Portable Roadside Sensors for Vehicle Counting, Classification, And Speed Measurement

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Abstract: **This paper focuses on the development of a portable roadside magnetic sensor system for vehicle counting, classification, and speed measurement. The earliest magnetic field detectors allowed navigation over trackless oceans by sensing the earth's magnetic poles. Magnetic field sensing has vastly expanded as industry has adapted a variety of magnetic sensors to detect the presence, strength, or direction of magnetic fields not only from the earth, but also from permanent magnets, magnetized soft magnets, vehicle disturbances, brain wave activity, and fields generated from electric currents. Magnetic sensors can measure these properties without physical contact and have become the eyes of many industrial and navigation control systems. This paper will describe the current state of magnetic sensing within the earth's field range and how these sensors are applied. Several applications will be presented for magnetic sensing in systems with emphasis on vehicle detection and navigation based on magnetic fields.**

Keywords: **Magnetic Sensors, Portable Traffic Sensor, Roadside Traffic Sensor, Vehicle Classification, Vehicle Detection, Vehicle Speed Measurement.**

I. INTRODUCTION

A portable sensor system is designed that can be placed adjacent to the road and can be used for vehicle counting, speed measurements and vehicle classification. The sensor system consists of magneto resistive devices that measure magnetic field and associated signal processing algorithms. The sensor system can make these traffic measurements reliably for traffic in the lane adjacent to the sensors. The vehicle detection rate accuracy is 99%. The developed signal processing algorithms enable the sensor to be robust to the presence of traffic in other lanes of the road. The velocity estimation has a max error of 2.5% over the entire speed range 5 – 60 mph. Vehicle classification is done based on the magnetic length and an estimate of the average vertical magnetic height of the vehicle. The sensor system can be used to reliably count the number of right-turns at an intersection. The developed sensor system is compact, portable, wireless and inexpensive. The increasing traffic volume over the last decades poses high challenges on today's traffic research and planning. Detection, Counting and classification of vehicles in a video have become a potential area of research due to its numerous applications to video-based intelligent transportation systems. For most traffic surveillance systems, major stages are used to estimate desired traffic parameters, i.e., vehicle detection, Counting, tracking, and classification. Each year, motor vehicle crashes account for about thousands deaths, more than million injuries. Counting vehicles over a period of time on a busy intersection will help the concerned authority to efficiently control the duration of traffic signal on road thus reducing the level of traffic congestion during rush hours. It helps in minimizing the possibilities of fraudulent activities in toll collection. It is necessary to provide better traffic surveillance to reduce the accidents. So the main Goal of our paper is to provide better traffic surveillance. For traffic surveillance application generally fixed cameras are used with respect to static background (e.g. stationary surveillance camera) and a common approach of background subtraction is used to obtain an initial estimate of moving objects. First perform background modeling to yield reference model. This reference model is used in background subtraction in which each video sequence is compared against the reference model to determine possible variation. The variations between current video frames to that of the reference frame in terms of pixels signify existence of moving objects.

Traffic congestion may be alleviated by improving the efficiency of the current transportation system through the implementation of advanced technologies. Real-time traffic surveillance is one of the most important components of such an approach, and real-time travel information is useful for advanced travel advisory systems. Emergency management agencies such as police, fire stations, and ambulance dispatchers may also benefit from real-time traffic information in routing their vehicles through the transportation network to save lives. Roadway safety and efficiency will be significantly enhanced by employing remote sensing and communication technologies capable of providing low-cost, scalable, and distributed data acquisition of road conditions. Such Intelligent Transportation System (ITS) applications require distributed acquisition of different traffic metrics such as traffic speed, volume, and density. In such systems, automated traffic control is possible only through real-time traffic information over distributed points on the transportation system. The existing measurement technologies are bending plates, pneumatic road tubes, piezoelectric sensors, inductive loops, infrared, microwave- Doppler/radar, passive acoustic, video image detection, and Bluetooth devices. The existing data acquisition technologies in transportation systems suffer from the following drawbacks:

A. Energy efficiency

Most of the existing technologies need to be constantly connected to a main power source or battery. Connection to the main power source limits deployment of the instruments, and using batteries imposes regular maintenance cycles. **High cost*:*** The majority of technologies require expensive instruments, which inhibit cost effectiveness of large-scale and distributed traffic measurements. **Installation and maintenance:** Most existing technologies need significant maintenance and calibration and are costly to install. Installation costs may include wiring of the instruments to power sources or the wiring required for communication. **Scalability*:*** The majority of existing technologies cannot be deployed on a large scale due to limitations such as installation cost, wiring, availability of energy sources, etc. **Low-speed and offline measurements:** The lack of low-cost real-time communication between measurement points and the decision-making centers inhibits fast and automated decision making.

