

Vehicle Classification Using Neural Networks with a Single Magnetic Detector

Peter Šarčević

Abstract In this work, principles of operation, advantages and disadvantages are presented for different detector technologies. An idea of a new detection and classification method for a single magnetic sensor based system is also discussed. It is important that the detection algorithm and the neural network classifier needs to be easily implementable in a microcontroller based system.

Keywords Neural networks · Vehicle detection · Magnetic sensors · Vehicle classification · Vehicle detection technologies

1 Introduction

New vehicle detection technologies are constantly being developed and existing technologies improved, to provide speed monitoring, traffic counting, presence detection, headway measurement, vehicle classification, and weigh-in-motion data.

Vehicle count and classification data are important inputs for traffic operation, pavement design, and transportation planning. In traffic control, signal priority can be given to vehicles classified as bus or an emergency vehicle.

In this work, principles of operation, advantages and disadvantages are presented for different detector technologies. An idea of a new detection and classification method for a single magnetic sensor based system is also discussed. It is important that the detection algorithm and the neural network classifier needs to be easily implementable in a microcontroller based system.

P. Šarčević (✉)

Széchenyi István University, Egyetem tér 1., 9026 Győr, Hungary
e-mail: peter.sarcevic@gmail.com

2 Vehicle Detection Technologies

The need for automatic traffic monitoring is increasing, which urges the manufacturers and researchers to develop new technologies and improve the existing ones. Today a big number of detector technologies and methods are available.

Three categories of detector technologies exist: intrusive (in-roadway), non-intrusive (above or on the sides of roads) and off-roadway technologies [13, 14].

2.1 Intrusive Detector Technologies

These devices are installed directly on the pavement surface, in saw-cuts or holes in the road surface, by tunneling under the surface, or by anchoring directly to the pavement surface as is the case with pneumatic road tubes.

Intrusive detector technologies include inductive loops, magnetic detectors, pneumatic road tubes, piezoelectric detectors, and other weigh-in-motion (WIM) detectors.

Advantages and disadvantages for intrusive technologies are shown in Table 1.

Inductive Loop. When a vehicle stops on or passes over the loop, the inductance of the loop is decreased. The decreased inductance increases the oscillation frequency and causes the electronics unit to send a pulse to the controller, indicating the presence or passage of a vehicle. The data supplied by conventional inductive loop detectors are vehicle passage, presence, count, and occupancy. Although loops cannot directly measure speed, speed can be determined using a two-loop speed trap or a single loop detector and an algorithm.

Magnetic Detector. Magnetic sensors are passive devices that indicate the presence of a metallic object by detecting the perturbation (known as a magnetic anomaly) in the Earth's magnetic field created by the object.

Pneumatic Road Tube. Pneumatic road tubes sense vehicle pressure and send a burst of air pressure along a rubber tube when a vehicle's tires pass over them. The pulse of air pressure closes an air switch and sends an electrical signal that marks the passage of a vehicle. Pneumatic road tubes can detect volume, speed, and classification by axle count and spacing.

Piezoelectric. Piezoelectric is a specially processed material capable of converting kinetic energy to electrical energy. When a vehicle passes over a detector, the piezoelectric material generates a voltage proportionate to the force or weight of the vehicle. The material only generates a voltage when the forces are changing.

Piezoelectric detectors can detect traffic volume, vehicle classification, speed, and vehicle weight. They classify vehicles by axle count and spacing. A multiple-sensor configuration is required to measure vehicle speeds.

Weigh-in-Motion (WIM). WIM is a sensor system imbedded in a roadway to measure vehicle force on the pavement when vehicle axles pass over the sensors. WIM

