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Safety IDEA Program

Sensor Integration for Low-Cost Crash Avoidance for Trucks

Final Report for
Safety IDEA Project 13

Prepared by:
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February 2011

TRANSPORTATION RESEARCH BOARD
OF THE NATIONAL ACADEMIES

INNOVATIONS DESERVING EXPLORATORY ANALYSIS (IDEA) PROGRAMS MANAGED BY THE TRANSPORTATION RESEARCH BOARD

This Safety IDEA project was funded by the Safety IDEA Program, which focuses on innovative approaches for improving railroad safety and intercity bus and truck safety.

The Safety IDEA Program is funded by the Federal Motor Carrier Safety Administration (FMCSA) and the Federal Railroad Administration (FRA) of the U.S. Department of Transportation. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the views of the sponsors of the Safety IDEA program.

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Acknowledgements

We would like to acknowledge the funding support of the Safety IDEA Program of the Transportation Research Board. We would also like to acknowledge the members of the Expert Review Panel for this project:

- Chirag Dua, Sales Manager, Vehicle Solutions, Eaton Corporation
- Chris Gerdes, Associate Professor, Mechanical Engineering, Stanford University
- Bryce Hansen, Michael Dusi Trucking
- Larry Humm, Manager, Collision Avoidance Systems, Delphi Delco Electronics
- Jim Misener, Program Leader, Transportation Safety Research, California PATH
- Jeff Ruel, Automotive Radar Sensors Group, Autoliv Electronics
- Tom Sloane, Senior Technologist, Advanced Concepts, PACCAR Technical Center
- Landon Torgerson, San Luis Obispo Operations Manager, Meathead Movers

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EXECUTIVE SUMMARY

This report describes the development and results of sensor integration for low-cost crash avoidance for over-the-road commercial trucks. The goal of this Safety IDEA project was to build and test a system composed of low-cost commercially available sensors arranged on a truck trailer to monitor other vehicles around the truck.

The system combines the data from each sensor to increase the reliability of the sensor system using a probabilistic data fusion approach. A combination of ultrasonic and magneto-resistive sensors was used in this project. In addition, radar and digital imaging were investigated as reference signals and possible candidates for additional sensor integration. However, the primary focus of this work was the integration of the ultrasonic and magneto-resistive sensors.

During the investigation, the individual sensors were evaluated for their use in the system. This included communication with vendors and lab and field testing. In addition, an analytical mathematical sensor model was developed to help understand and predict the sensor behavior. Next, an algorithm was developed to fuse the data from the individual sensors. A probabilistic approach was used based on Bayesian filtering with a prediction-correction algorithm. Sensor fusion was implemented using a joint probability algorithm. The output of the system is a prediction of the likelihood of the presence of a vehicle in a given region near the host truck trailer. The algorithm was demonstrated on the fusion of an ultrasonic sensor and a magnetic sensor. Testing was conducted using both a light pickup truck and a class 8 truck.

Various scenarios were evaluated to determine the system performance. These included vehicles passing the host truck from behind and the host truck passing vehicles. Also scenarios were included to test the system at distinguishing other vehicles from objects that are not vehicles such as sign posts, walls or railroads. These other objects were chosen because they could produce electronic signals similar to those of vehicles and confuse the system. The test results indicate that the system was successful at predicting the presence and absence of vehicles and also successful at eliminating false positives from objects that are not vehicles with overall accuracy ranging from 90 to 100% depending on the scenario. Additional improvements in the performance are expected with future improvements in the algorithm and related testing, as discussed in the report.

The report includes a discussion of the mapping of the algorithm output with the implementation of current and future safety and crash avoidance technologies based on the level of confidence of the algorithm output and the seriousness of the impending crash scenario. For example, irreversible countermeasures such as firing an airbag or engaging the brakes should only be initiated if the confidence of the signal is very high, while reversible countermeasures such as warnings to the driver or nearby vehicles can be initiated with a relatively lower confidence.

The work in this Safety IDEA project has been presented in several technical conferences including a poster session at the January 2009 TRB Annual Meeting in Washington, DC; a presentation at the May 2009 California State University Research Competition in Los Angeles, CA; a presentation at the June 2009 Enhanced Safety of Vehicles (ESV) conference in Stuttgart, Germany; and a paper at the ASME IMECE Conference in November 2009. Future plans for implementation of the system include addressing some technical issues identified in this work: statistical modeling of a variety of traffic scenarios, managing the magnetic sensor bias due to changes in the host vehicle direction, and integration of the prediction model with infrastructure to vehicle communication and GPS data.

The results indicate that the system shows good potential as a low cost alternative to competing systems which require multiple, high cost sensors. Truck fleet operators will likely adopt technology only if the costs are justified by reduced damage and insurance costs. Therefore developing an effective crash avoidance system at a low cost is required for the technology to be adopted on a large scale. We will continue to work on further improvements to the system while working with industry contacts to commercialize the technology. Although the system was designed for crash avoidance for moving trucks, it also has applications in traffic monitoring from stationary infrastructure locations. We will also work with partners in highway and transportation agencies for commercialization opportunities in that sector.

The results obtained clearly show the ability of the probabilistic approach to further enhance the prediction of object detection and discrimination capabilities of an ultrasonic-magnetic sensor fusion system. The project has shown that the sensor with this filter is effective for systems such as blind spot detection and vehicle classification systems.

1. IDEA PROJECT

The project was aimed at developing a sensing system for Class 8 trucks that detects objects around the vehicle, discriminates between object types, and determines object threat levels. This system provides data to enable multiple accident avoidance countermeasures, such as:

- Support decision-making in engaging on-board safety systems (e.g. airbags)
- Warn driver of potential threat objects in projected path (audible, visual, or haptic)
- Prevent drivers from engaging in risky maneuvers (e.g. turning across a vehicle’s path)
- Perform preventative measures to avoid accidents (e.g. braking or stabilizing)
- Perform protective measures to reduce accident severity (e.g. braking or deployments)

To achieve these goals, this project focused on developing a sensor integration system to gather and process data from a wide selection of low-cost exterior sensors. By taking advantage of multiple sensors, the system fills the gaps in coverage and avoids the limitations in detection that a single type of sensor inevitably has. In addition, the system uses the different sensor results returned from the same object to improve object discrimination and threat decisions.

The research has resulted in a system consisting of multiple sensors connected by one or more digital computer processors. The computers host a software algorithm which handles communication from the sensors, signal processing and filtering, and data fusion. The output of the algorithm is capable of providing feedback to the driver and triggering safety device deployment.

2. CONCEPT AND INNOVATION

Several systems are currently on the market to monitor the road in front, side and rear of commercial vehicles. Systems that monitor the sides and rear primarily use multiple radar sensors to cover the driver and passenger sides and the rear. They are relatively expensive due to the high cost of the radar sensors. This research project has made use of low-cost readily available sensors to detect objects around the commercial vehicle. Because the data from these individual sensors may not be reliable enough to make irreversible decisions, a critical data fusion step has been taken. Data from the multiple sensors is integrated, or ‘fused’ together to create a situational awareness within the system that is far greater than the individual sensors can provide, at a price far less than a new custom-designed sensor or multiple radar sensors.

The output of the system is a prediction of the presence of a vehicle in a region around the host vehicle. This prediction can be used to initiate crash avoidance countermeasures ranging from simple warnings to the driver or other vehicles, to more aggressive countermeasures such as providing haptic feedback through the steering wheel or pedals, or in the extreme taking partial control of the brake or steering to try to avoid the crash.

Although not all accidents can be eliminated, a properly functioning detection system should be capable of predicting more than 90% of the potential accident situations. Many of these can be avoided by warning the truck driver to avoid maneuvers (such as lane changes or turns), or with an appropriate warning system for other drivers at the side or the rear of the truck. In addition, new automated systems, such as a resistance to turning, or automated braking, may be used to prevent further crashes.

Implementation of these systems in commercial vehicles should result in reduction in the number and severity of crashes. In addition, these technologies should apply to passenger vehicles. Further migration of the technology should result in additional reduction in the number of accidents.

3. INVESTIGATION

The investigation was organized into two Stages. Stage 1 consisted of literature review, identifying partners, and acquiring and testing candidate sensors. Stage 2 consisted of algorithm development, system testing, data analysis, result mapping and final documentation and review.

STAGE 1

Stage 1 dealt with identifying, procuring, testing, and modeling individual sensors. The report is divided by task instead of by sensor in order to be consistent with the project proposal and organization. As a result, information on specific sensors (magnetic, radar, ultrasonic) is spread across multiple sections.

3.1. TASK 1: LITERATURE REVIEW

Two objectives of the literature review were to:

- Collect accident data and identify a project focus area.
- Identify state-of-the art sensors and their capabilities and limitations.

Truck accident data was reviewed to confirm the type and circumstances of current accidents. From this data, and information about the current commercial activities relating to accident prevention, a research focus area was identified.

A thorough literature review was completed to identify the state-of-the-art sensors and their applications in today's crash avoidance systems. Most technical research in this area focuses on a specific type of sensor and its application limitations. Instead of focusing on a particular sensor type, this literature search was aimed at reviewing all sensor types being used in crash avoidance and similar applications.

Although many different crash avoidance systems were identified, all of them rely on one of more of the following technologies: radar, LIDAR, computer vision, ultrasonic, infrared, or magneto-resistive.

3.2. TASK 2: IDENTIFY PARTNERS

In this task, we identified individuals with expertise and interest in the projects goals who would be willing to support the project through participation on the expert review panel, providing materials, providing technical assistance, or providing testing support. Individuals were sought in four key areas: Academic Researchers, Sensor Suppliers, Truck Manufacturers and Truck Operators.