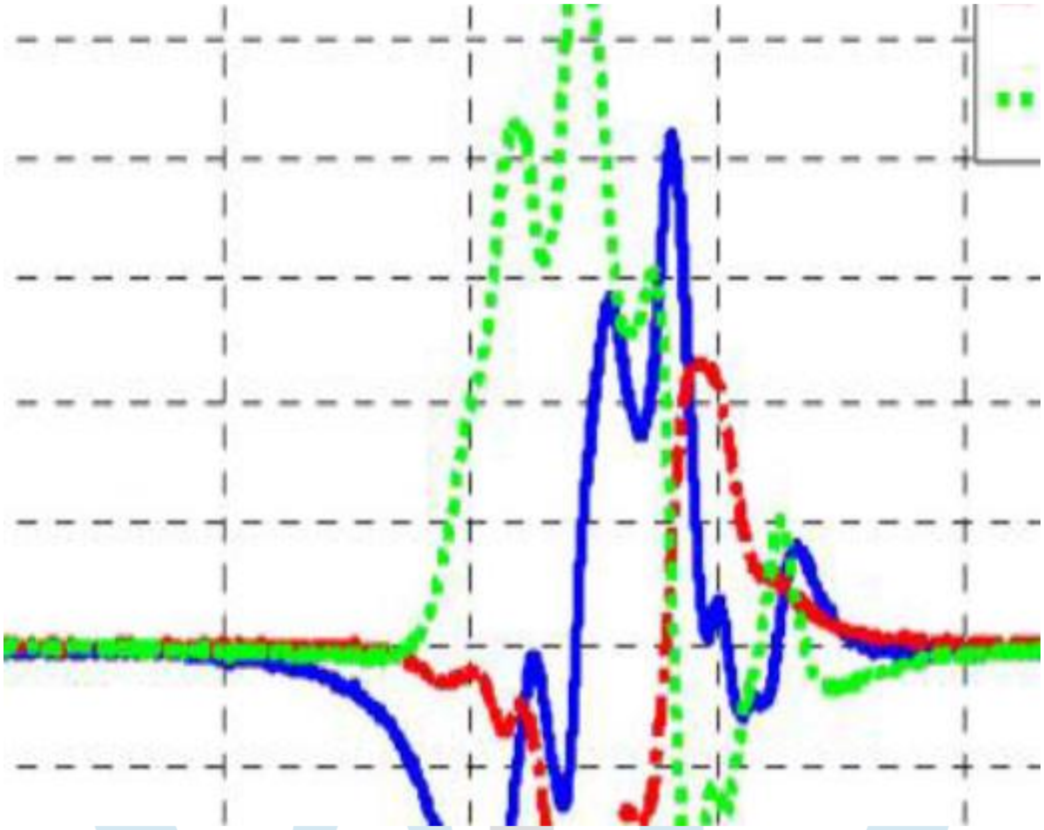


Fig.1. Magnetic field readings for a Ford Ranger from a magnetic sensor embedded in the road.

First, magnetic field readings were obtained from a magnetic sensor that was embedded on top of the road surface at the center of a lane and compared with the magnetic field readings when the sensor was placed adjacent to the road. Fig. 1 shows the magnetic field readings of the *x*-, *y*-, and *z*-axes, with the sensor placed at the center of the road lane. This paper is organized as follows. In Section II, the Anisotropic Magnetoresistive (AMR) is discussed. In Section III, Vehicle Classification .A method of counting the number of vehicles that make a right turn at an intersection is discussed in Section IV. Conclusions are presented in Section V.