Table 1 Advantages and disadvantages for intrusive technologies

Technology	Advantages	Disadvantages
Inductive loop	<ul style="list-style-type: none"> ● Provides basic traffic parameters (volume, presence, occupancy, speed, headway, and gap) ● High frequency excitation models provide classification data 	<ul style="list-style-type: none"> ● Installation requires pavement cut ● Decreases pavement life ● Installation and maintenance require lane closure ● Wire loops subject to stresses of traffic and temperature
Magnetic detector	<ul style="list-style-type: none"> ● Insensitive to inclement weather such as snow, rain, and fog ● Less susceptible than loops to stresses of traffic ● Some models transmit data over wireless RF link ● Some models can be installed above roads, no need for pavement cuts 	<ul style="list-style-type: none"> ● Difficult to detect stopped vehicles ● Installation requires pavement cut or tunneling under roadway ● Decreases pavement life ● Installation and maintenance require lane closure
Pneumatic road tube	<ul style="list-style-type: none"> ● Quick installation ● Low power usage ● Low cost and simple to maintain 	<ul style="list-style-type: none"> ● Inaccurate axle counting ● Temperature sensitivity of the air switch ● Not suitable for permanent counting system
Piezoelectric	<ul style="list-style-type: none"> ● High accuracy in classification because the output signals are proportional to the tire pressure 	<ul style="list-style-type: none"> ● Disruption to traffic during installation and repair ● Sensitive to pavement temperature and vehicle speed

systems measure the weight proportions carried by each wheel assembly (half-axle with one or more tires), axle, and axle group on the vehicle. The primary WIM technologies are bending plate, piezoelectric, load cell, capacitance mat and fiber optic. They provide traffic data such as traffic volume, speed, and vehicle classification based on the number of and spacing of axles.

2.2 Non-intrusive Detector Technologies

Above ground sensors can be mounted above the lane of traffic they are monitoring or on the side of a roadway where they can view multiple lanes.

Non-intrusive detector technologies include active and passive infrared, microwave radar, ultrasonic, passive acoustic, and video image processing. Active in-

Table 2 Advantages and disadvantages for non-intrusive technologies

Technology	Advantages	Disadvantages
Active and passive infrared	<ul style="list-style-type: none"> • Active sensor transmits multiple beams for accurate measurement of vehicle position, speed, and class • Multizone passive sensors measure speed • Multiple lane operation available 	<ul style="list-style-type: none"> • Operation of active sensor may be affected by fog or blowing snow • Passive sensor may have reduced sensitivity to vehicles in its field of view in rain and fog
Microwave radar	<ul style="list-style-type: none"> • Generally insensitive to inclement weather • Direct measurement of speed • Multiple lane operation available 	<ul style="list-style-type: none"> • Antenna beamwidth and transmitted waveform must be suitable for the application • Doppler sensors cannot detect stopped vehicles
Ultrasonic and passive acoustic	<ul style="list-style-type: none"> • Multiple lane operation available 	<ul style="list-style-type: none"> • Some environmental conditions such as temperature change and extreme air turbulence can affect performance • Large pulse repetition periods may degrade occupancy measurement on freeways with vehicles traveling at moderate to high speeds
Video image processing	<ul style="list-style-type: none"> • Monitors multiple lanes • Rich array of data available • Provides wide-area detection • Easy to add or modify detection zones 	<ul style="list-style-type: none"> • Performance affected by many factors including fog, rain, snow, vehicle shadows, day to night transition • High installation and maintenance cost

frared, microwave radar, and ultrasonic are active detectors that transmit wave energy toward a target and measure the reflected wave. Passive infrared, passive acoustic, and video image processing are passive detectors that measure the energy emitted by a target or the image of the detection zone.

Table 2 shows the advantages and disadvantages of non-intrusive detectors.

Active and Passive Infrared. The detectors convert received energy into electrical signals that determine the presence of a vehicle by real time signal processing. There are active and passive infrared detector models. An active infrared detector emits invisible infrared low-energy by light-emitting diodes or high-energy by laser diodes to the detector zone and measures the time for reflected energy to return to the detector. A lower return time denotes the presence of a vehicle. The detectors measure vehicle speed by transmitting two or more beams and recording the times at which the vehicle enters the detection zone of each beam.

Any object that is not at absolute zero emits thermal radiation in the far infrared part of the electromagnetic spectrum. The amount of radiation depends on the object's surface temperature, size, and structure. Passive infrared detectors respond to thermal radiation changes in proportion to the product of emissivity difference (the difference between the emissivities of road surface and the vehicle) and temperature difference (the difference between the temperature of the road surface and the environment).

Two types of detectors exist: non-imaging and imaging. Non-imaging detectors use one or several energy-sensitive elements to collect infrared energy and cannot divide objects into pixels within the detection zone. Imaging detectors use two-dimensional arrays of energy-sensitive elements and can display pixel-resolution details.

Active infrared sensors can detect volume, presence, classification (length), and speed. Passive infrared sensors can detect volume, presence, occupancy and speed within multiple detection zones.