- Chirag Dua, Sales Manager, Vehicle Solutions, Eaton Corporation

- Chris Gerdes, Associate Professor, Mechanical Engineering, Stanford University
- Bryce Hansen, Michael Dusi Trucking
- Larry Humm, Manager, Collision Avoidance Systems, Delphi Delco Electronics
- Jim Misener, Program Leader, Transportation Safety Research, California PATH
- Jeff Ruel, Automotive Radar Sensors Group, Autoliv Electronics
- Tom Sloane, Senior Technologist, Advanced Concepts, PACCAR Technical Center
- Landon Torgerson, San Luis Obispo Operations Manager, Meathead Movers

3.3. TASK 3: ADDITIONAL SENSORS

Task 3 consisted of the consideration and procurement of sensors for inclusion in the project, based on the results of the literature search. Potential sensor candidates were evaluated based on their cost, signal characteristics and availability. Sensors procured include:

- *Radar sensor* – 24 GHz RADAR sensors were donated by an OEM sensor manufacturer.
- *Computer Vision sensor* – A Uni-brain fire wire camera was purchased to act as a test validation tool as well as being used for image processing. The camera resolution is 640 x 480 with a FOV of 42° horizontally and 32° vertically [1].
- *Ultrasonic sensor* – MaxBotix 42 KHz LV-MaxSonar®-EZ1 ultrasonic sensors were purchased [2]. This sensor transmits a pulsed inaudible 42 kHz sound wave at a sampling rate of 20 Hz to detect range up to 6 m. Range is measured using a time-of-flight (TOF) method, where the time it takes for a transmitted signal to return to the sensor face is analyzed. Relating this time and the velocity of sound the range can be determined.
- *Magneto-resistive sensor* – The particular sensor selected for the present project is the HMC 2003 series 3-axis magneto-resistive sensor manufactured by Honeywell [3]. This sensor type has been shown to function as either a compass by measuring the earth's magnetic field with respect to the sensor's orientation or as a vehicle detecting device by measuring only localized distortions in a magnetic field (presence of ferromagnetic material) [4]. This project focuses solely on vehicle detection and any effect due to the earth's constant magnetic field and sensor orientation is filtered out for all the analyses presented. This sensor uses three nickel-iron, permalloy magneto-resistive sensors with a magnetic field sensing range of 2 Gauss and has a resolution of 40 μGauss. With a sensing bandwidth of 1 kHz, this sensor is capable of vehicle proximity detection even at high relative speeds [3].

Based on the literature search, each of these sensors appeared to meet the project goals of low cost, readily available, and having useful signal characteristics. Two other possible sensors were identified during the literature review but were later rejected: A scanning LIDAR sensor could not obtained at a reasonable cost for the project. Infrared (IR) sensors were rejected due to their inherent limitations (confusion by existing IR sources) and development cost (image processing).

Each of the procured sensors were tested, modeled, and evaluated for their potential to contribute to the goals of the project. These steps will be discussed for each sensor in the following sections.

3.4. TASK 4: REFINE TEST MATRIX

The original project anticipated the investigation of radar and ultrasonic sensors and included testing for these sensors. As discussed, magneto-resistive and computer vision sensors were also selected as possible sensor candidates. Task 4 consisted of revising the testing matrix to include the magneto-resistive and computer vision sensors.

The magneto-resistive sensor has not been used for this application in the past and its characteristics are not well established. Therefore testing was planned that would characterize the sensor behavior under a tightly controlled environment. This consisted of a special test fixture on a lab bench setting. Next static and mobile traffic environment testing was planned. The results of these tests are described along with the other sensors in Task 6 – Baseline Testing.

The computer vision sensor also required testing to verify its capabilities. A basic test plan was developed to record video in relevant settings (on-highway, multiple vehicles, daylight) and successively test the computer vision algorithms with one, two, and several vehicles. Since the major effort for vision sensing is in the processing algorithms, this was the extent of the baseline test plan. If algorithm development proceeds smoothly, additional video will be collected in different conditions (hill climb, nighttime, fog, etc).

3.5. TASK 5: SENSOR MODELING

Mathematical models of the sensors were constructed to provide a means of simulating their performance and to facilitate algorithm development during Stage II of the project. In addition, the modeling helped to understand the behavior of the sensors when it was not obvious (especially with the magnetic sensor).

The Honeywell HMC 2003 series three-axis anisotropic magnetic sensor hybrid has its sensor elements oriented as a resistive “Wheatstone bridge” that varies resistance slightly as the magnetic field changes in each element. This change in resistance causes a change in output voltage.

The MaxBotix 42 KHz LV-MaxSonar®-EZ1 is a piezoelectric transducer that emits an inaudible sound wave when electricity is applied to it. The time it takes to receive an echo from a transmitted signal can be analyzed to measure range.

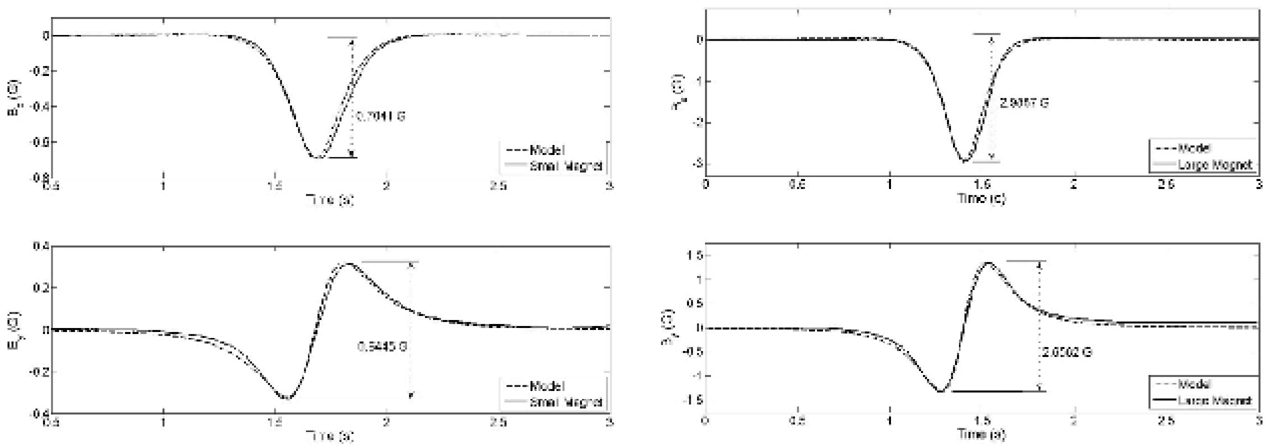
3.6. TASK 6: BASELINE TESTING

Baseline testing was conducted on the magnetic, radar, and ultrasonic sensors to establish critical performance characteristics. Testing was conducted first in a lab workbench environment, then in a static traffic environment and finally in a moving traffic environment. Baseline testing was not conducted on the vision sensor because it was concluded that this sensor is not suitable for the proposed crash avoidance algorithm; however, the sensor is still used to reference the presence of objects detected by the other sensors.

3.7. TASK 7: SIMULATIONS

Simulations were conducted to compare the magnetic sensor mathematical models with the testing to validate the models. It was decided that the radar and ultrasonic sensors were well understood and established for similar applications, so further simulations of these sensors were not necessary.

A simple 2-D single dipole model was used to perform simulations replicating the bench tests that were conducted. Using appropriate parameter values for the dipole length, dipole angle and empirical relations the response was obtained and compared with the experimental results. Figure 1 shows a good match between theory and experiment justifying the ability of the model to predict the magnetic phenomenon recorded in experiments. A higher order 3D dipole model was also developed to account for results that are typical from larger vehicles such as trucks.



(a) Small magnet. (b) Large magnet.

Figure 1. Comparison of simple dipole model experiment and simulation

Magnet Type Detection

Magnetic sensor output depends of the strength of the induced magnetic field, which in turn is dependent of the size of the magnet. Hence, the magnetic sensor can possibly be used to detect the magnet size. Figure 2 shows a clear distinction (from a magnitude standpoint) between the magnetic fields induced by the two different magnets, thereby corroborating this claim. However, these magnetic fields are sign-dependent and flip sign when the dipoles are flipped. Hence, in order to clearly distinguish the different sized magnets, appropriate mathematical functions that not only eliminate this sign dependency, but also produce a pronounced difference in the values were studied. Two such functions are,

$$|B_x| + |B_y| \tag{1}$$

$$(B_x)^2 + (B_y)^2 \tag{2}$$

The results obtained by using these functions are as shown in Figure 2. Both the functions were able to achieve the desired objective and the sum-square function in particular was able to provide a more comprehensive threshold difference that could be used to clearly distinguish the smaller magnet from the bigger one.

Figure 3 shows a comparison between the mathematical model response and the experimental response from the road tests. The relative velocity of the vehicles was 20 mph. The distance between the vehicle and the sensor was 6-7ft. The high fidelity 3-D mathematical model comprised of two dipoles for modeling the effect of cars, and five dipoles to obtain an accurate representation of typical class-8 trucks.

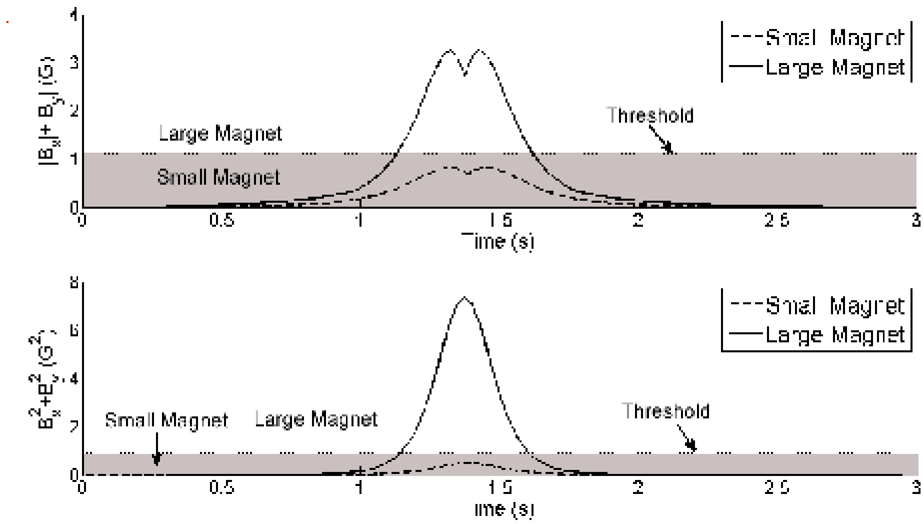
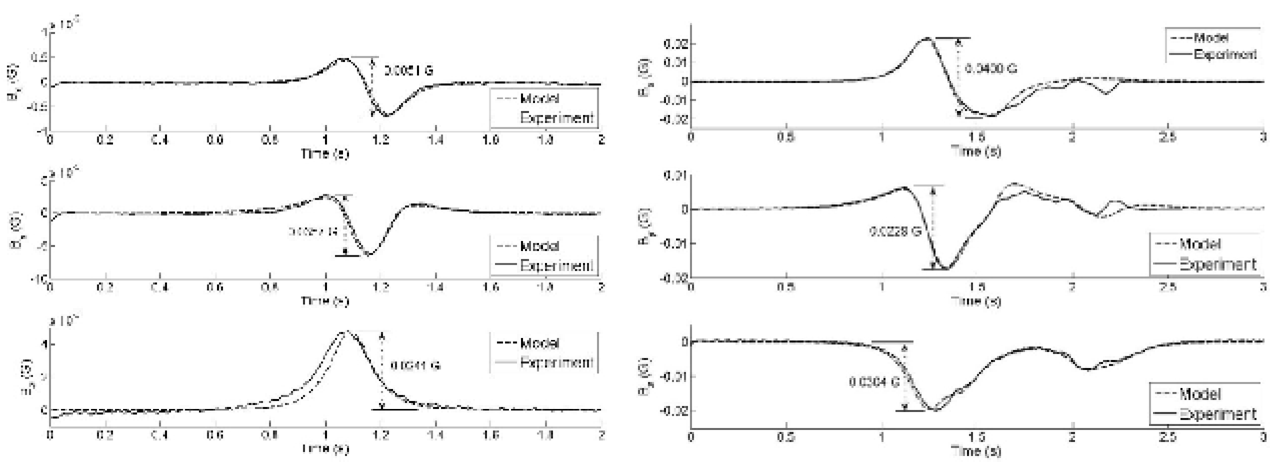


Figure 2. Magnetic threshold for object discrimination for simple dipoles.