II. ANISOTROPIC MAGNETORESISTIVE (AMR)

William Thompson, later Lord Kelvin, first observed the magnetoresistive effect in ferromagnetic metals in 1856. This discovery had to wait over 100 years before thin film technology could make a practical sensor for application use. Magnetoresistive (MR) sensors come in a variety of shapes and form. The newest market growth for MR sensors is high density read heads for tape and disk drives. Other common applications include automotive wheel speed and crankshaft sensing, compass navigation, vehicle detection, current sensing, and many others. The anisotropic magnetoresistive (AMR) sensor is one type that lends itself well to the earth's field sensing range. AMR sensors can sense dc static fields as well as the strength and direction of the field. This sensor is made of a nickel-iron (Perm alloy) thin film deposited on a silicon wafer and is patterned as a resistive strip. The properties of the AMR thin film cause it to change resistance by 2-3% in the presence of a magnetic field. Typically, four of these resistors are connected in a Wheatstone bridge configuration (Fig.2) so that both magnitude and direction of a field along a single axis can be measured. A common bridge resistance is 1 kohm. For typical AMR sensors, the bandwidth is in the 1-5 MHz range. The reaction of the magnetoresistive effect is very fast and not limited by coils or oscillating frequencies. The key benefit of AMR sensors is they can be bulk manufactured on silicon wafers and mounted in commercial integrated circuit packages. This allows magnetic sensors to be auto-assembled with other circuit and systems components.

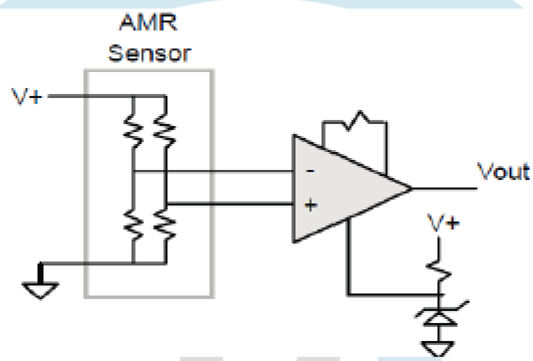


Fig.2. AMR sensor circuit. A. AMR Sensor Characteristics

AMR sensors provide an excellent means of measuring both linear and angular position and displacement in the earth's magnetic field. Permalloy thin films deposited on a silicon substrate in various resistor bridge configurations provide highly predictable outputs when subjected to magnetic fields. Low cost, high sensitivity, small size, noise immunity, and reliability are advantages over mechanical or other electrical alternatives. Highly adaptable and easy to assemble, these sensors solve a variety of problems in custom applications. A characteristic of the Permalloy film is that it changes resistance (ΔR) when exposed to a variation in an applied magnetic fieldhence the term magneto resistance. This causes a corresponding change in voltage output as shown in Fig. 3.

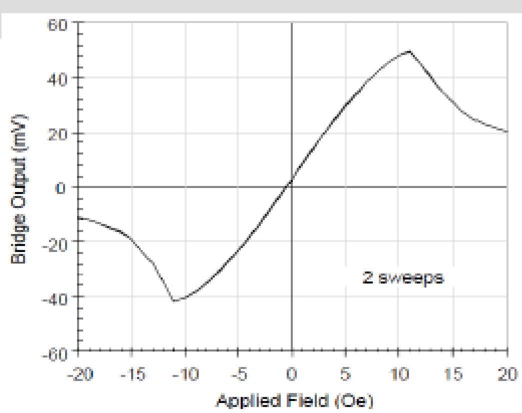


Fig.3. AMR output transfer curve.

The sensitivity of the bridge is often expressed as mV/V/Oe. The middle term (V) of this unit refers to the bridge voltage, Vb. When the bridge voltage (Vb) is set to 5 volts, and the sensitivity (S) is 3mV/V/Oe, then the output gain will be 15mV/Oe. Through careful selection of a bridge amplifier, output levels of 1 microvolt can be achieved. This results in a magnetic resolution of 67 micro Oersted, or 1 part in 15,000 per Oersted. If the bridge output is amplified by a gain of 67, then the total output sensitivity would be 1V/gauss (=67 x 15 mV/gauss). If a full scale range of ±2 gauss is desired, this implies a 4-volt output swing centered on the 2.5V bridge center value—or a span of 0.5 to 4.5V. This signal level is suitable for most A/D converters. Using an AMR sensor and amplifier, precise magnetic field information can provide field magnitude as well as directional information. There are well described design techniques to build extremely sensitive magnetic sensor subsystems. By simply switching the magnetic properties of the Permalloy film, the sensor offset voltage as well as the sensor and amplifier offset drift with temperature can be eliminated. On-chip offset straps can be used to auto-calibrate the AMR sensor while in an application during normal operation. Output gain variation with temperature can be greatly reduced by using a closed loop feedback technique so that the sensor always operates in a zero field environment.