Microwave Radar. There are two types of microwave detectors: Doppler Microwave Detectors and Frequency-modulated Continuous Wave (FMCW) Detectors.

Doppler microwave detectors transmit low-energy microwave radiation at the detection zone. The Doppler effect is a frequency shift that results from relative motion between a frequency source and a listener. If both source and listener are not moving, no Doppler shift will take place. If the source and the listener are moving closer to each other, the listener will perceive a higher frequency. If the source and listener are moving farther apart, the listener will perceive a lower frequency. For traffic detection, motion of a vehicle causes a frequency shift in the reflected signal. Microwave detectors measure this shift to determine vehicle passage and speed.

FMCW detectors, sometimes referred to as true-presence microwave detectors, transmit continuous frequency-modulated waves at the detection zone. Frequency varies over time. Detectors measure the range from the detector to the vehicle to determine vehicle presence. To obtain speed, the distance between two range bins is divided by the time that the detected vehicle travels that distance.

Doppler microwave detects volume, occupancy, classification and speed. However it only recognizes vehicles above a minimum speed. True presence detectors can detect vehicle presence, volume, occupancy, classification, and speed.

Ultrasonic and Passive Acoustic. Ultrasonic detectors can detect volume, presence, classification and speed. They are active acoustic sensors and can transmit sound waves toward the detection zones. The detectors sense acoustic waves reflected by objects in the detection zones. Pulsed ultrasonic detectors and continuous wave

ultrasonic detectors are based on the different data-measurement methods. Pulsed ultrasonic detectors transmit a series of ultrasonic pulses. The detector measures the wave's travel time between the detection zone and the detector. The detectors differentiate between waves reflected from the road surface and waves reflected from the vehicles to determine vehicle presence. A continuous ultrasonic detector transmits a continuous wave of ultrasonic energy. The detector analyzes the acoustic sound reflected back from the detection zone based on the Doppler principle.

Passive acoustic detectors can detect volume, speed, occupancy, and classification. They measure the acoustic energy or audible sounds produced by a variety of sources within a passing vehicle. Sound energy increases when a vehicle enters the detection zone and decreases when it leaves. A detection threshold determines the termination of the vehicle presence signal.

Video Image Processing (VIP). VIP systems measure changes between successive video image frames. Passing vehicles cause variations in the gray levels of the black-and-white pixel groups. VIP systems analyze these variations to determine vehicle passage. Variations due to non-vehicle factors, such as weather and shadows, are excluded.

VIP systems detect a variety of traffic data. They classify vehicles by length and measure volume, presence, occupancy, and speed for each vehicle class. Other data include density, travel time, queue length, headway, and turning movements.

2.3 Off-Roadway Technologies

Off-Roadway Technologies refer to those that do not need any hardware to be setup under the pavement or on the roadside. It includes probe vehicle technologies with Global Positioning System (GPS) and mobile phones, Automatic Vehicle Identification (AVI), and remote sensing technologies that make use of images from aircraft or satellite.

Probe Vehicles with Global Positioning System (GPS). For traffic surveillance, probe vehicles equipped with GPS receivers are driven through the traffic sections of interest. Their position and speed information determined from the GPS is transmitted back to the Traffic Management Center (TMC) for travel time and section speed analysis. Drawbacks include lack of point traffic statistics at a fix location, and the fact that system coverage is limited by the number of probe vehicles.

Probe Vehicles with Mobile Phones. The localization technique is similar to that of a GPS system, with the satellites replaced by phone antenna base stations, and GPS receivers replaced by mobile phones. Because of the high penetration rate of mobile phones, at least one mobile phone can be found in a traveling vehicle.

Remote Sensing. Remote sensing refers to the technologies that collect traffic information without direct communication or physical contact with the vehicles or roads. Basically, high-resolution imagery from aircraft or satellite is used to extract traffic information like traffic count and speed.

3 Magnetic Sensor System

The used magnetic detector system is a HMC5843 based unit developed by “SELMA” Ltd. and “SELMA Electronic Corp” Ltd., companies from Subotica, Serbia. Two types of magnetic detectors have been developed, one with cable and one with wireless communication.

Wireless magnetic sensor networks offer an attractive, low-cost alternative to inductive loops, video and radar for traffic surveillance on freeways, at intersections and in parking lots.