(a) Passenger car. (b) Class 8 truck.

Figure 3. Comparison of on-road simulation and road test.

Vehicle Type Discrimination

Similar to the case of the 2-D model, mathematical functions were employed to not only extract the magnitude information, but also magnify the combined magnetic effects along all three axes of measurement. Two functions employed were

$$|B_x|+|B_y|+|B_z| \quad (3)$$

$$(B_x)^2+(B_y)^2+(B_z)^2 \quad (4)$$

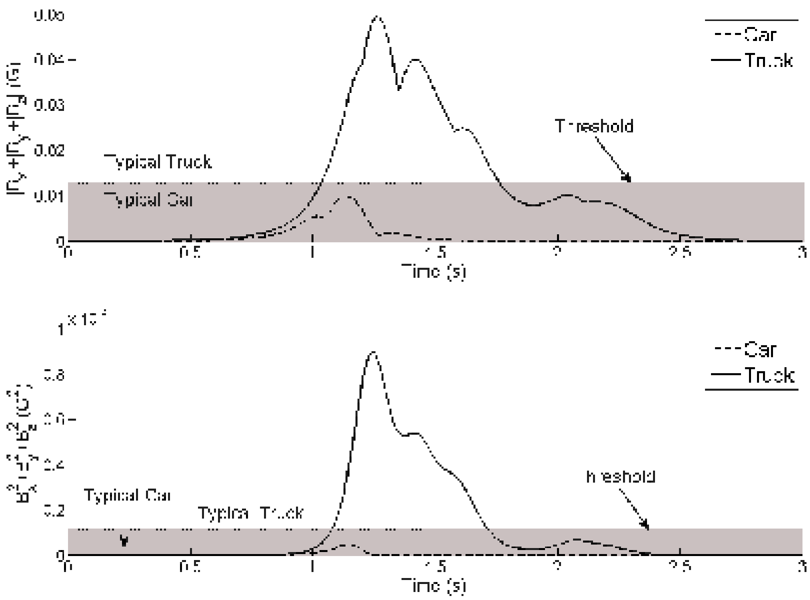


Figure 4. Magnetic threshold for object discrimination for vehicles.

From Figure 4 it can be seen that there exists a clear threshold in the magnitude obtained for a typical truck when compared with that for passenger car. It can also be observed that the sum-square function is able magnify this threshold to a much greater extent. The extensive modeling, testing, and simulations performed with the magnetic sensor have confirmed its capabilities for object type discrimination.

One issue that was identified was related to the change in the magnetic sensor bias due to changes in the orientation of the sensor and vehicle relative to the earth's magnetic field. As the host vehicle changes directions, such as during a turn maneuver, the bias changes. This behavior is used for electronic compasses. However it can also affect the behavior of the crash avoidance system. Further work is needed to eliminate the bias. It is likely that GPS or other infrastructure information can be used for this purpose. For the current work, tests were conducted along straight paths and the bias was removed by subtracting the bias from the magnetic raw data.

3.8. TASK 8: INTERIM DOCUMENTATION

A Stage I Report completed Task 8. This report was reviewed by the sponsor and the panel of experts prior to the start of Stage II.

STAGE II

From Stage I, radar, ultrasonic sensors, and magnetic sensors were identified as suitable sensors to be used in a low-cost truck side and rear crash avoidance system. Through modeling, simulation, and baseline testing the strengths and weaknesses of these sensors were identified. Because of the environmental and process noise inherent in monitoring a region around a vehicle, the data from these individual sensors are not reliable enough to make irreversible decisions. An intelligent algorithm is required to integrate data from the multiple sensors to create a situational awareness within the system that is far greater than the individual sensors can provide, at a price far less than a new custom-designed sensor.

3.9. TASK 9: ALGORITHM DEVELOPMENT

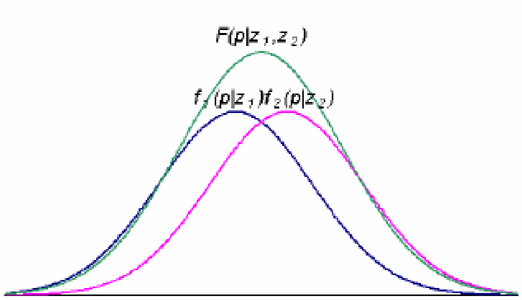
It is necessary for any warning or countermeasure taken by a crash avoidance system to be completed as soon as possible without false positives or overreacting in the situation. Simply interpreting the sensor data is not sufficient to identify threats because these sensors usually carry data that is noisy or incomplete. It is crucial that any sensor noise created by the environment (especially that of a large truck) is considered and reinforced by other sensor information. A probabilistic approach has been taken to help manage measurement of uncertainty and perform multi-sensor fusion. The following sections discuss the basic concepts used in probability, the basic concepts of Bayesian filtering and its uses, how this Bayesian filtering may be applied to vehicle identification, and how this technique facilitates sensor fusion.

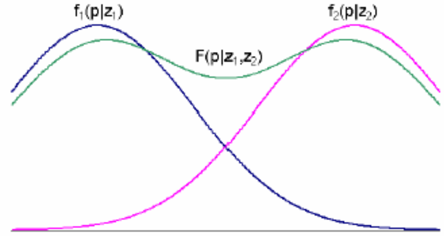
3.9.1. Basic Concepts in Probability

For this application, voltage measurements taken from individual sensors are treated as random variables using probability density functions (PDFs). It is common for sensor PDFs to be that of the one-dimensional normal distribution with mean μ and variance σ^2. The information from an individual sensor can be compared with data from other sensors when applying a probabilistic approach for multiple sensors; this process is called joint distribution. Joint distribution describes the probability that the random variable $X = x$ and that $Y = y$. If X and Y are independent the joint distribution is given to be

$$p(x, y) = p(x)p(y) \tag{5}$$

Joint distribution is important for multi-sensor fusion in vehicle detection because presence of an object and its type is difficult to positively identify with a single sensor. The above equation can be used to integrate multiple sensors because the information of each sensor is independent of the other. Figure 5 shows the results of joint distribution between two sensor belief curves. If two sensors are in agreement, the joint likelihood has a unique mode (the value that occurs most frequently) at the estimated state variable; however, when the sensors are in disagreement, the joint likelihood is bimodal and has a low likelihood at the estimated state variable. This idea of joint distribution can be applied to the ultrasonic sensors and magnetic sensors to check for the presence of an object and to ascertain if the object is a vehicle.





(a) Joint likelihood of two sensors in agreement. (b) Joint likelihood of two sensors in disagreement.

Figure 5. Joint likelihood of two sensors [5].

3.9.2. Bayesian Filtering

Bayesian filters can be created to filter this noisy or partial sensor data using the basic concepts in probability from the previous section [6], [7]. A Bayesian filter is a recursive state estimation model with the ability to output the likelihood of an event occurring. The state of the surroundings around sensors cannot be measured directly due to environmental and process noise; however, the likelihood of the state can be inferred through sensor data and a Bayesian filter. The filter is completed in two steps: the prediction step and correction step.

Prediction Step: At each time update, the state is predicted according to the following update rule [6], [8].

$$Bel^{-}(x_t) = \int p(x_t \mid x_{t-1}) Bel(x_{t-1}) dx_{t-1} \tag{6}$$

The predicted belief of the state variable at time t, $Bel^{-}(x_t)$, is represented by the integral or sum of the product of two distributions: the prior distribution, $Bel(x_{t-1})$, and a predicted belief based on the prior belief. The term $p(x_t|x_{t-1})$ describes the system dynamics, which ascertains how the state of the system changes over time. This term predicts the likelihood of the system state based on the last measurement. The prediction parameters are described in the following section.

Correction Step: Whenever new sensor information z_t is received, the measurement is used to correct the predicted belief using the observation [6], [8].

$$Bel(x_t) = hp(z_t \mid x_t) Bel^{-}(x_t) \tag{7}$$

The term $p(z_t|x_t)$ is the perceptual model that describes the likelihood of making observation z_t given that a state variable is equal to x_t. For location estimation, the perceptual model is usually considered a property of a given sensor technology. It depends on the types and positions of these sensors and captures a sensor's error characteristics. The term η is a normalizing constant which ensures that the posterior over the entire state space sums up to one. This constant is discussed in more detail in the following section.

3.9.3. Bayesian Filter Algorithm

Bayesian filtering can be directly applied to the sensors for the purposes of vehicle detection. To clearly explain how the Bayes filter algorithm is developed; consider only the ultrasonic sensor with the state variable of interest being the presence of an object. This procedure will later be expanded to include the magnetic sensor and other state variables. As mentioned in the previous section, the Bayesian filter is completed in two steps: prediction and correction.

