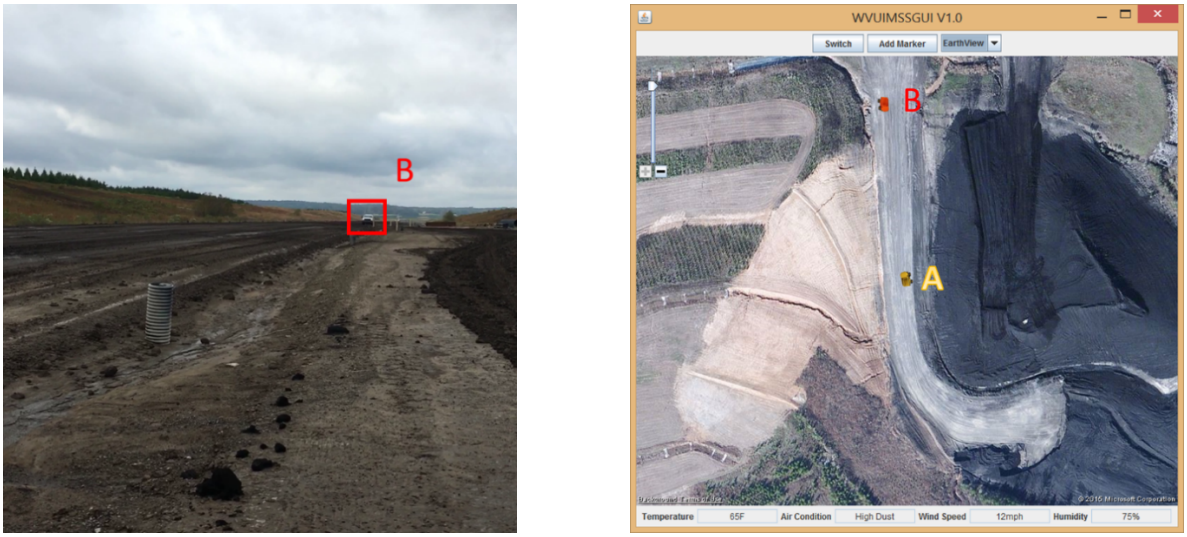
Warning type	Signal dimensions	
	Visual	**Audio**
No warning		
Cautionary warning		
Imminent warning		

Table 5: Signal dimensions used for cautionary and imminent warnings

Other features of GUI can also be seen in Figure 26(b). These features include: (1) ability to *switch* between the earth view and normal map view, and (2) ability to *add marker* (Once this button is clicked on, a window shown in Figure 28 pops up that let the user perform run-time customization of maps), and (3) ability to display different environmental parameters on the same GUI panel.

Figure 27 shows the real-time positions of pick-up truck B on the GUI and a moving worker with respect to primary truck A. This particular demonstration was at Liberty Fuels Mine. The position of the worker is shown using a red dot and using a proximity warning panel. Result of this testing showed that the GUI was able to simultaneously show the data acquired using the GPS and proximity sensors.



(a) (b)

Figure 26: Testing GUI using realistic earth-view map with GPS data. A and B in the GUI represent primary truck and pick-up truck, respectively. Primary truck is not visible in (a)

(a) (b)

Figure 27: Testing GUI with realistic earth-view map with GPS and proximity sensor data. A and B in the GUI represent primary and pick-up trucks, respectively. Red dot represent position of the worker.

5.3.2 Dynamic markers for run-time customization and warnings

A novel run-time customization technique was added to enable drivers to tag important events and hazardous conditions directly on the GUI and then broadcast it to other drivers through the Wi-Fi ad-hoc network. Some examples of such warnings include slippery conditions, road construction, new intersections, etc. The interface used to generate warnings with map masking is shown in Figure 28 (a).

For example, if the dispatcher wants to mask a certain part of the road and insert a slippery road warning, it can be done by providing the corresponding latitude and longitude information, selecting shape and color functions (in future this can be modified to incorporate a touch screen interface). This information is then transmitted wirelessly through the Wi-Fi ad-hoc network. Once one of the trucks has updated the information, it can in turn transmit to other vehicles when it comes within communication range. This way, the information can be spread to other vehicles without intervention by the driver.