Vehicles are detected by measuring the change in the Earth’s magnetic field caused by the presence of a vehicle near the sensor. Two sensor nodes placed a few feet apart can estimate speed [6]. A vehicle’s magnetic ‘signature’ can be processed for classification.

3.1 HMC5843

The Honeywell HMC5843 [10] is a small ($4 \times 4 \times 1.3$ mm) surface mount multi-chip module designed for low field magnetic sensing. The 3-Axis Magnetoresistive Sensors feature precision in-axis sensitivity and linearity, solid-state construction with very low cross-axis sensitivity designed to measure both direction and magnitude of Earth’s magnetic fields, from tens of micro-gauss to 6 gauss. The highest sampling frequency is 50Hz.

3.2 Detection Algorithm

Magnetic detectors are capable of very high, above 97% [5, 11] detection accuracy with proper algorithms. Most of the algorithms use adaptive thresholds [5, 19].

It is known that HMC magnetic sensor measurements are affected by temperature. As the temperature on the pavement can change a lot in the course of a day, but the changes in the measured values are very slow [5], the detection algorithm has to change threshold values when no detection is available.

Currently an own algorithm using thresholds is being tested. It seems to be very accurate, but no exact detection rates are yet available. The main detection failures are caused by motorcycles with low metallic content.

The principles of the algorithm:

- During calibration the maximum and minimum values are determined in a period of time at all three axis (if even at one axis the difference between the maximum and minimum exceeds a previously defined value, the calibration starts from the beginning). After this stage, the range is equally stretched to a previously defined width, and the upper and lower thresholds are now determined at all three axis. This method makes the further algorithm immune to noise.

- If two or more axis have exceeded the range determined by the thresholds, a detection is generated (detection flag is “1”).
- In case of a detection, if measures in all three axis are between thresholds for the time of ten measurements, the detection flag goes back to “0”.
- If all three axis are in the range determined by the thresholds, and no detection is available, the algorithm calculates new thresholds.

The axis along the direction of travel can be used to determine the direction of the vehicle [2]. 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.

3.3 Vehicle Classification

Vehicle classification with other technologies. As with vehicle detection, a number of technologies were developed for classification. Vision-based, inductive loop, microwave, piezo-electric and acoustic-based classification technologies are the common ones in use nowadays.

The major limitation of vision-based classification is that the system’s performance is greatly affected by the environmental and lighting conditions. In a simple single camera system, a vehicle may be categorized according to its length and height according to its two dimensional image. In [7], such a system is described, and the results show a classification rate of 70 % for classifying the vehicles into two classes (passenger and non-passenger).

In [17] also pixel-based vehicle length is used for classification but with uncalibrated video cameras. The classification rate was above 97 %, but vehicles were classified only into two classes (cars and trucks).

A new approach is presented to vehicle-class recognition from a video clip in [8]. The concept is based on probes consisting of local 3D curve-groups for recognizing vehicle classes in video clips, and Bayesian recognition based on class probability densities for groups of 3D distances between pairs of 3D probes. They achieved 88 % correct classification with only three vehicle classes.

Vehicle classification rate of over 92 % was obtained with a rule based classifier using range sensors in [9] (14 vehicle classes).

An algorithm, which performs line by line processing of laser intensity images, produced by laser sensory units, and extracts vehicle features used for the classification into five classes achieved 89 % efficiency [1]. The features include vehicle length, width, height, speed, and some distinguishable patterns in the vehicle profile.

Classification stations with highly calibrated inductive loops are also in use. However, the infrastructure and maintenance costs of such a vehicle classification station are high.

Reference [18] developed an artificial neural network method to estimate classified vehicle volumes directly from single-loop measurements. They used a simple three-layer neural network with back-propagation structure, which produced reliable

estimates of classified vehicle volumes under various traffic conditions. In this study four classes (by ranges of length) were defined, and all classes had an own ANN. All networks had 19 nodes in the input layer, 1 node for the time stamp input and 9 pairs of nodes for inputting single-loop measurements (volume and lane occupancy). All networks had one output node (each was one class bin), but the number of hidden neurons differed for each class (35 for class1, 8 for class2, 5 for class3 and 21 for class4).