Prediction Step: The predicted model for the ultrasonic sensor is based on the Theorem of Total Probability. The following equation represents the predicted probability of an object's presence at time t based on the probability of an object's presence at time $t-1$ [6].

$$p(x_t') = p(x_t'|x_{t-1})p(x_{t-1}) + p(x_t'|\neg x_{t-1})p(\neg x_{t-1}) \tag{8}$$

Here, the terms $p(x'_t|x_{t-1})$ and $p(x'_t|\neg x_{t-1})$ describe the predicted probability that an object is present at time *t* based on the probability that an object is present at time *t-1* and the probability that an object is absent at time *t-1* respectively. In detecting an object's presence, this conditional probability is referred to as the motion model where the vehicle might be at time *t*, given its location at x_{t-1}.

<u>Correction Step:</u> Using the information from the prediction step, the likelihood of a vehicle's presence $p(x)$ and a vehicle's absence $p(\neg x)$ are evaluated using the correction step. The correction step of the algorithm is represented by [6]:

$$p(x) = \eta p(z_t|x'_t)p(x'_t) \tag{9}$$

$$p(\neg \mathbf{x}) = \eta p(z_t|\neg \mathbf{x}'_t)p(x'_t)p(\neg \mathbf{x}'_t) \tag{10}$$

$$\eta = [p(z_t|x'_t)p(x'_t) + p(z_t|\neg \mathbf{x}'_t)p(\neg \mathbf{x}'_t)]^{-1} \tag{11}$$

where η represents the normalizing parameter to ensure the probability of a $p(x)$ and $p(\neg x)$ are between 0 and 1.

3.10. TASK 10: SYSTEM TESTING

For algorithm development, system testing was completed in three stages: preliminary data collection, simulation, and a full scale test. The data collection was performed using a small test vehicle with the various sensors attached. Data collected from this test vehicle was used to create the sensor probability density functions explained in the previous section. The data collected was post processed and used to simulate the effectiveness of a Bayes filter algorithm. Finally, the complete system was mounted on a heavy truck and data were collected and analyzed using the proposed algorithm.

3.10.1. Data Collection

The test vehicle seen in Figure 6 was modified to include two ultrasonic sensors, two magnetic sensors, and two radars. Information was collected from all sensors as vehicles passed the lateral side of the vehicle. A digital camera was used as reference to positively identify the presence of a passing vehicle (not shown in figure).

Figure 6. Test vehicle (pickup truck).

Figure 7 shows the typical data set for a passing vehicle. As the vehicle passes, three distinct regions based on the vehicle's location in reference to the sensors are taken into consideration: region A, B, and C. These regions are defined relative to time to discriminate different location regions of the approaching car. It is clear that Region B has the most potential to positively identify the presence of a vehicle.

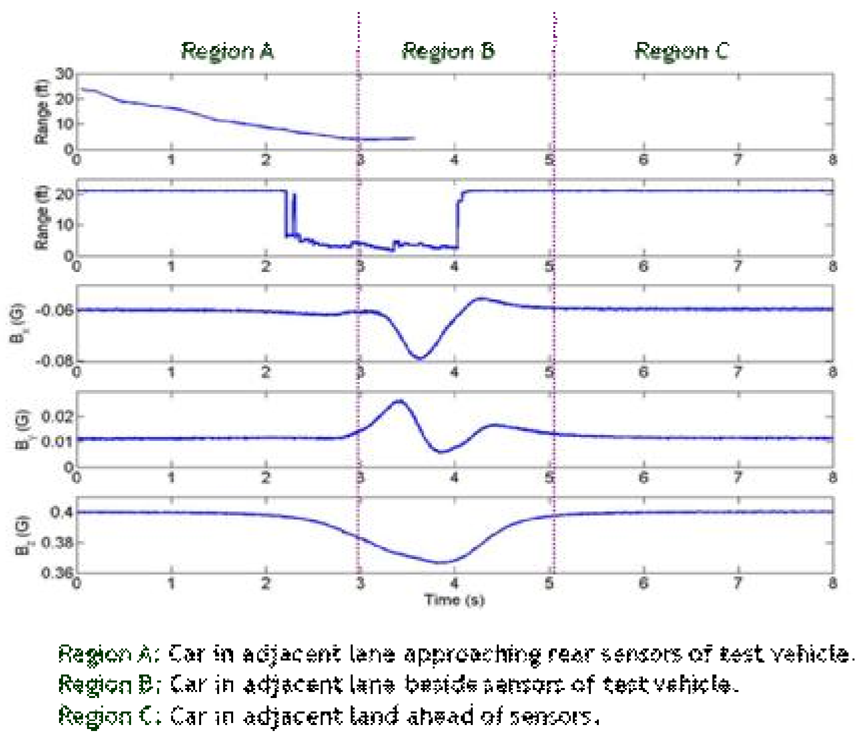


Figure 7. Sensor data for vehicle passing scenario.

3.10.2. Statistical Sensor Modeling (Individual Sensors)

The Bayesian filter requires specific parameters for both the prediction and correction steps. Data was collected for vehicles passing on the left at a distance of 6 feet on average and a speed of 10 to 20 mph as the test vehicle was parked on the side of a road. Video was used to determine when a car was present or absent. Statistical models were developed from the data for the ultrasonic sensor distance reading when a vehicle is present and also when no vehicle is present, and similarly with the magnetic sensor signal. These models are only valid for passing scenarios and traffic conditions similar to the conditions used in this test. Additional testing and statistical modeling can be conducted to characterize other common scenarios. However, only one scenario was tested for this work due to the limitations in time and budget.

The histograms shown below represent the behavior of an ultrasonic sensor when vehicles are present and absent, respectively (Figure 8 and Figure 9). The average distance of a passing car from this model is about 6.25ft (sensor voltage of 0.71 V). It is important to note that some transmitted signals from the ultrasonic sensor may be reflected off a vehicle's body and not be received by the sensor. This causes the sensor behavior to be somewhat bimodal. The information from this belief distribution is utilized in the prediction step to account for this sensor characteristic.

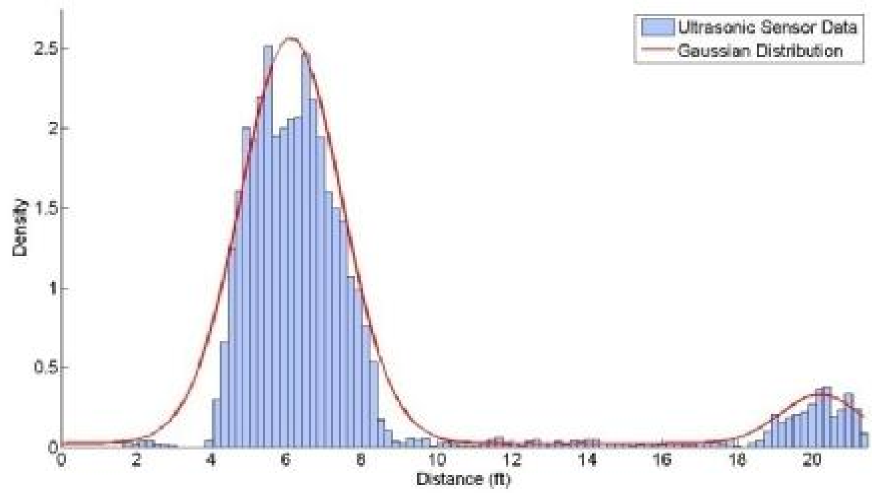


Figure 8. Ultrasonic sensor belief distribution when vehicle present.

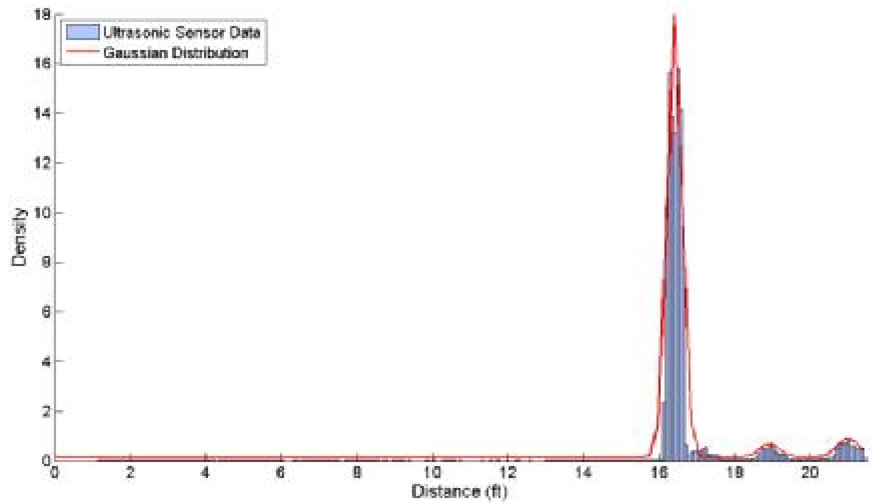


Figure 9. Ultrasonic sensor belief distribution when vehicle absent.

Prediction Model

The prediction step requires the probability that an event will occur in the next step based on the correction from the previous step. The prediction model can be based on a variety of ideas. In the case of predicting the likelihood of a vehicle being present, two prediction schemes were used. One prediction phase is in effect when a vehicle is detected and the other prediction phase is in between vehicles. The first prediction step takes into account the number of “present” measurements taken by the ultrasonic sensor when a vehicle passes; the number of “present” samples varies with the physical length of a vehicle and its relative velocity. As the number of “present” measurements increases, the predicted probability of a vehicle being present in the next sensor measurement will decrease. This process can be further refined by integrating the magnetic sensor to identify the vehicle type allowing adjustments in the number of predicted “present” measurements based on vehicle length. The same approach mentioned is used for the prediction parameter when a vehicle is absent; however, the number of “absent” measurements can be based off of vehicle frequency or traffic flow information provided from intelligent transportation systems. As traffic flow increases, the likelihood of a vehicle being absent in the next “absent” measurement will decrease. Figure 10 shows the ultrasonic sensor measurement and predicted likelihood when a vehicle is present and absent.