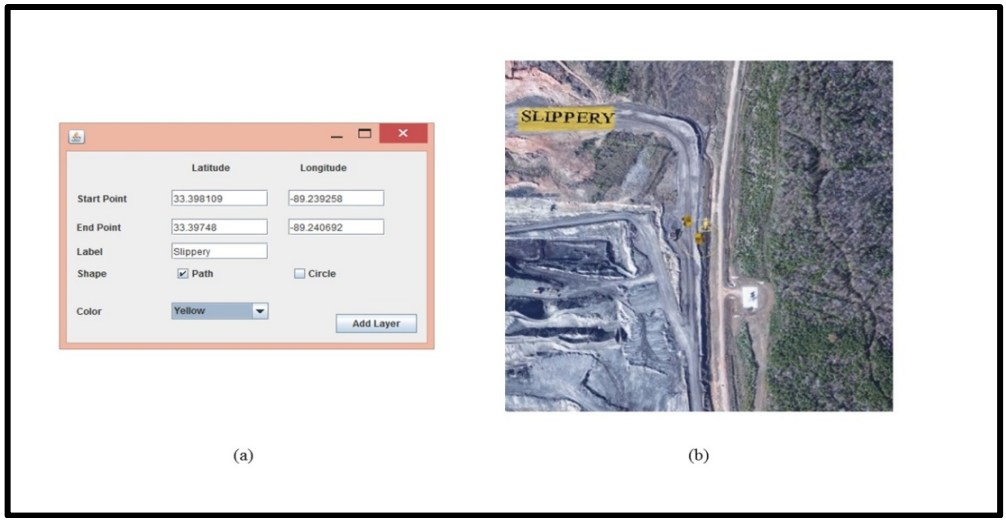


Figure 28: (a) Snapshot of special marking/editing tool for generating custom warnings (b) Snapshot of map with custom warning

5.3.3 Automated GUI Evaluation tool

We designed an automated tool based on computer vision techniques that can measure the distraction associated with usage of a GUI system. Specifically, we designed a camera-based activity recognition system that classifies a driver's activities into one of several classes such as driving, looking sideways, changing gear, changing controls or viewing the GUI, talking on the radio, etc. By doing so, several metrics related to the time spent by a driver on GUI and control-related activities can be computed. This can provide valuable insights into the effectiveness of the GUI system by showing the time that it takes for each GUI-related interaction, including viewing a map or interacting with the GUI by pressing buttons, switching screens, etc.

Figure 29: Driver action correctly classified as "Changing controls" by the automated activity recognition tool

An example output is shown in Figure 29. When the driver is focusing on changing controls on the console, the system classifies it accurately as shown by the probability graphs on the right. The output obtained from the system over time can be used to compute the distraction levels due to GUI and even to radio-related operations.

Deep learning system

Action recognition systems are widely used for public surveillance and entertainment [31]. They can be combined with any other systems, including user emotional state identification, face recognition, etc. An action recognition system can be used to detect what the driver/subject is doing. Given proper video data, the action recognition system can detect whether a driver is wearing seat belt or not, how long drivers are talking on the radio, and how long they are sitting idle, etc. The system can (given proper data examples) differentiate whether a driver is speaking on the radio with other drivers or a driver is talking on a phone. However, traditional action recognition systems used for public surveillance cannot be applied in mines because most of the techniques are based on spatio-temporal activity detection. Many make assumptions such as the presence of a static background, tracking and stacking optical flow information, efficient foreground extraction, or assume that subjects are wearing same clothes throughout the experiment [32-34]. Based on the data we collected in the mine, we noticed that drivers come in with different clothes, different head-wear (helmets, caps), and different eye wear (some wear cooling shades, glasses, no glasses) on every different shift in which they are in the driver's seat. This makes it very difficult to apply traditional action recognition approaches.