In [15], Sun studied the use of existing infrastructure of loop detectors for vehicle classification with two distinct methods. The seven-class scheme was used for the first method because it targets vehicle classes that are not differentiable with current techniques based on axle counting. Its first method uses a heuristic discriminant algorithm for classification and multi-objective optimization for training the heuristic algorithm. Feature vectors obtained by processing inductive signatures are used as inputs into the classification algorithm. Three different heuristic algorithms were developed and an overall classification rate of 90 % was achieved. Its second method uses Self-Organizing Feature Maps (SOFM) with the inductive signature as input. An overall classification rate of 80 % was achieved with the four-class scheme.

Vehicle classification with magnetic detectors. In the last few years a big number of studies have been made with classification algorithms using magnetic detectors.

In [4] the rate of change of consecutive samples is compared with a threshold and declared to be +1 (−1) if it is positive and larger than (negative with magnitude larger than) the threshold, or 0 if the magnitude of the rate is smaller than the threshold. The second piece of information was the magnetic length of the vehicle. 82 % efficiency was achieved, with vehicles classified into five classes. Ref. [3] achieved a vehicle detection rate better than 99 % (100 % for vehicles other than motorcycles), estimates of average vehicle length and speed better than 90 %, and correct classification into six types with around 60 largest value of the samples and the also as in [4], rate of change of consecutive samples.

In [12], with x and z dimension data and without vehicle length information, a single magnetic sensor system, with a Multi-Layer Perceptron Neural Network, 93.5 % classification efficiency was achieved, but vehicles were only separated into two classes. In a double sensor system 10 classes were selected for development, and 73.6 % was achieved with length estimation and a methodology using K-means Clustering and Discriminant Analysis.

Classification algorithm. The basic idea is to gather data during and after the detection, and calculate the inputs of the neural network.

A three-layer back-propagation neural network (Fig. 1) will be used and implemented into a microcontroller. The neurons in the hidden layer will have logarithmic sigmoid transfer functions, while the output neurons will have saturating linear transfer functions.

Previously collected data should be used for network training. During the training process equal number of training and validation samples will be used for each class. Weight updating will be done after every sample. Mean squared errors and recognition rates will also be calculated. Weights will be saved during training when highest recognition rates on training samples, highest recognition rates on validation sam-

