A Field Experience for a Vehicle Recognition System using Magnetic Sensors

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Abstract—**This paper describes the development and testing of a vehicle recognition prototype based on magnetic sensors. The aim of this research is to design a low cost, low power consumption and simple hardware platform for vehicle recognition. The goal is to recognize four types of vehicles (car, bus, mini-bus or camper) as they run over a set of magnetic sensors. We describe all steps for correct vehicle presence detection, pattern pre-processing, speed and length detection using a combination of an empirical and an analytical method for signal alignment. We collected a set of data regarding this types of vehicles and explain how to differentiate them. Our classification tests reach a confidence factor greater than 91%.**

Keywords-component; classification; vehicle recognition; magnetic sensors; cyber-physical systems; traffic monitoring.

I. INTRODUCTION

Cities are getting bigger, roads increase their number and sizes and an increasing number of vehicles uses them daily. It is getting more and more important to know how they move, which fluxes they generate and their size, and also which types of vehicle compose these fluxes. Many methods are used to perform this task like cameras and image processing [9][10]. This work is focused on getting complementary traffic information from other types of sensors. In particular, we develop a vehicle monitoring and recognition system based on magnetic sensors, trying to achieve a contained hardware complexity. The rest of the paper describes the state of art of vehicle recognitions in section 2, the adopted hardware platform in sections 3, 4 and 5, all the implemented methods and mechanisms made to provide enoughaccuracy level finalized to vehicle recognition based on magnetic sensor (sections 7 and 8).

The main contributions of this paper are:

- Numerical field data for a traffic monitoring cyber-physical system,
- methodology for vehicle recognition based on magnetic sensors.

II. DETECTION AND CLASSIFICATION OF VEHICLES

A. State of the art

To perform vehicle detection different methods are used, depending on the requirements and the area where they are deployed. Most common technologies include: magnetic coils, pneumatic tubes, piezoelectric sensors, microwave radars, infrared sensors, video recognition, magnetic sensors [1]. Not all of them offer the same amount of information: magnetic sensor based detection is one of the technologies that allow us to gather information in a simple and accurate way [8]. The choice of magnetic sensors for this work was influenced by two other factors: low costs for installation and limited sensitivity to various types of noise (Table 1). In addition to detecting the passing of vehicles, we want to figure out which category they belong to, such as cars, camping van, buses and mini-buses.

B. Vehicle Recognition using magnetic sensors

Earth's magnetic field provides ways to build magnetic sensors that does not require magnetic materials on the vehicles. When magnetic flux lines condense or became widen because a vehicle is perturbing them, a magnetic sensor placed in proximity of vehicle is under the same magnetic perturbation created by the vehicle itself (Figure 1). Earth's magnetic field has a constant magnetic background for a fixed installation. Its intensity is about 0.5 G for a single axis and a 0.7 G variation from natural magnetic range [2][3]

TABLE I. VEHICLE RECOGNITION SYSTEM CAPABILITIES COMPARISON

Technology	Data Type				
	Count	Speed	Classification	Occupancy	Presence
Intrusive					
Inductive Loop	Y	Y	Y	Y	Y
pneumatic road tube	Y	Y	Y	N	N
piezoelectric cable	Y	Y	Y	N	N
Non-Intrusive					
WIM system	Y	Y	Y	N	N
Microwave Radar					
CW Doppler	Y	Y	Y	Y	N
FMCW	Y	Y	Y	Y	Y
Infrared					
Active	Y	Y	Y	N	N
Passive	Y	Y	Y	Y	Y
Video Image Processing	Y	Y	Y	Y	Y
Ultrasonic	Y	N	N	N	Y
Passive Acoustic	Y	Y	Y	Y	Y
Wireless Sensor Network					
Magnetometer	Y	Y	Y	Y	Y