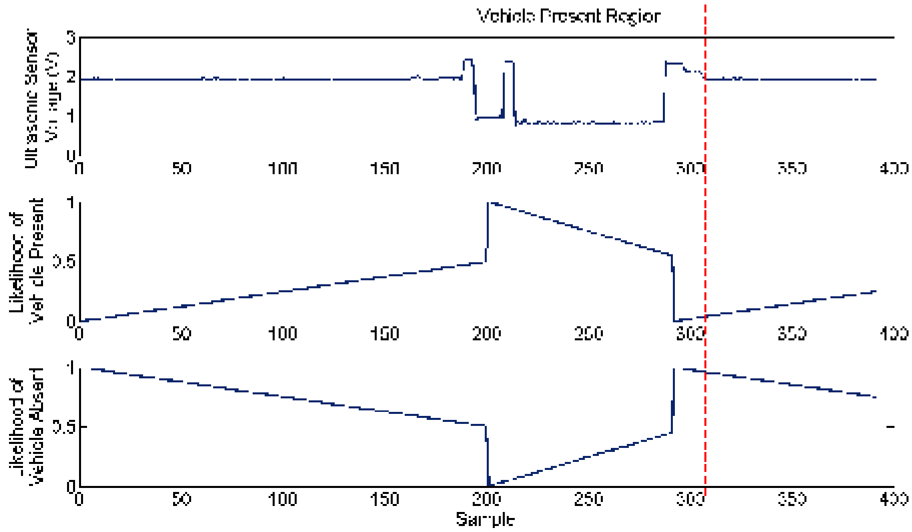


Figure 10. Ultrasonic sensor raw data and predictive models.

Correction Model

The correction step uses the sensor models to make correction in the predicted measurements. With the ultrasonic and magnetic sensor models and a prediction model, the probability of an object being present and being of specific type can now be identified using equations (9)-(11). The results for this prediction and correction methods being applied to both individual sensor case and sensor fusion case are presented in the next section.

3.10.3. Bayesian Filter Results (Individual Sensors)

The Bayesian filter is complete with both the prediction and correction models produced above as shown in the following schematic (Figure 11). The following shows the resulting behavior of the Bayesian filters for the ultrasonic sensor and magnetic sensor.

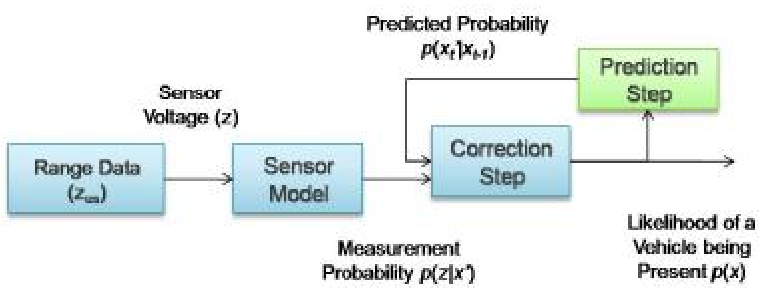


Figure 11. Bayesian filter algorithm (individual sensor).

As vehicles pass the ultrasonic sensor, the data is recorded and entered into the Bayesian filter algorithm (Figure 11). The prediction model and the correction model, in this algorithm, work together to output the likelihood that a vehicle is present. It can be seen in Figure 12 that the noise in the ultrasonic sensor—such as the large spike at time 220—has little effect on the belief that a vehicle is present. The same procedure is used for the magnetic sensor (Figure 13). With this

Bayesian filter, the uncertainties that arise from partial and noisy ultrasonic data are accounted for and the belief of a vehicle's presence can be evaluated to make decisions in vehicle identification.

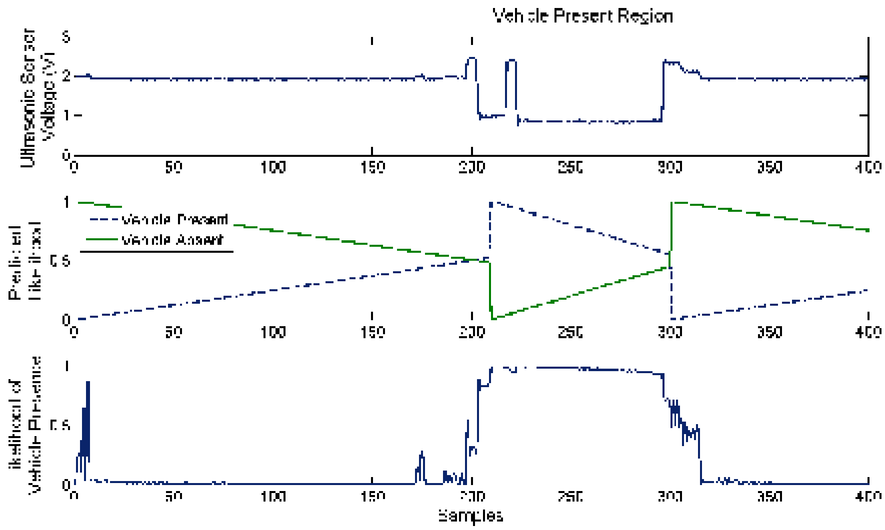


Figure 12. Likelihood of vehicle presence (ultrasonic sensor).

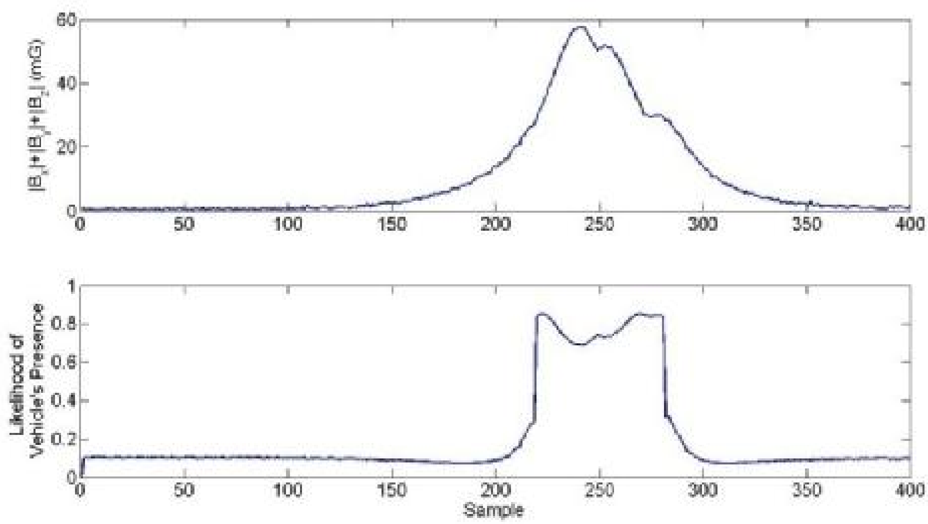


Figure 13. Likelihood of vehicle presence (magnetic sensor).

3.10.4. Sensor Fusion

The outputs from the Bayesian filter only represent the belief of individual sensors. Thus, a joint probabilistic method is required to "fuse" this information together (Figure 14). If the ultrasonic sensor is represented as S_1 and the magnetic sensor as S_2, the joint belief distribution can be represented as [6]:

$$p(x|z_{S1}, z_{S2}) = p(x|z_{S1})p(x|z_{S2}) \tag{12}$$

where, *x* and *y* represent independent state variables for the sensors and *z* represents the joint distribution.

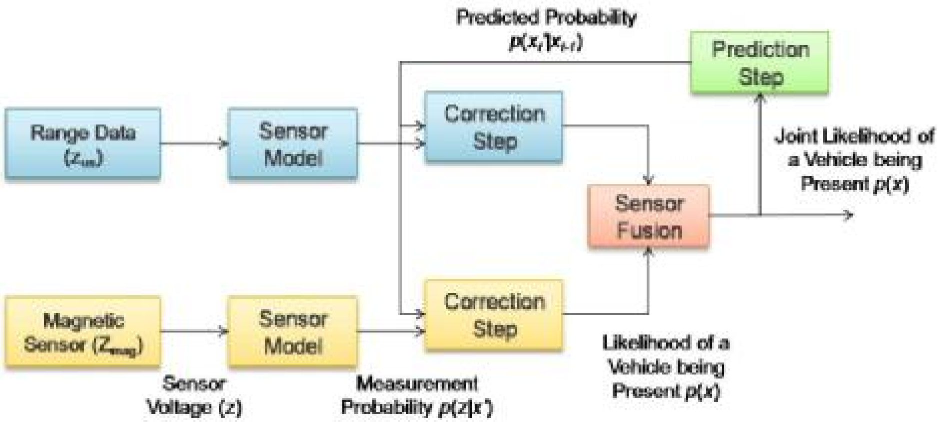


Figure 14. Bayesian filter algorithm (multiple sensors).

Figure 15 and Figure 16 show the detection of two objects. In Figure 15 the joint likelihood being high (about 0.8) suggests the presence of a vehicle and on the other hand, Figure 16 has a zero joint likelihood suggesting the presence of a non-metallic object. This prediction is justified by observing that the magnetic sensor data is low while only the ultrasonic picks up the presence of an object.

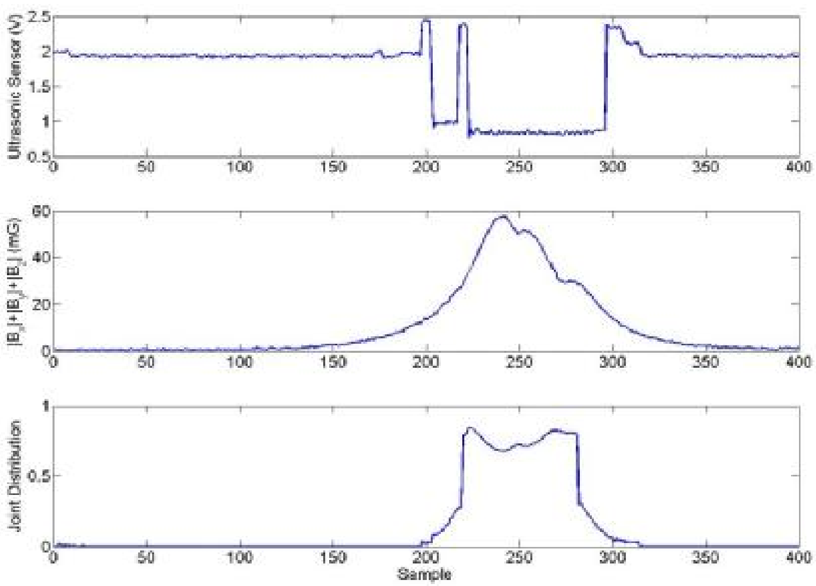


Figure 15. Joint likelihood of vehicle presence.