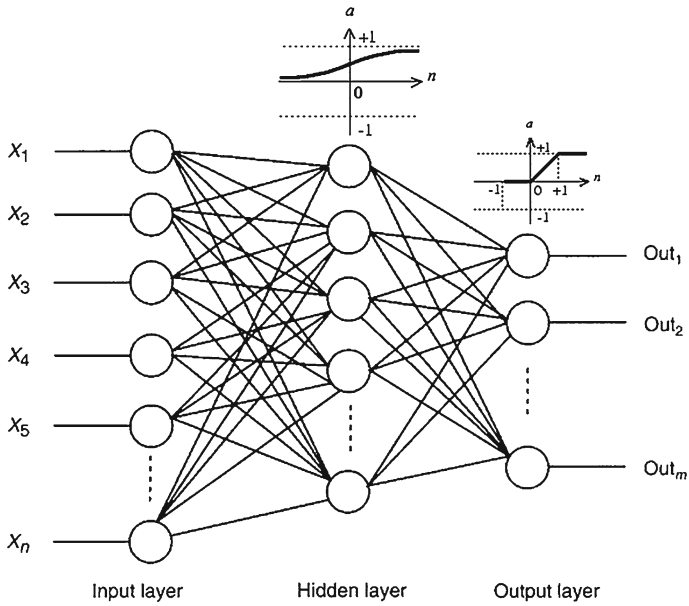


Fig. 1 Three-layer back-propagation neural network

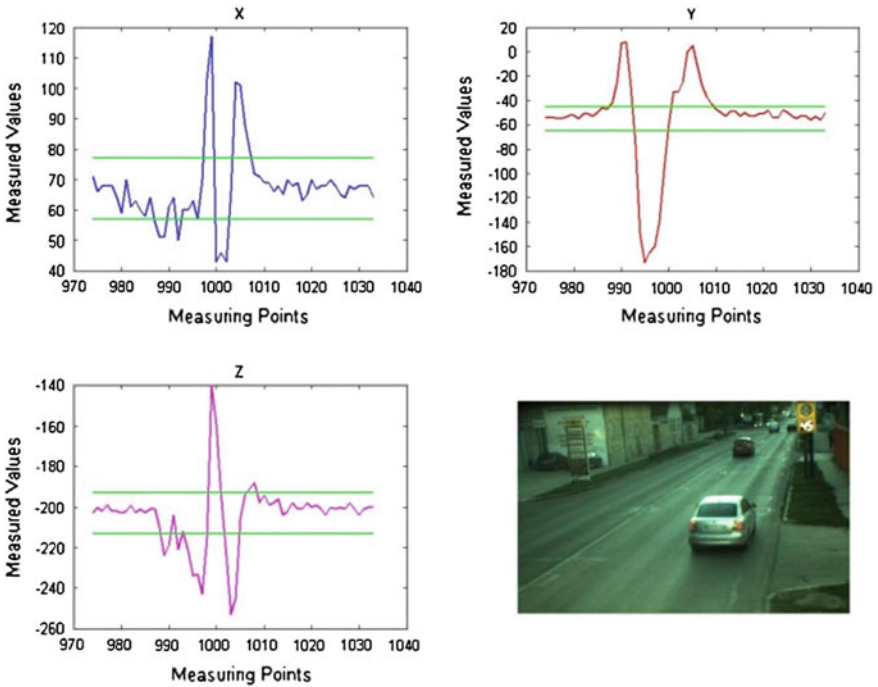


Fig. 2 Measurements of X, Y and Z axis, and a picture of the passing car

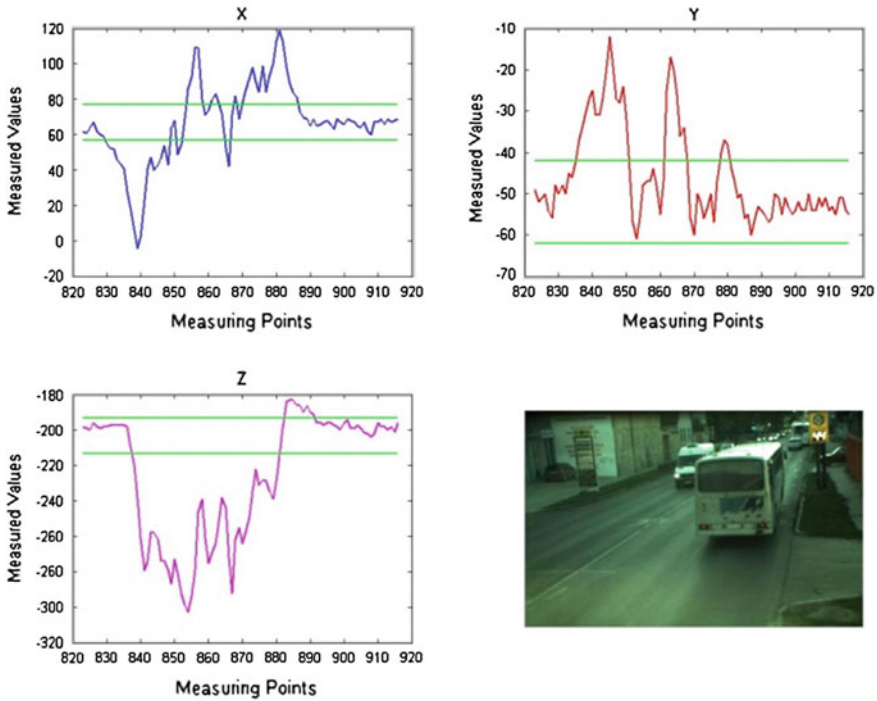


Fig. 3 Measurements of X, Y and Z axis, and a picture of the passing bus

ples, smallest mean squared errors on training samples and smallest mean squared errors on validation samples are found. The saved weights will be later tested on test samples.

Every vehicle class will have an assigned neuron in the output layer. The class with the biggest output will be declared as the class of the passed vehicle.

Possible input data:

- The biggest differences between measured values and thresholds (the difference between the highest measured value and the upper threshold, and the difference between the lower threshold and the smallest measured value) at all three axis should be applied to network.
- Detection length—the number of samples made during detection.
- Number of local maximums (if the measured values are above the upper threshold), and local minimums (if the values are under the lower threshold). These numbers could lead to the determination of axle numbers.

Figure 2 shows the measurement values of all three axis made during a car passing over the detector.

Measurement changes are shown in Fig. 3 during a bus passing over the detector.