B. AMR Sensor Applications

AMR sensors available today do an excellent job of sensing magnetic fields within the earth's field—below 1 gauss. These sensors are used in applications for detecting ferrous objects such as planes, trains, and automobiles that disturb the earth's field. Other applications include magnetic compassing, rotational sensing, current sensing, underground drilling navigation, linear position sensing, yaw rate sensors, and head tracking for virtual reality.

C. Vehicle Detection

The earth's field provides a uniform magnetic field over a wide area—say several kilometers2. Fig. 4 shows how a ferrous object, a car, creates a local disturbance in this field whether it is moving or standing still. AMR magnetic sensors can detect the change in the earth's field due to the vehicle disturbance for many types of applications.

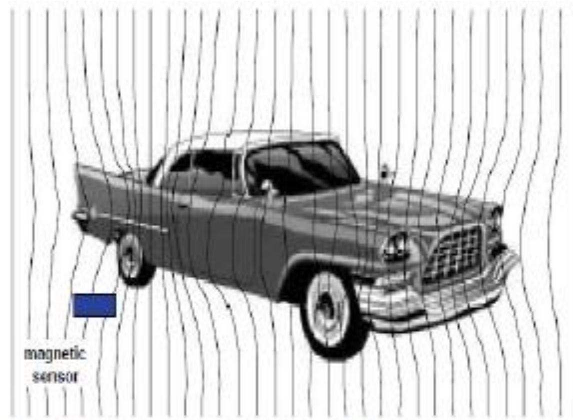
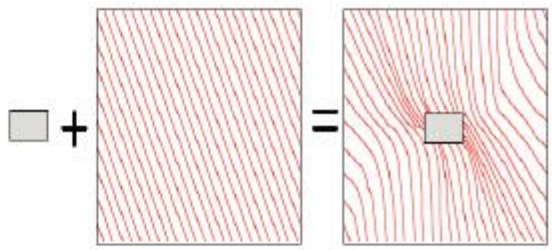


Fig.4.Vehicle disturbance in earth's field.



Ferrous Object + Uniform Magnetic Field = Field Disturbance

Fig.5. Ferrous object disturbance in uniform field.

Applications for vehicle detection can take several forms. A single axis sensor can detect when a vehicle is present, or not. The sensing distance from the vehicle can extend up to 15 meters away depending on its ferrous content. This is useful in parking garages to give drivers entering it a choice of where the most available spaces to park. Another use is to detect approaching trains to control the crossing gates. In this application, two sensors could be used to detect presence, direction of travel, and speed to give the controller enough information to control the crossing gates. The magnetic disturbance of a large ferrous object, such as a car, can be modeled as a composite of many dipole magnets. These dipoles have north-south orientations that cause distortions in the earth's magnetic field. The distortions are most obvious at the engine and wheel locations but can also vary depending on what ferrous items are in the interior, on the rooftop, or in the trunk locations. The net result is a characteristic distortion, or anomaly, to the earth's magnetic field that is unique to the shape of the car (see Fig.5). These distortions are also referred to as hard iron effects, or distortion, of the vehicle.

III. VEHICLE CLASSIFICATION

Magnetic disturbances can be used to classify different types of vehicles—cars, vans, trucks, buses, trailer trucks, etc. When a vehicle passes close to the magnetic sensor, or drives over it, the sensor will detect all the different dipole moments of the various parts of the vehicle. The field variation will reveal a very detailed magnetic signature of the vehicle. A three-axis AMR magnetometer placed in the lane of traffic will provide a rich signal output for vehicles passing over it a three-axis magnetometer output for two vehicles passing directly over it. The vehicle in a Silhouette van and the vehicle is a Saturn sedan. The four curves represent the X, Y, Z, and magnitude of the variation in the earth's field for the vehicle driving south. The X-axis points west, the Y-axis points south and the Z-axis is in the up direction. The starting point for each curve is the earth's magnetic field values for the sensor location: Field at location (X, Y, Z) = (-24, -187, -554) magus The type of vehicle can be classified using these variations with the use of pattern recognition and matching algorithms. From the magnetometer output curves, several observations reveal how the vehicles cause variations in the earth's magnetic field. The largest deviation in each curve is when the engine block passes over the sensors. This produces the largest peak around time mark 51. The Y and Z axes between the two vehicles have a lot of similarities, but for this case, the X-axis is unique to each vehicle type. If the vehicle speed is known, then the length of the vehicle can be determined. By using a second Y-axis sensor placed, for example, six feet apart, the peak signal from the engine variation can be used to measure the time it takes for the vehicle to pass six feet. Vehicle speed is determined from the time traveled over a specific distance (6 ft.). Having calculated the vehicle's speed, its length can be determined by observing the magnitude of the disturbance curves—bottom curves. The vehicle length is a critical input to the classification algorithm in making the vehicle type selection.