3.10.5. Full Scale Testing

To proficiently test the vehicle detection algorithm described in the previous section, data collection was extended to a class 8 vehicle and collected during normal operation of the vehicle. A test fixture was fabricated to attach the sensors and data acquisition system to a class 8 trailer without disturbing normal operation. The design of this test fixture takes into account: powering the system, protecting the system from excessive vibration, protecting the system from roadway debris, providing the system with proper cooling and ventilation, maintaining accessibility to all components, and attaching the fixture to the exterior of the trailer.

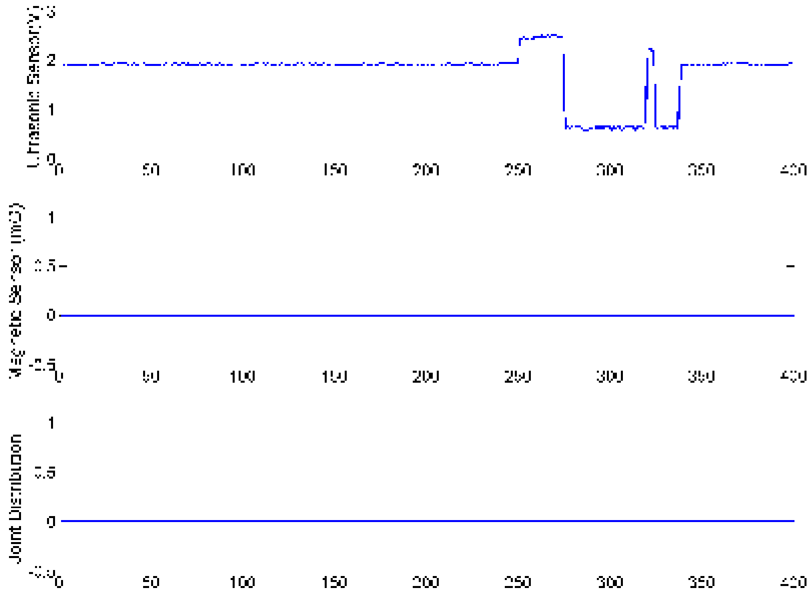


Figure 16. Joint likelihood of a non-metallic object.

The final test fixture is shown in Figure 17. The data acquisition hardware required includes a 16 channel data acquisition system for the ultrasonic and magnetic sensors, CAN bus system for radar sensors, and FireWire for the reference camera. The system also includes a 12 V deep cycle battery and a 120 V pure sin wave inverter to make the system self-powered. This helps to avoid introducing any noise from the truck's power supply. All hardware in the test fixture are secured or isolated from vibration to avoid any damage that may be incurred from the trailer's vibration. To protect the computer used for data acquisition from excessive vibration, a solid state hard drive is used and the computer is surrounded by packaging foam. To protect the system from roadway debris the text fixture is enclosed in 5/8" wood and secured to a metal frame with fasteners. The rear panels were fitted with cooling vents to provide ventilation for the computer and the power inverter. All components of the test fixture are accessible through removable rear and top panels.

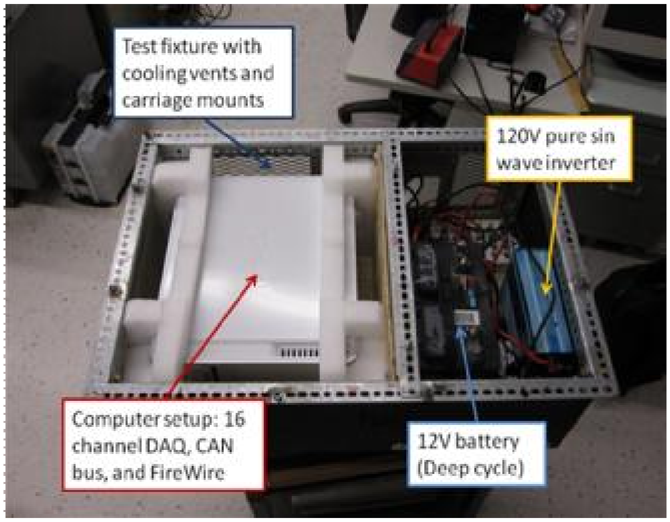


Figure 17. Equipment housing for road testing.

This fixture was designed to attach underneath the trailer to allow for normal use of the trailer. The test fixture is attached to the trailer using a carriage that is secured to the trailer using I-beam clamps (Figure 18). The test fixture is slid into the carriage and is secured using fasteners (Figure 19).

Figure 18. Carriage for equipment housing.

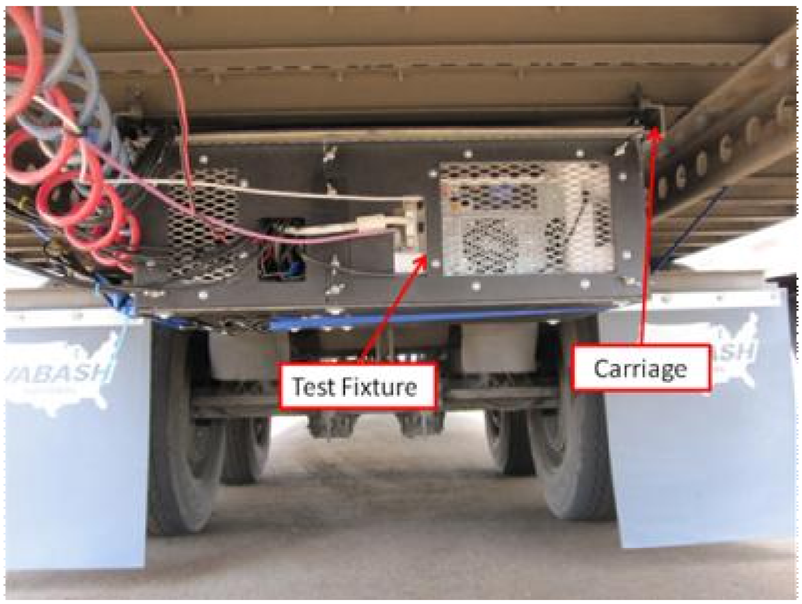


Figure 19. Equipment housing and carriage on large truck.

The ultrasonic sensors, magnetic sensors, and rear facing radar were attached on the left and rear of the trailer (Figure 20). A combination of one ultrasonic sensor and one magnetic sensor was placed at the rear corner of the trailer and another 6 feet ahead.

Figure 20. Sensor placement on large truck.

The Class 8 truck was taken out on its normal delivery route and through several specific passing scenarios. After completion of the testing it was discovered that the ultrasonic sensor data was noisy due to an electrical grounding issue and the data from both ultrasonic sensors could not be used. The results indicated that the magnetic and radar sensors functioned as expected. Video was also acquired for reference.

Due to time constraints, additional testing on the class 8 truck could not be conducted for this project. The final tests were conducted using a pickup truck driven through various passing scenarios. The data from these tests is free from the induced noise of the full scale test and is comparable to the conditions of the full scale tests. The data analysis presented in the following section uses this data.

3.11. TASK 11: DATA ANALYSIS

Several road tests were carried out to test the performance of the Bayesian filter algorithm in the detection of vehicles and the rejection of false targets. The tests conducted assess the performance of the filter while passing a variety of targets that could affect the sensors, such as non-vehicle magnetic objects and objects with dimensions similar to vehicles.

The performance of the Bayes filter is quantified using the percentages of true and false outputs of the filter. Using the camera data as a reference of true vehicle presence and the vehicle presence likelihood output of the filter, the number of true and false filter outputs can be calculated. Figure 21 shows the four possible outputs of the filter. The definitions and case names that will be used for the remainder of this paper are described in Figure 21. The video was use only to verify whether or not a vehicle was present, as a means to determine the accuracy of the sensor prediction. The video time stamp and pictures were not used in the algorithm. When a vehicle was seen in the video the time stamp was recorded and used as a reference point in the sensor data. The presence of a vehicle can easily be seen because there is a clear drop in voltage (2.5V - 1V). So, the presence of a vehicle is defined between the initial voltage drop (vehicle enters) and the voltage rise (vehicle exits) for both the ultrasonic sensor and magnetic sensor. It is difficult to identify the presence of a vehicle solely with the magnetic sensor because the measurement of magnetic field is independent of the sensed object's range, thus the time stamp for the ultrasonic sensor was used to define the presence of a vehicle in the magnetic data. The output of the Bayesian filter is the probability that a vehicle is present based on the above definition. This definition may introduce some error; however it can be refined with further study to minimize error.

The performance of the Bayes filter can now be calculated by classifying the filter outputs. Three types of percentages are used to describe the performance of the filter: the overall performance, the vehicle present percentage, and the vehicle absent percentage (See Table 2). The overall performance is the percentage of how many true filter outputs (Case 1 and 2) were made over the entire data set. The vehicle present performance percentage shows how many true present outputs (Case 1) were made for the total number of data points where vehicles were present. The *vehicle absent* performance percentage shows how many ***true absent*** outputs (Case 2) were made for the data points where vehicles were not present. The *overall* performance shows how many correct outputs the filter can produce while the *vehicle present* and *vehicle absent* performances show whether the filter is biased to positive or negative detections of vehicles.

Table 1.

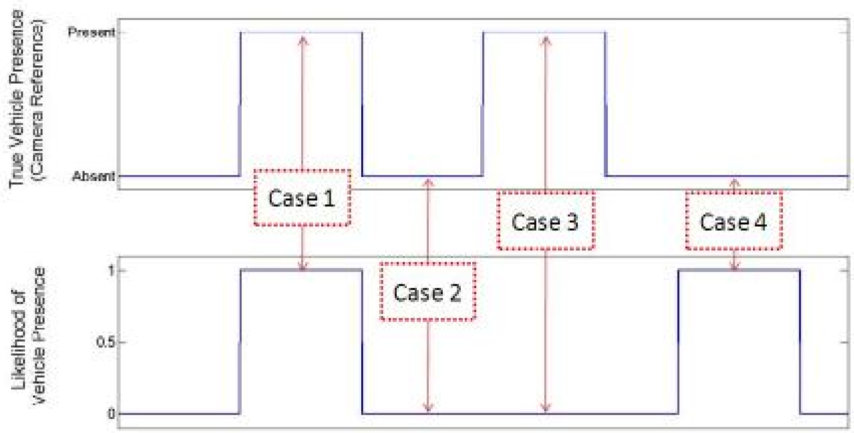


Figure 21. Filter performance.