The placement of the detector will be also important. The axis have to point always in the same direction as they pointed during the collection of training data.

4 Future Work

In the future data collection will be finished and used for neural network training. Two types of networks will be made, one for 5 and one for 9 vehicle classes. The training will be done with different number of neurons in the hidden layer, and with various input data (combinations of the previously discussed possible inputs will be tested, to find which are useful).

The measurements will be also processed via fuzzy grids [16], and tested for the same type of classifications, to compare efficiency of the neural network and fuzzy grid classification method.

Acknowledgments I would like to thank companies “SELMA” Ltd. and “SELMA Electronic Corp” Ltd. for the technical resources and support during my work.

References

1. Abdelbaki, H.M., Hussain, K., Gelenbe, E.: A laser intensity image based automatic vehicle classification system. In: Intelligent Transportation System Conference Proceedings, Oakland (2001)
2. Caruso M.J., Withanawasam L.S.: Vehicle Detection and Compass Applications using AMR Magnetic Sensors. Honeywell Inc, New York (2007)
3. Cheung S.-Y., Coleri S., Dundar B., Ganesh S., Tan C.-W., Varayra P.: Traffic measurement and vehicle classification with a single magnetic sensor. In: 84th Annual meeting of the Transportation Research Board, pp. 173–181 (2005)
4. Cheung S.-Y., Coleri S.E., Varayra P.: Traffic surveillance by wireless magnetic sensors. In: ITS World Congress, San Francisco, California (2005)
5. Cheung S.-Y., Varayra P.: Traffic Surveillance by wireless sensor networks: final report, California PATH Research Report (2004). UCB-ITS-PRR-2007-4
6. Deng X., Hu Z., Zhang P., Guo J.: Vehicle Class Composition Identification Based Mean Speed Estimation Algorithm using Single Magnetic Sensor. Beijing Transportation Research Center, China (2009)
7. Gupte, S., Masoud, O., Martin, R.F.K., Papanikolopoulos, N.P.: Detection and classification of vehicles. *IEEE Trans. Intel.l Transp. Syst.* **3**(1), 37–47 (2002)
8. Han D., Leotta M.J., Cooper D.B., Mundy J.L.: Vehicle class recognition from video based on 3D curve probes. In: Proceedings of IEEE International Workshop on Visual Surveillance and Performance Evaluation of Tracking and Surveillance, (2005). pp. 871–878
9. Harlow, C., Peng, S.: Automatic vehicle classification systems with range sensors. *Transp. Res. Part C* **9**, 231–247 (2001)
10. HMC5843 datasheet
11. Isaksson, M.: Vehicle detection using anisotropic magnetoresistors. Thesis for the degree of Master In Engineering Physics, Chalmers University Of Technology (2007)
12. Liu H., Jeng S.-T., Tok J.C.A., Ritchie S.G.: Commercial Vehicle Classification using Vehicle Signature Data. In: 88th Annual meeting of the Transportation Research Board (2009)

13. Martin P.T., Feng U., and Wang X.: Detector Technology Evaluation, Mountain-Plains Consortium, Report No. 03–154 (2003)
14. Mimbala L.E.Y., Klein L.A.: A Summary of Vehicle Detection and Surveillance Technologies Used In Intelligent Transportation Systems. The Vehicle Detector Clearinghouse, Washington (2000)
15. Sun, C.: An Investigation in the Use of Inductive Loop Signature for Vehicle Classification. California PATH Research Report, California (2000)
16. Tormási A., Kóczy T.L.: Comparing the efficiency of a fuzzy single-stroke character recognizer with various parameter values. *IPMU* **1**, 260–269 (2012)
17. Zhang G., Avery R.P., Wang Y.: A video-based vehicle detection and classification system for real-time traffic data collection using uncalibrated video cameras. Annual meeting of the Transportation Research Board, Washington (2007)
18. Zhang G., Wang Y., Wei H.: An artificial neural network method for length-based vehicle classification using single-loop outputs. *J. Transp. Res. Board* **1945**, 100–108 (2007)
19. Zhang, W., Tan, G.-Z., Shi, H.-M., Lin, M.-W.: A distributed threshold algorithm for vehicle classification based on binary proximity sensors and intelligent neuron classifier. *J. Inf. Sci. Eng.* **26**, 769–783 (2010)