A. Vehicle Direction and Presence

For vehicle presence and direction detection the field variations do not require so much detail as for vehicle classification. It is also undesirable to make cuts in the road to bury a sensor in the lane of traffic. It is preferred to place the sensor curbside, along the lane of traffic being monitored, without cutting into the road surface. AMR magnetic sensors can easily be configured to reliably detect vehicles curbside based on the earth's field variation it creates. The test setup for vehicle direction and presence is shown in Fig.6. The three-axis magnetic sensor is at ground level and the X, Y, Z axes orientations are shown above with respect to the vehicle direction.

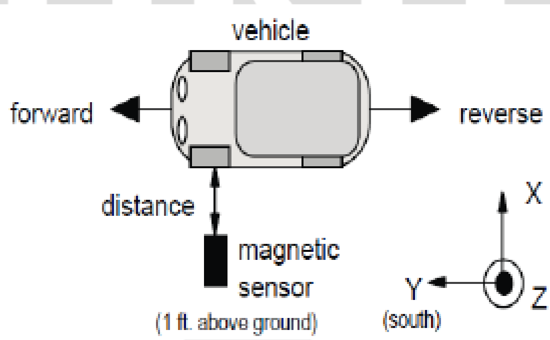


Fig.6. Vehicle and magnetic sensor orientations for drive-by tests. B. Vehicle Direction

Another useful type of vehicle detection is the direction a vehicle is moving past the sensor. This may be useful for safety reason such as highway on-ramps that are not obvious, traffic through tunnels to activate warning lights, and train movement detection to operate crossing gates. By understanding the variation of the earth's field from a vehicle passing by, the direction can be determined just by using a single axis sensor. The axis along the direction of travel can be used to determine the direction of the vehicle (see Fig.7). When there is no car present, the sensor will output the background earth's magnetic field as its initial value. As the car approaches, the earth's magnetic field lines of flux will be drawn toward the ferrous vehicle. If the sensitive axis of the magnetic sensor points to the right and the car is traveling left to right, then the magnetometer will initially see a decreasing field as more flux lines bend toward the oncoming car. That is, the first magnetic deviation from the sensor's initial value will be to swing in the negative direction. When the car is directly in line with the sensor, the magnetic variation through the car looks the same as the starting point the sensor output curve returns to the initial value. As the car leaves to the right, the flux lines will bend toward the car in the positive sensor axis.

This will cause the sensor output to increase above the initial value. When the car is out of range of the sensor, it will again return to the initial value. The left-hand curve in Fig. 7 shows the sensor response to a vehicle moving left-to-right. When the car is traveling in the opposite direction, the flux lines are attracted toward the car in the positive sensor direction causing an initial increase in the sensor output. The right-hand curve in Fig.7 shows the sensor response to a vehicle moving right-to-left. As the vehicle approaches from the left (driving south), with the sensor axis also pointing south, the initial sensor output should be a field change moving in the negative direction (refer to Fig.7). The Y-axis in that it indeed drops—becomes a larger negative field around the 51 time mark. As the vehicle leaves to the right of the sensor, the field will increase as the flux lines follow the vehicle away from the sensor. The sensor output increases as the vehicle leaves and returns to the initial level when it is out of range. Note that there are two bumps in the tail end of the curve, around the 60 time mark. The rear axle and spare tire in the trunk of the car most likely causes these.