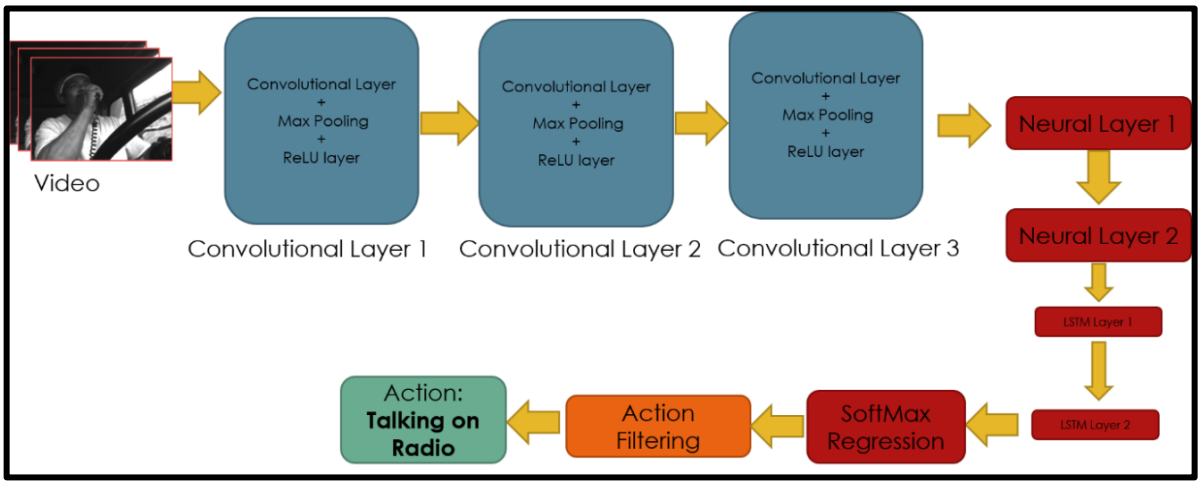


Figure 30: Block diagram of deep learning system for automated driver activity recognition

To address this issue, we took a more practical approach to solving this problem by applying state-of-the-art action-recognition systems available today. In the past three years, deep learning has made great strides in the area of image recognition, action recognition, etc [35-36]. In this project, we applied deep learning with convolutional neural networks for activity recognition inside haul trucks at Red Hills Mine. We used a convolutional neural network-based action recognition system with LSTM memory. In Figure 30, we show a block diagram of the approach.

We collected training and test data at Red Hills Mine using a self-configuring camera setup. The components of the system are shown in Figure 31. The setup was installed on 3 trucks with 3 different drivers, once during day shift and once during night shift. The data collected was divided into actions of different categories: driving with eyes on road, looking sideways, changing controls, talking on radio, and no driver. Approximately 60% of the samples were used for training while the rest were used for testing. The Table 6 shows the classification accuracy of this system.

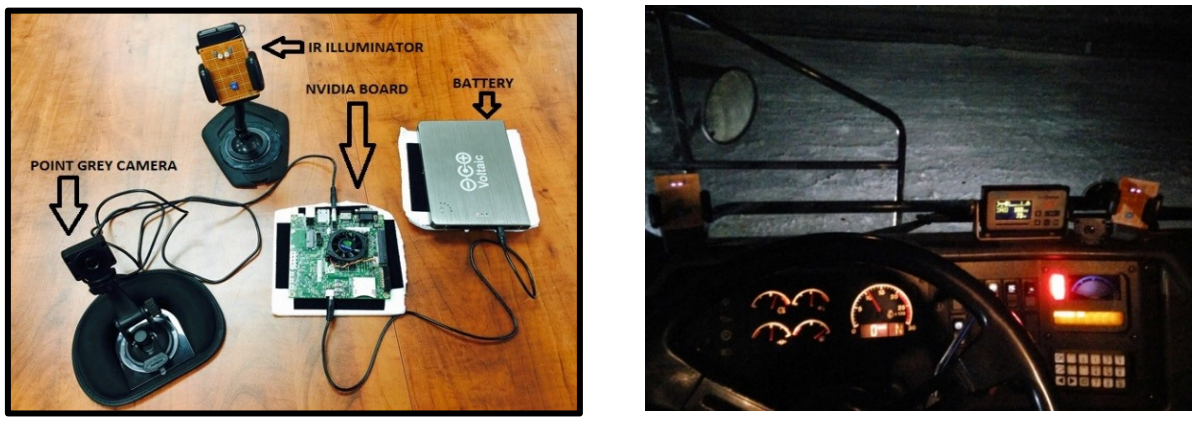


Figure 31: (left) Hardware for IR based data collection (right) IR Setup inside the truck during nighttime

Deep Learning Action Recognition accuracy	
Action	**Accuracy %**
Changing Controls	85.36
Driving	87.57
Talking on Phone / Radio	91.48
Some Other Activity	93.80
No Driver	99.41

Table 6: Accuracy of action recognition system with deep learning convolutional neural network

Figure 32: Subject performing various actions in the simulator: 1) driver speaking on radio/phone, 2) driver turning left while driving, 3) driving using controls while driving, and 4) driver yawning during driving. This data is used to train classifiers.