The video was use only to verify whether or not a vehicle was present, as a means to determine the accuracy of the sensor prediction. The video time stamp and pictures were not used in the algorithm. When a vehicle was seen in the video the time stamp was recorded and used as a reference point in the sensor data. The presence of a vehicle can easily be seen because there is a clear drop in voltage (2.5V - 1V). So, the presence of a vehicle is defined between the initial voltage drop (vehicle enters) and the voltage rise (vehicle exits) for both the ultrasonic sensor and magnetic sensor. It is difficult to identify the presence of a vehicle solely with the magnetic sensor because the measurement of magnetic field is independent of the sensed object's range, thus the time stamp for the ultrasonic sensor was used to define the presence of a vehicle in the magnetic data. The output of the Bayesian filter is the probability that a vehicle is present based on the above definition. This definition may introduce some error; however it can be refined with further study to minimize error.

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Table 1. Filter performance cases.

Case	Filter Output	Case Name	Description	Action Taken
1	True	True Present	Filter reports a vehicle accurately	Proper action or warning taken
2		True Absent	Filter reports a "non-vehicle" target accurately	No action taken
3	False	False Present	Filter reports a "non-vehicle" target when a vehicle is present	Required action or warning not taken
4		False Absent	Filter reports a vehicle when no vehicle is present	Over-correction or false warning

Table 2. Performance percentages.

Performance (%)	Equation
Overall	$\frac{(True\ Present + True\ Absent)}{Total\ Number\ of\ Data\ Points} \times 100\%$
Vehicle Present	$\frac{True\ Present}{Total\ Number\ of\ Present\ Points} \times 100\%$
Vehicle Absent	$\frac{True\ Absent}{Total\ Number\ of\ Absent\ Points} \times 100\%$

Analyzing the Bayes filter performance also requires considerations of the testing environment. The sensor models described in Section 3.10.2 were created in a controlled environment where vehicle data was collected when the sensors were stationary. During the road testing, it was apparent that sensor environment has more variance and is more volatile than the environment where data was collected for the statistical sensor modeling. To improve the implementation of the filter in this unstable environment, further testing and data collection are required to include the sensor variations into the statistical sensor model. Other considerations for improving the filter performance are discussed in Section 3.11.2.

To demonstrate the effects of the sensor behavior on the filter performance, the results presented in the following section show the behavior of the Bayes filter algorithm using two independent methods: First, with the ***developed*** sensor model described in Section 3.10.2, and second, using a ***tuned*** sensor model. The *tuned* sensor model is created by modifying the ultrasonic sensor variance and the expected magnetic field ranges of the ***developed*** sensor model. The ***tuned*** sensor model optimizes the performance of the Bayes filter algorithm in each of the individual scenarios presented in the following section. The results for each individual scenario are presented with in the format of Table 3. This data can be interpreted as a best and worst case performance measure. This table presents the *overall*, *vehicle present*, and *vehicle absent* performance percentages for both the ***developed*** and ***tuned*** sensor models.

Table 3. Example performance results table.

	Overall	Vehicle Present	Vehicle Absent
Developed Model	--%	--%	--%
Tuned Model	--%	--%	--%

3.11.1. Filter Performance

The following section shows the performance of the filter algorithm and the percentage of true and false detection when the host vehicle passes various types of targets. The results presented are based off single trials. These results showed typical behavior from the sensors. The sensor behavior for both the ultrasonic sensor and magnetoresistive sensor are well understood from bench tests, controlled parking lot experiments, and preliminary road testing.

Two Passenger Vehicles

In this scenario, the host vehicle passes two passenger vehicles in quick succession. This scenario tests the baseline performance of the Bayes filter. It can be seen in Figure 22 that the ultrasonic sensor voltage goes low and the magnetic sensor voltage goes up when a vehicle is present (34.5-35.5 s and 35.7-36.6 s). The ***developed*** sensor model does not report the presence of the first vehicle because the magnetic field amplitude is expected to be between 29 and 62 mG. With the ***developed*** model the overall performance is 70.6%. For maximum performance, the ***tuned*** sensor model shifts the expected magnetic field amplitude to the range of 10-30 mG. This brings the overall sensor performance to 90%. Further testing of similar scenarios will likely enable more algorithm 'tuning' to improve the performance further.

It can be seen in Table 4 that the filter is biased toward *Vehicle Absent*; meaning that the filter is more likely to report that a vehicle is not present. This has an advantage of not setting off false alarms, but also indicates that further testing is necessary for irreversible decision making.

Table 4. Filter performance while passing two passenger vehicles.

	Overall	Vehicle Present	Vehicle Absent
Developed Model	70.6%	26.4%	100.0%
Tuned Model	90.7%	78.4%	99.1%

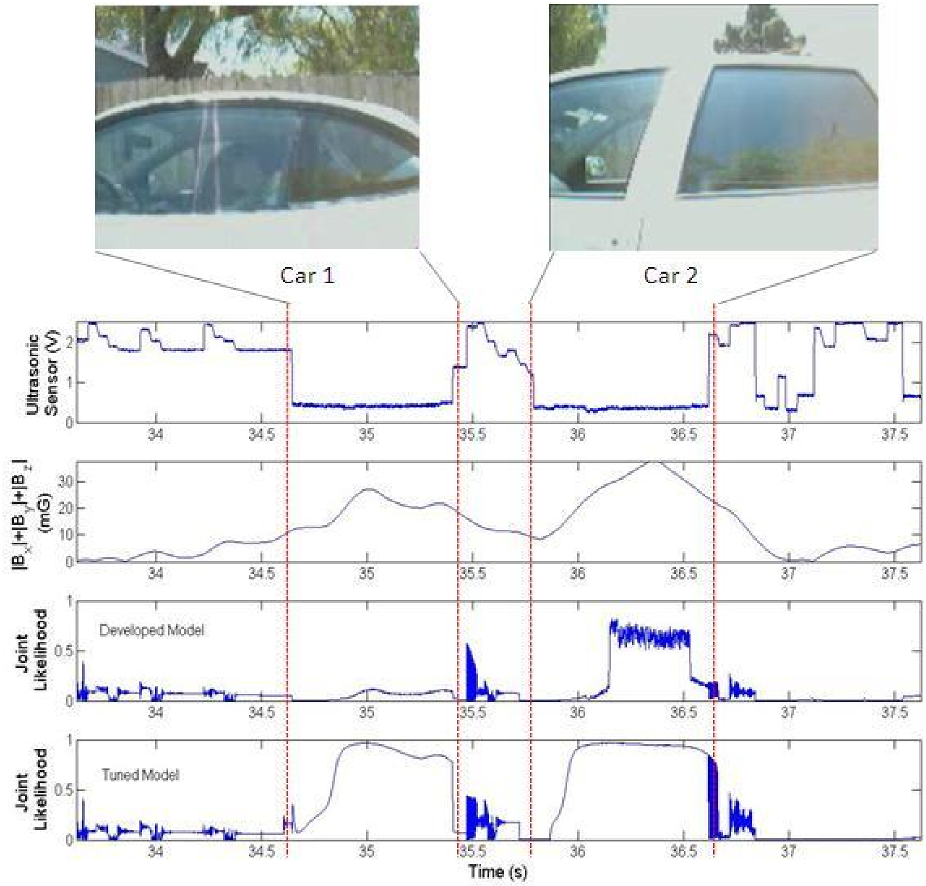

Figure 22. Filter performance while passing two passenger vehicles using *developed* and *tuned* sensor models.

Passenger Vehicle and Set of Garbage Containers

In this scenario the host vehicle passes a vehicle then a set of trash containers. The trash containers produce an ultrasonic signature that is similar to vehicles. As the host vehicle passes the target the Bayes filter is able to distinguish between the vehicle and the trash bins.

The filter performs with 91.7% accuracy with the *developed* model and 98.2% with the *tuned* model (

Table 5). This scenario shows that the Bayes filter has the ability to reject non-vehicular objects that have heavy influence on one of the two sensors.

Table 5. Filter performance while passing a vehicle and trash containers.

	Overall	Vehicle Present	Vehicle Absent
Developed Model	91.7%	56.0%	100.0%
Tuned Model	98.2%	90.7%	99.9%

Railroad Tracks

The next scenario conducted had the host vehicle drive over railroad tracks. The railroad tracks have a high magnetic influence, but no influence from the ultrasonic sensors. In this scenario, the Bayes filter performed at 100% with the *developed* model (Table 6). The use of a *tuned* model was not applied to this scenario because the filter performance could not be further enhanced.

Table 6. Filter performance while driving over railroad tracks (high magnetic signature).

	Overall	Vehicle Present	Vehicle Absent
Developed Model	100.0%	N/A	100.0%

Building Wall

In this last scenario, the host vehicle is driven past a metal warehouse. The building wall has high influence on both range and magnetic signature. When the host vehicle first passes the building the filter has a high belief that a vehicle is present; however, that belief changes after a short time due to the prediction model. The prediction model expects a vehicle to be in the sensor's field of view for 1.5 s. As time increase the likelihood that a vehicle is present is reduced because a vehicle is expected to be within some dimensional constraints.

Note that in final implementation of this system, the expected duration of vehicle presence could be controlled by host vehicle speed and road type (if available). However, this prediction technique still has an issue if a vehicle pulls alongside a truck and then matches speeds. More work is needed to address that scenario.

Table 7. Filter performance while passing building wall (high magnetic signature and high range influence)

	Overall	Vehicle Present	Vehicle Absent
Developed Model	84.2%	N/A	84.2%
Tuned Model	97.9%	N/A	97.9%

3.11.2. Improving Filter Performance

The system performance is good under some circumstances but shows room for improvement in others. Several areas have been identified where the Bayes filter algorithm may be improved. These recommendations are based off observations from testing and data analysis; however, further testing is required to justify the feasibility of implementation and to quantify the improvements. The two areas where the filter may be improved are the predictive model and the corrective model of the algorithm. The following sections discuss the specific tasks that have an opportunity to improve the filter's performance as well as increase the consistency of that performance.

Prediction Model

Correction model input - The current prediction model is based on edge detection of the ultrasonic sensor, thus is influenced by noise of the sensor. To minimize these noise effects the prediction model must see a consistent low voltage or high voltage (about 300 ms) before it can take any action. Using the correction step to input the prediction step instead of using the sensor reading will allow the filter to act without this delay and the effects of the ultrasonic sensor will not affect the prediction step. To modify the current prediction model a study of when the correction step can be triggered to properly identify the presence of a vehicle must be completed. While the current trigger takes a continuous low voltage for a period of 300 ms to identify the presence of a vehicle, a prediction model based off the correction step may only require one data point above 50% belief, for example.