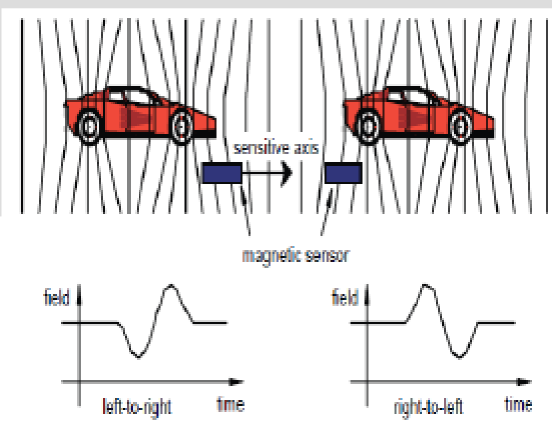


Fig.7. Direction sensing for vehicles driving over magnetic sensor

For the last half of the car is backing up and traveling by the sensor in the opposite direction. This part of the curve is a mirror reflection of the first half. It is stretched out a little more during to the slower speed backing up. The key characteristic is that the signal level will first peak low when going past the sensor in this direction as opposed to first peaking high when passing in the opposite direction. A simple check of the initial field strength deviation will indicate which direction the car is traveling.

IV. RIGHT-TURN DETECTION

The objective of the system described in this section is to count the number of right turns versus the number of straight driving vehicles at a traffic intersection. This portable system can be used to count the number of right turns at an intersection, replacing the current method, which is based on manual counting. This information can be used for adjusting the traffic lights. The sensors are placed at an intersection, as shown in Fig. 8. Our objective is to determine the percentage of the vehicles that move in lane 1 and make a right turn to lane 2. Recall that, for traffic measurement, when vehicles travel in a straight line, the magnetic sensors could be placed on the side of the road, and vehicles should typically pass within a distance of 2.5 m from the sensors to be detected. However, when the sensors are placed at the corner of an intersection, half of the turning radius (~2–3 m) is added to the lateral distance from the passing vehicles in lane 1 to the sensors. Thus, most of the vehicles that pass straight in front of the sensors in lane 1 or 2 are not typically detected. The vehicles that are being detected are the vehicles that make a right turn or larger vehicles that move straight on lane 1 or 2.

Fig.8. Right-turn detection and placement of the AMR sensors.

By placing one magnetic sensor at the corner side of the road, as shown in Fig. 8, the number of right turns at an intersection can be counted. During the experiments, 56 out of 59 right turns were correctly counted, resulting in a detection rate of 95%. As aforementioned, typically, straight-driving vehicles are not detected, because they pass at a larger distance from the sensor compared to vehicles that make a right turn. However, larger straight-driving vehicles can create large enough signals to be miscounted as vehicles that make right turns. During the experiments, 18 straight-driving vehicles created large enough signals to be miscounted as vehicles that make a right turn, which results in a detection error of 31%. Two methods, A and B, are proposed to identify and reject the errors caused by straight-driving vehicles, using two and four magnetic sensors, respectively. Considering the sensor configuration shown in Fig. 10, in method A, signals from magnetic sensors 2 and 3 are used. In method B, signals from all the four magnetic sensors are used. The two methods are presented in the following sections. Note that the sensor configuration used for right-turn detection, as shown in Fig. 10, is different from the sensor configuration shown in Fig. 9.

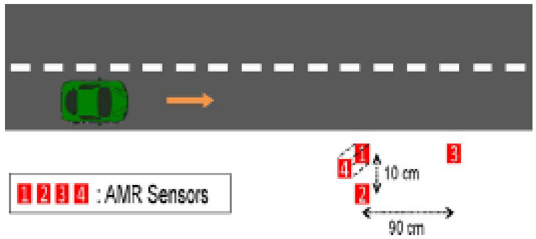


Fig.9. Sensor configuration for data collection.

A. Method A

As mentioned, it can be shown through both analytical modeling and experimental measurements that the magnetic field intensity around a vehicle has a relation that approximately varies as $1/x$ with distance, where x is the lateral distance from the vehicle. This phenomenon is used in that case to reject the traffic in the nonadjacent lane, which creates large enough signals to affect the sensors. In a right-turn detection system, generally, the traffic going straight in lanes 1 and 2 will pass at a larger lateral distance from the sensors than a vehicle that makes a right turn. Hence, for magnetic sensors 2 and 3, we expect that the ratio $r = Bmax-2/Bmax-3$ is closer to 1 during scenarios 1 and 3 compared to scenario 2, as shown in Fig. 10.