Multi-camera extension

We also explored how action recognition can be finer grained, such as recognizing changing gears versus changing controls on the GUI, or typing on the radio versus talking on the radio. A single camera view is often not enough to distinguish between actions at this level. So we developed a multi-camera extension to our initial camera-based system. This system was tested in the indoor driving simulator that was designed as part of this project (Figure 32). Specifically, we installed three cameras surrounding the driver. Data from all three cameras is fused to obtain a finer-grained and more accurate classification of human actions (Table 7).

Deep learning multi-camera Action Recognition accuracy on the driver	
Action	**Accuracy %**
Changing Gear	90.04
Driving	95.64
Talking on Phone	98.3
Picking up a Phone	87.24
Changing Controls	96.74
Looking Right	73.42
No Driver	100
Looking Left	73.09

Table 7: Accuracy of action recognition system with deep learning convolutional neural network using multiple cameras inside a lab simulator

5.4 Capacity building and workforce training

In this project, we conducted interdisciplinary education and training of computer science and electrical engineering, mining engineering, and industrial engineering graduate students. Graduate students in these fields visited the Red Hills Mine for data collection and evaluation of the systems. By visiting and working in the mine, they got practical experience in surface mine operations and safety procedures in the mines. This experience is expected to help in refining the design of sensor systems to suit the real world requirements in a surface mines. A mining engineering student collaborated with the computer science students in carrying out the experiments in the lab and mine, thereby learning about developed sensor systems. This aspect enhanced interdisciplinary training of students on this project.

The outcomes of the project are also being included in the graduate curriculum at West Virginia University. Dr. Kulathumani teaches a graduate course on sensor actuator networks. The research results arising from this project will be discussed in this course, giving to students insights into applications of sensing and communication technologies for real-world problems such as surface mines. Some of the developed tools such as the camera-based activity recognition system, the cloud-based logging system, and fatigue monitoring system will also be used to develop student projects in this course. Dr. Kecojevic teaches surface mining classes to mining and civil engineering students at the undergraduate and graduate levels, and the results of this project will be included in the safety sections of these courses. Dr. Nimbarte teaches courses in the areas of human factors and ergonomics, and the knowledge gained through the development and testing of the integrated GUI will be used to educate students about the occupational safety concerns in surface mines.

6. Dissemination efforts and highlights

6.1 Presentations and papers

1. A detailed presentation of the project's outcomes and findings were made at the following venues:
    a. The 2015 SME/PCMIA Joint Annual Meeting at Canonsburg, Pennsylvania
    b. The 2015 Fall Meeting of West Virginia Coal Mining Institute at White Sulphur Springs, West Virginia
    c. Red Hills Coal Mine, Ackerman, Mississippi
    d. Liberty Fuel Mine, DeKalb, Mississippi
2. A poster summarizing the collision avoidance and drowsiness warning innovation was presented at the TransTech Energy Conference in Morgantown, West Virginia
3. One peer-reviewed journal paper, describing the use of wireless communication systems for collision avoidance and proximity warning has been published [50].
4. A journal paper summarizing the integrated GUI and the run-time customization of maps has been submitted to a peer-reviewed journal.
5. A paper describing the use of lightweight brain sensing headbands for drowsiness detection is currently under preparation and will be submitted within the next two months to a peer-reviewed journal.
6. A paper describing the camera based automated GUI evaluation tool that utilizes deep learning techniques to compute distraction caused by GUI systems is currently under preparation and will be submitted within the next two months to a peer-reviewed journal.
7. The project's outcomes and findings will also be presented at (i) International Symposium on Mine Safety Science and Engineering, and (ii) Mine Planning and Equipment Selection, both in 2016.

It should be noted that management of both surface mines, Red Hills Mine and Liberty Fuels Mine, were very pleased with the results of this project and will follow appropriate procedures and policies in implementing all developed technologies in their mines.

6.2 Software, Data, Tools, and Inventions

All the software developed in this project and the data collected have been archived in network storage system at our lab at WVU. This data and software can be made available to the Alpha Foundation upon request. Some of the datasets are large in size as they contain several hours of high-quality video. The data used in papers and presentations will be separately tagged.