Y: available, N: not available

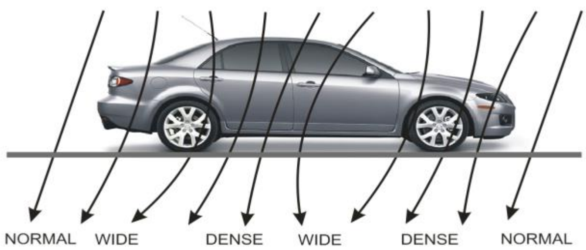

Figure 1:Earth magnetic field variations performed by a vehicle

III. PROJECT OVERVIEW

A. Project Phases

The project was divided into the following phases:

- Research in the literature about possible techniques for vehicles recognition.[6][7]
- Designing and assembling the sensor.
- Implementation of an analysis and post-processing software and data collection.
- Collection of samples in the field.
- Development of mechanisms for the correct vehicles segmentation, to ensure a proper construction of the input samples for the AI.
- Development of a MLP neural network suitable to recognize the four categories listed above.
- On-line and off-line testing phase

The last three steps were obviously not consecutive and clearly distinct. They were repeated and retraced several times, in order to find the right balance between the components involved.

B. Main components

The system consists of three main components:

- Sensors devices
- A Microcontroller and a CPU
- Recognizer algorithm (Java based)

IV. SENSORS DEVICE AND PLATFORM

A. Magnetic sensors hardware

We decided to use two Honeywell HMC 5843 (3-axis) magnetometer placed on a plastic support 1.2 m. (Figure 3) far one each other. We placed the two sensors with the same axis orientation.

Sensors orientation is very important. In theory, if a vehicle runs over two sensors with a constant speed and with direction parallel to the line passing through the two sensors, we expect to read the same output response on both sensors. This allows us to determine a time gap between the two signals and consequentially a distance.

B. Platform

To implement our prototypes we need the following features: a low power consumption platform, a CPU that runs a Java VM, a microcontroller interfacing with sensors and a wireless connection. We also want to reduce costs and simplify the hardware connections. As shown in Table 1 we choose the UDOO [12] as this reduces costs for our specification and its heterogeneous architecture also simplify the hardware implementation.

UDOO and Raspberry have similar price but we prefer UDOO for the higher performance CPU, for the flexibility and future upgrades[12].

The chosen microcontroller is an Arduino Due to simplify the interfacing with several magnetic sensors. Each sensor detects the following states:

- State 0: No vehicles over the sensors.
- State 1:The device hypothesize that a vehicle starts
- State 2: A vehicle is over the sensors.
- State 0-tail: A vehicle was over the sensors and now we suppose that is terminated. Therefore we are going on sending data to allow subsequent analysis on effective vehicle ending.

V. VEHICLE DETECTION SYSTEM

For some vehicles magnetic field signal tends to Earth's bias in random points of its length, with no speed dependency. It is an individual characteristic of each vehicle model. So it is not possible to avoid vehicle classification segmentation only using an amplitude threshold (Figure 2).

Now we will explain how the device makes a decision about the presence or absence of a vehicle on the sensors. The algorithm we developed uses the following sensitive points (Figure 4):

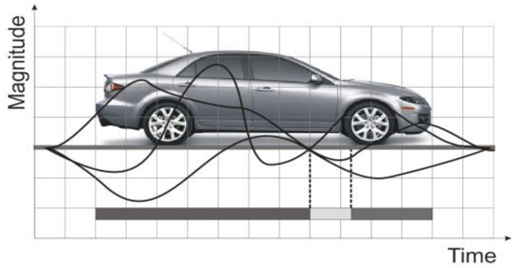

Figure 2: Vehicle with a convergent magnetic field in the middle of his lenght

A. up/down threshold: amplitude threshold is not a single value but we introduce an hysteresis cycle with two different up and down values.

B. under-threshold cycles: all 3 magnetic axis-components must be under this down threshold for n samples.

C. zero-crossing: magnetic axis-components must not change sign for m samples.

D. decreasing derivative: derivative of all magnetic axis-component modules must be negative for p samples.

E. tail: if all criteria are satisfied microcontroller goes on sending data for q samples. It allows to the recognizer to analyze data and determine if two sample set were wrongly subdivided.