Correction Model

Sensor model variance - The correction model that was used in the project was created from sensor data collection in a single controlled environment which consisted of the host vehicle parked on a roadside while other vehicles passed at low speeds. This data was used to generate the correction model. Vehicle detection was consistently above 80% accurate when the algorithm was operated under similar conditions. However, when the system was tested under conditions that differed significantly from those used to generate the correction model, the consistency and accuracy was lower. To improve the performance of the filter, sensor data collection should be extended to include more extensive "real-world" scenarios. In the road tests that were conducted the ultrasonic sensor variance is much greater than the controlled scenario that the sensor model was based on. In the tuned sensor models shown above the standard deviation of the sensor model was increased to allow the likelihood of the vehicle presence to decrease at a slower rate as the vehicle were detected closer and farther than the expected value of the sensor model. The system could be designed to change from one correction model to another depending on external factors such as location from GPS system, live traffic data, or vehicle-to-vehicle communication. For example one correction model could be used at low speeds on surface roads, a second for low speeds on highways, a third for high speeds on highways, etc.

Weighting individual sensors – Observations were made while comparing the video of vehicles passing to the ultrasonic sensor and magnetic sensor. It was seen that in some cases, the ultrasonic sensor produced a belief that better represented the true vehicle presence than the magnetic sensor and vice a versa. The correction step may be further improved if the algorithm is extended to give an influential weight to the sensor that has a better representation of the true vehicle presence or the higher belief. An influential weight allows the algorithm to internally judge its own belief. An investigation on different statistical methods to change weighting factors is recommended. Additionally the weighting factors could be changed based on road conditions in a similar manner as the correction model.

3.12. TASK 12: RESULTS MAPPING

This project focused primarily on integrating data from sensors to provide information that can be used to trigger crash avoidance countermeasures. To aid in implementation of such a system, in Task 12 the team focused its attention on the best way to use the system to avoid real-world accidents. The result of this task was a link between specific countermeasures and sensor output.

The result of implementing these countermeasures should be to reduce accidents by a combination of (a) improved truck driver awareness, (b) improved other vehicle driver awareness, and (c) action-based warnings or reactions of the truck system. These actions should result in a significant decrease in accidents, once the system is deployed across much of the nationwide truck fleet.

The side impact sensor system was designed to continuously output a probability assessment (0 to 100%) of vehicle presence near a pair of (ultrasonic and magnetic) sensors. Because these sensor pairs would be located along the length of both sides the truck's trailer, the system will actually report 8-10 probabilities, one for each pair. As a result, information will be available on the likelihood of a vehicle presence, and the approximate position.

If all sensor pairs report less than 33% likelihood:

The system is not tracking any vehicles near the trailer sides. No actions will be triggered.

If any sensor pairs report between 33% and 66% likelihood:

The system is tracking potential vehicles near the trailer sides. A low-level (caution) warning should be triggered, including position information if possible. If a driver steers toward the potential vehicle, the warning should increase in intensity (flashing lights, louder noise). Possible countermeasures include:

- A situation display or status indicator light in the cab may glow or flash yellow.
- Lights located in the side-view mirrors may glow or flash yellow.
- A low-level noise simulating a vehicle may be played over the right or left speakers.
- If approach distance becomes small, an external flashing warning light may be lit on the truck sides to warn off the other driver.
- If vehicle-to-vehicle communication is available, location information should be transmitted.

If any sensor pairs report greater than 66% likelihood, and distance is not decreasing significantly:

The system is tracking vehicles near the trailer sides. A warning should be triggered to notify the driver of vehicle presence.

- A situation display or status indicator light in the cab may glow or flash red.
- Lights located in the side-view mirrors may glow or flash red.
- A moderate noise simulating a vehicle may be played over the right or left speakers.
- If vehicle-to-vehicle communication is available, location information should be transmitted.

If any sensor pairs report greater than 66% likelihood, and distance decreases below 6 feet:

The system is tracking vehicles near the trailer sides, approaching an impact. An urgent warning should be triggered to notify the driver and other vehicles to take action.

- An external flashing warning light may be lit on the truck sides to warn off the other driver.
- Steering wheel vibration or torque may be applied if driver turns toward other vehicle.
- Warning beeps may sound if driver turns toward other vehicle.

Pro-Active Countermeasures

Despite the potential benefits of active steering, braking, or acceleration to avoid an impact, the risks are too great to take these actions without high certainty of vehicle presence. As a result, pro-active countermeasures are not currently recommended for any level of the sensor system output. More data on the sensor system performance is needed before this type of countermeasure could be considered.

3.13. TASK 13: DOCUMENTATION

This Draft Final Report and the companion Draft Technical Report will be distributed to the Safety IDEA review panel and this project expert review panel for review. A final version of the two reports will then be distributed.

3.14. TASK 14: DOCUMENTATION REVIEW/ COMMENT AND REVISE FINAL REPORT

Comments from the Safety IDEA committee review and the expert panel review for this project report will be incorporated into the final drafts which will be distributed to both panels.

4. PLANS FOR IMPLEMENTATION

The goal of this project was to develop and test a prototype system for integrating, or 'fusing' data collected from multiple low-cost truck exterior sensors. The prototype algorithm fuses the sensor data from a magneto-resistive and an ultrasonic sensor and outputs a prediction of vehicle presence. For the four scenarios tested, a version of the system ('tuned') successfully predicted the presence or lack of nearby vehicles, with an accuracy of 90-100%. These results indicate that the system shows good potential as a low cost alternative to competing systems which require multiple, high cost sensors. Truck fleet operators will likely adopt technology only if the costs are justified by reduced damage and insurance costs, therefore developing an effective crash avoidance system at a low cost is required for the technology to be adopted on a large scale.

To aid in the implementation of a low-cost sensor fusion system, three specific steps were taken throughout this project. First, the Expert Review Panel for the project was selected to include representatives from three vehicle exterior safety sensor manufacturers and one heavy truck manufacturer. By including these members on the panel, and providing earlier access to the test data and system development, potential implementation issues could be identified early and addressed as part of the project. In addition, the completed system is now available for these manufacturers to take forward for further testing and development.

The second step toward implementation dealt with identifying accident avoidance system acceptance concerns by traveling and interviewing truck drivers. Their inputs were directly considered during Task 12, when specific truck countermeasures were proposed and evaluated.

The third step consisted of publicizing the system at several conferences. A poster session of the project was presented at the January 2009 TRB Annual Meeting in Washington, DC. Interim system results were presented at the June 2009 Enhanced Safety of Vehicles (ESV) conference in Stuttgart, Germany. A portion of the final system results will also be presented in a paper at the November 2009 ASME International Mechanical Engineering Conference and Exhibition (IMECE).

The team plans to continue working toward implementation of the system by:

- Addressing the technical issues identified in this work:
  - Including statistical modeling of a variety of traffic scenarios (only one traffic scenario was used throughout this work due to time and scope limitations).
  - Managing the magnetic sensor bias due to changes in the host vehicle direction.
  - Integrating the prediction model with infrastructure to vehicle communication and GPS.
- Working with industry contacts to:
  - Quantify the total system (including countermeasures) cost and benefits to fleet operators.
  - Identify and address other hurdles to implementation.
  - Test the system under a wider variety of traffic conditions.

In addition, although the system was designed for crash avoidance in moving trucks, it also has potential applications in traffic monitoring from stationary infrastructure locations. We will also work with partners in highway and transportation agencies for commercialization opportunities in that sector.

5. CONCLUSIONS

This project addressed identifying opportunities to reduce the cost of current crash avoidance systems for large trucks. A sensor evaluation was conducted and several technologies were identified for this system: magnetic sensors, ultrasonic sensors, vision system, and radar.

The magnetic sensor was identified as a cost reducing technology for crash safety; however, it has primarily been developed for vehicle identification at intersections and electronic compasses, but not for vehicle type classification and real time crash avoidance. In this report, preliminary work was conducted in the form of 2-D analytical modeling of dipoles and experimental bench tests to corroborate the findings of previous studies. A 3-D analytical single dipole model was then developed to better represent the magnetic phenomenon of real-world objects. A detailed parameter study was conducted to better understand the magnetic behavior of 3-D dipole models and the insights gained from the exercise were used for model matching with the experimental data. Road tests were conducted to capture the 3-D magnetic behavior of vehicles. The single 3-D dipole model was then extended to incorporate multiple dipoles for capturing the complex magnetic footprints recorded from vehicles. Mathematical functions capable of both eliminating the sign dependency of magnetic signals and producing a magnitude threshold for the different vehicle types were developed. The analytical and experimental study thus conducted showed that vehicle magnetic behavior could indeed be captured by mathematical models and that a magnetic sensor could be used to identify vehicle types.

The magnetic sensor used in this project has been shown to function as either a compass by measuring the earth's magnetic field with respect to the sensor's orientation or as a vehicle detecting device by measuring only localized distortions in a magnetic field (presence of vehicle). For this project, the focus solely on vehicle detection and any effect due to the earth's constant magnetic field and sensor orientation is filtered out for all the analysis by testing in short durations (minimal orientation change) and removing the bias voltage. Future work will address this issue with the possible integration of GPS.

The magnetic sensor was identified as a suitable sensor for vehicle classification; however, due to the sensor's range dependency, sensor fusion is required with a range sensor. This report investigated the application of statistical algorithms in the form of a Bayesian filter to enhance vehicle identification that uses an ultrasonic sensor and a magnetic sensor combination. This research project utilized the knowledge gained by the authors in a previous project on the applicability of ultrasonic and magnetic sensor fusion for vehicle detection. This report presents a detailed description of the procedure to formulate a two step prediction/correction based Bayesian filtering algorithm for both the ultrasonic and magnetic sensors. Statistical sensor models were developed for each type of sensor and individually utilized in the Bayesian filter algorithm. The results obtained showed a reduction in process noise and sensor anomalies that negatively influence the credibility of vehicle detection. A joint Bayesian filter algorithm was then developed to facilitate sensor fusion. Typical results of the filter performance indicates that the filter performs at greater than 80% accuracy overall. The results obtained clearly show the ability of the probabilistic approach to further enhance the prediction of object detection and discrimination capabilities of an ultrasonic-magnetic sensor fusion system. The project has shown that this filter is effective for systems such as blind spot detection and vehicle classification systems.

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