In addition, we would like to explore opportunities to commercialize certain parts of the tools and software so that they can be adopted at a larger scale. These are listed below.

1. A provisional patent is being filed on the novel use of wearable EEG sensors for driver drowsiness detection. We expect this tool to have large impact on driver safety, not only in surface coal, metal, and non-metal mines but also in operating passenger cars and large truck fleets.
2. The *MapMyTruck* cloud based data logging software has been currently installed on a few trucks at the Red Hills Mine. We would like to acquire hardware and deploy this tool on a larger scale within this mine to collect data over longer term, which could lead to analysis of traffic patterns. At the same time, we are also working on licensing the technology for use in other surface mines.

3. We are also working on licensing the automated software tool for assessment of driver distraction using cameras. We believe this tool will be of use in surface and underground mines, passenger cars, and other vehicles as well.

6.3 Outreach

We also expect to use many of the tools produced in this project, including the EEG-based fatigue monitoring system, cloud-based logging system, and collision avoidance systems in outreach activities for high school and middle school students. These tools will highlight the impact of sensing, communication and embedded systems technology for real-world safety problems, and can be expected to interest them in a career in science and engineering.

7. Conclusions and Impact Assessment

With collision avoidance and driver drowsiness as the main focus, in this project ***we have delivered a comprehensive suite of technologies that can be expected to significantly improve safety in surface mines***. The near- and long-term impact of specific technologies developed in this project are listed below, along with a long-term strategy to continue implementing and refining these technologies.

7.1 Drowsiness detection using EEG sensor

We demonstrated the use of a wearable EEG sensor for detecting onset of drowsiness in drivers. For this project, we utilized the MUSE headband developed by Interaxon Inc., but the software can be extended to other commercially available platforms as well. The use of these sensors overcomes many of the deficiencies of IR camera-based systems for drowsiness detection, which require a good, stable view of the eye region to produce accurate analysis of blinks and blink durations. Unlike IR camera-based solutions, the proposed system is not adversely affected by obstructed views, wearing glasses, lighting glares, or the subject looking sideways. As a result, a much more accurate analysis of blinks and blink durations can be obtained, which can be used to correlate with the onset of drowsiness. In addition, we have also showed that spectral analysis of EEG signals can be used to detect the onset of drowsiness.

With respect to this technology, our future plan is to install several of these devices in surface mines and collect and analyze data collected over the long term. Data collected using these devices over long term can also be used to understand the issue of driver fatigue in more detail and help in designing better work hours and shifts. Drowsiness data can also be used to develop personalized work shifts for drivers based on their specific pattern of drowsiness. We are also working on real-time warning systems that use a combination of blink analysis and spectral data for more accurate and timely warnings. We would also like to explore response strategies upon detection of drowsiness in drivers. For example: *Is the use of a loud sound appropriate? Or, is a bright light appropriate? Or, is it sufficient to notify the control room and start a conversation with the driver*. Finally, we would like to point out that this technology has applications beyond surface mines –operators in underground mining and drivers of passenger cars and large truck fleets are also impacted by drowsiness during driving and this technology is equally significant to these areas as well. A provisional patent is being filed on the use of lightweight, wearable EEG sensors for drowsiness detection.

7.2 RF-based proximity warning

We have designed and demonstrated the use of low-cost RF sensors for a zone proximity warning system. Unlike far more expensive technologies such as cameras and LIDARS, the RF-based system is unaffected by line-of-sight restrictions or dirt and mud depositing on the lens. The system is easy to deploy and maintain. The system was demonstrated at the Red Hills Mine as well as Liberty Fuels Mine and was shown to accurately track a subject carrying an RF sensor and walking around a truck. The system is especially useful for detecting personnel and pick-up trucks within close proximity of large trucks when backing up or starting from a stopped position. Moving forward, we would like to focus on appropriate form factors and locations of the truck where the RF sensors could be deployed.

7.3 GPS+WiFi based collision avoidance

We designed and demonstrated the use of WiFi technology in a peer-to-peer ad-hoc mode for warning drivers about approaching vehicles. Surface mine topology has multiple benches, slopes, and hidden intersections, and the use of wireless networks for timely warnings can be expected to greatly improve collision safety. Our technology does not require the use of a cellular or centralized infrastructure and is easy to set up: location data is exchanged only when vehicles come within communication range of each other. We also completed a comprehensive analysis of feasible communication ranges with different IEEE 802.11 radio technologies under different surface mine topologies.