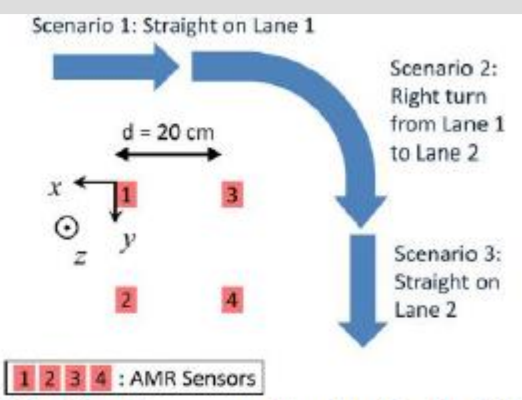


Fig.10. Magnetic-sensor configuration for the right-turn detection system.

B. Method B

Using all the information from all the four magnetic sensors, the following is expected when integrating the signals of each detected vehicle: Scenario1: $Bint -1 \cong Bint -3 > Bint -2 \cong Bint -4$ (1) Scenario 2: $Bint -3 > Bint -1 \cong Bint -4 > Bint -2$ (2) Scenario 3: $Bint -3 \cong Bint -4 > Bint -1 \cong Bint -2$ (3) Now, consider four points in a 3-D space located at (0, 0, *intB*1), (0, *d*, *intB*2), (−*d*, 0, *intB*3), and (−*d*, *d*, *intB*4), where *x* and *y* of each point show the position of a magnetic sensor with respect to the origin (sensor 1), and *z* shows the value of *Bint−i* for each sensor. Next, we fit a plane with a normal vector *n* to these four points and define *n p* as the projection of *n* into the *xy* plane and *γ* as the angle between *n p* and the *x*-axis. It is expected that, for scenarios 1, 2, and 3, the angle *γ* will be close to 90◦, 45◦, and 0◦, respectively. The angle *γ* is calculated as follows. The equation of a plane is *n* · *p* − *p*0 = 0 (4) Where, *p*0 is the position of a known point on the plane, *n* is a nonzero vector normal to the plane, and *p* is a point on the plane. Expanding this equation, we get

$$n_x(x-x_0)+n_y(y-y_0)+n_z(z-z_0)=0 \rightarrow ax+by+c=z$$

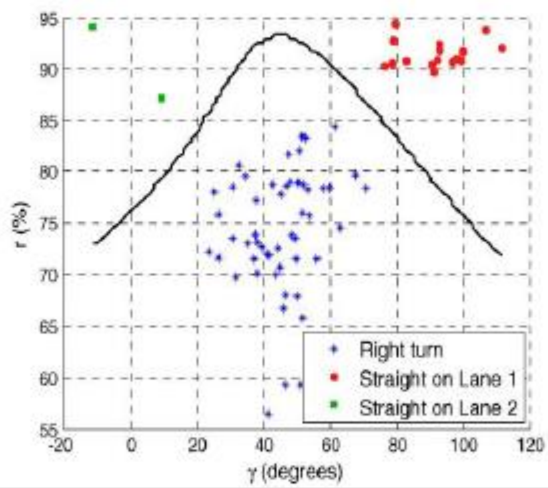


Fig.11. Results of applying the support vector machine algorithm to obtain classification boundaries.

Hence

$$\gamma = atan\left(\frac{n_y}{n_x}\right) = atan\left(\frac{b}{a}\right) \qquad (7)$$

Therefore, we should obtain a, b, and c, which can be done using a least squares method, i.e,

$$y = H_x + v \rightarrow \hat{x} = (H^T H)^{-1} H^T y \qquad (8)$$

where

$$x = \begin{bmatrix} a \\ b \\ c \end{bmatrix} \; H = \begin{bmatrix} 0 & 0 & 1 \\ 0 & d & 1 \\ -d & 0 & 1 \\ -d & d & 1 \end{bmatrix} \; y = \begin{bmatrix} B_{int-1} \\ B_{int-2} \\ B_{int-3} \\ B_{int-4} \end{bmatrix} \qquad (9)$$

and v is the measurement noise.