7.4 MapMyTruck: Cloud-based logging of GPS and other sensor data

We have designed a software tool called "*MapMyTruck*" which can log GPS and other sensor data on a remote cloud database. Currently, this system has been integrated and tested with GPS sensors, but can potentially be incorporated with any sensor mounted within a truck. The software has already been installed on multiple trucks at the Red Hills Mine and GPS tracks of those trucks are logged into a cloud server whenever the truck is in operation. GPS location data that is collected from all the trucks and pick-up trucks over a long duration of several months will enable a detailed traffic analysis that can be used to understand near-misses that were not caught by the real-time system. It will also point out traffic distribution in the mines along with median speeds in various areas. Such an analysis can lead to better and safe route planning.

We would like to install this software on multiple trucks within our partner surface mine (Red Hills Mine) and collect long term data. We would like to apply data mining tools to utilize the data towards analyzing traffic patterns. We are also looking into ways to license the technology for use in other surface mines.

7.5 Integrated GUI with dynamic markers

A user-friendly GUI was designed that combines RF-based proximity warnings and GPS-based warnings into the same display. Integrating multiple sensor data into a single GUI greatly improves the effectiveness by reducing distraction and confusion. A novel dynamic marker feature was designed and tested, in which drivers can tag important events and hazards directly on their GUI console. This information gets updated to other vehicles through the ad-hoc WiFi network without driver intervention.

7.6 Automated tool for GUI assessment and driver activity recognition

We developed a novel tool for assessing distraction levels caused by GUI and operator consoles using a camera-based activity recognition system. The software is based on deep learning techniques and can classify driver activities with a high degree of accuracy. The action classification can be used to generate metrics that characterize the interaction time with GUIs and operating consoles. Our plan is to further test this software with more data collected in the driving simulator and our mine partner. We are also looking at venues to commercialize the software by licensing the technology.

8. Future work

8.1 Collision avoidance

With regards to proximity warning, we have designed and demonstrated the use of low-cost RF sensors for a zone proximity warning system. Moving forward, we would like to focus on appropriate form factors and locations of the truck where the RF sensors could be embedded.

With respect to Wi-Fi based collision avoidance, we would like to install the system on multiple vehicles and evaluate the effectiveness in real-time operation in the presence of multiple vehicles. We would also like to evaluate the effectiveness of the system in broadcasting dynamic markers added by drivers to indicate hazardous conditions.

Furthermore, we would like to install the *MapMyTruck* cloud-based logging software on multiple trucks owned by our partner surface mine (Red Hills Mine) and collect long-term data. We would like to apply data mining tools to utilize the data towards analyzing traffic patterns, near misses, collision prone-areas, and route planning.

8.2 Drowsiness detection

We demonstrated the novel use of a wearable EEG sensor for detecting the onset of drowsiness in drivers. We have currently designed a tool to analyze blink patterns and have primarily used blink duration and frequency for drowsiness detection. In current work, we are exploring whether neurological data obtained from spectral analysis of EEG can be additionally used for detecting the onset of drowsiness. Our aim is to combine both blink patterns and spectral analysis to design a real-time drowsiness warning system.

In addition, we are also interested in exploring effective response strategies upon the detection of drowsiness in drivers. For example, is the use of a loud sound appropriate, or is a bright light appropriate, or is it sufficient to notify the control room and start a conversation with the driver?

Finally, we are also interested in installing several of these devices in surface mines and collecting and analyzing data collected over long term. Data collected using these devices over long term can also be used to understand the issue of driver fatigue in more detail and help in designing better work hours and shifts. Drowsiness data can also be used to develop personalized work shifts for drivers based on their specific pattern of drowsiness.

8.3 User interface

The map run-time customization tool that we developed requires the user to know the approximate latitude and longitude of the location when creating custom warnings or map layers. The functionality of this tool can be improved such that users can add map layers by simply tapping on the map locations within the GUI.

The signal dimensions that we have used in the development of cautionary and imminent warnings are based on the recommendations made in the scientific literature. Additional testing of these signal dimensions is required to quantify their effect on user annoyance and urgency.

In addition to the audio and visual signal, the feasibility of using tactile signals in providing cautionary and imminent warnings should also be explored.

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