C. Experimental Results

Methods A and B were applied to the data set obtained from the experiments. The data set was obtained by placing the sensors (with the configuration shown in Fig. 10) at two different intersections and recording signals from passing vehicles. The experiments were performed during noon hours under clear-sky conditions. Fig. 11 shows the results. As shown in Fig. 11, both methods can be used separately or in combination to reject the straight-driving vehicles, which have created a large-enough signal to be incorrectly detected as a vehicle that makes a right turn. A support vector machine is used to obtain the classification boundaries in Fig. 11. If only one of the methods is used, the separation between the classes will be smaller, and the measurements will be less separated.

These results show that straight-driving vehicles that have created a large-enough signal to be detected by the sensors can completely be excluded, reducing the 31% misdetection error to 0%.

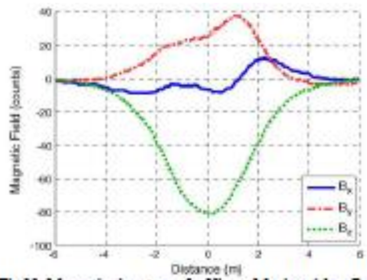


Fig.12. Magnetic signature of a Nissan Maxima (class I) that passes at 1.6 m from the sensors.

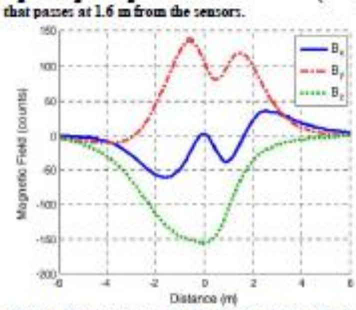


Fig.13. Magnetic signature of a Toyota Highlander SUV (class II) that passes at 1.4 m from the sensors.

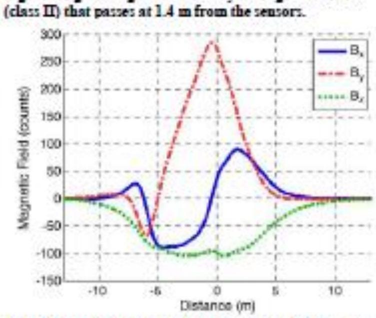


Fig.14. Magnetic signature of a cement truck (class III) that passes at 1.5 m from the sensors.

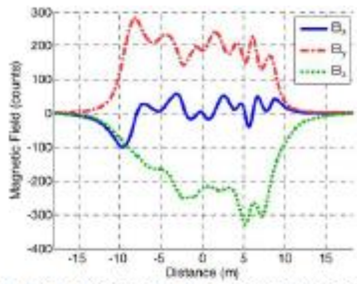


Fig.15. Magnetic signature of an articulated bus (class IV) that passes at 1.2 m from the sensors.

V. CONCLUSION

In the project, we have presented a computer vision system which uses a video to count and classify vehicles with the aim of replacing ILDs, particularly on highways. Additionally, this system distinguishes itself from other computer-vision-based approaches in the way in which it can handle the system without the need for any hardware other than cameras, such as GPS. This makes the system inexpensive to use. In this, we have presented two different parameters for the traffic surveillance system, one is counting the vehicles and other is classification of the vehicles. The processing is carried out on pre recorded video. Vehicle counting is done by finding the centroid and the distance between the marked border and the vehicle. Classification is done by finding the area and thresholding method. New traffic sensing devices based on wireless sensing technologies were designed and tested. Such devices encompass a cost-effective, battery-free, and energy self-sustained architecture for real-time traffic measurement over distributed points in a transportation system. This scalable technology can monitor traffic parameters such as flow, occupancy, point speed, and vehicle classification on road systems in real-time.
The data collector device is also equipped with a memory card reader, which makes it suitable for temporary installation and short-term data collection. A weather-resistant enclosure was designed and manufactured to protect the sensor from vehicle impacts on the highway. In addition to traditional traffic parameters, the sensors can measure and report the temperature of their surroundings because they are surface-mounted. The sensors developed as a result of this project are also capable of capturing a digital magnetic signature of vehicles within any intervals required by clients. The digital magnetic signature was processed to calculate traffic volume, vehicle speed, and vehicle length estimation for classification. Finally, it is shown that the sensing system can be used to reliably count the number of right turns at an intersection, with an accuracy of 95%. The challenge in counting the number of right turns is the false calls created by larger straight-driving vehicles, which, if uncorrected, cause 31% over detection. Two methods are proposed based on using two and four magnetic sensors, which totally eliminate this error.

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