VI. CLASSIFICATION METHODOLOGY

A. Data transmission and storage

Sensors data are transmitted on internal UART serial with a 115200 baud rate. All data are stored on database that includes: raw data, formatted data, pattern predictions, and other debug information used during development.

B. Preprocessing

Data is stored in a vector of "Magnetic Values", representative of the passing of a vehicle. The values contained in the vector cannot be used immediately as a feature for the neural network based recognizer. It is necessary to perform a pre-processing phase on the data, in order to make as homogeneous as possible the samples vector with each other.

Smoothing: A first step consists in smoothing pattern. To do this we scroll through all the vector of the samples, and for each step we apply a linear filter defined as follows:

$$S_t = 0.33\ V_{t-2} + 0.66\ V_{t-1} + V_t + 0.66\ V_{t+1} + 0.33\ V_{t+2}$$

Removing "dead zones": In our application context a vehicle may slow down or even stop. In a second step we try to remove those areas in which magnetic field values are stable within a certain threshold.

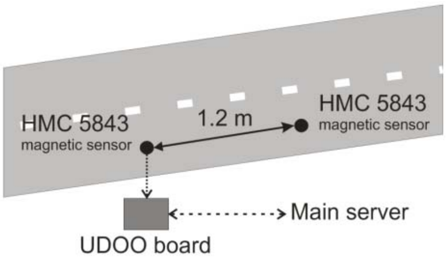

Figure 3: Hardware overview

C. Speed estimation

We can then proceed with one of the most delicate steps: estimating the speed of the vehicle. To do this it is necessary to find the distance in terms of time between the two sensors curves. Then we proceed to search for *significant points*, in order to make an attempt to alignment. First, we look for the maximum and minimum on all three axes.

Other notable points of the curve that we consider are the points of change of sign. In this case, however, we do not take all the changes of sign, but only those which occur very abruptly (a 100 mG gap).

Once we have the largest number of sensitive points on the two curves, we just have to look for alignment. For each point found in the curve of the first sensor, we look for the same point with the same type in the curve of the second sensor.

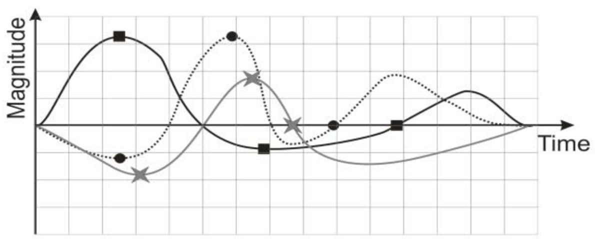

Figure 4: Vehicle sensitive points on 3-axis graph

The search is carried out within a certain window. Once this limit has been reached, if the maximum is not found, we consider that point as not alignable with the previous ones.

The problem with this method is that there is not any guarantee about the homogeneity of the points on which the alignment is attempted. So there is no certainty that the average velocity has been assessed during the entire passing of the vehicle (Figure 5).

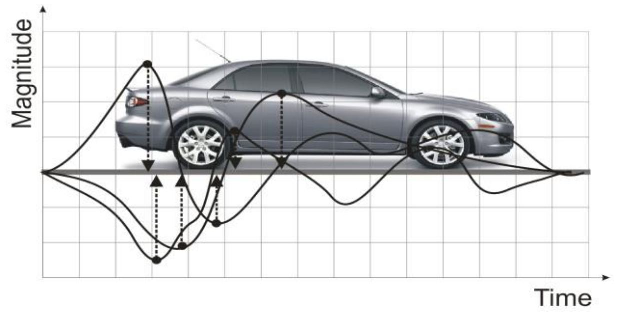

Figure 5: Uneven distribution of sensitive points in a vehicle

D. Dynamic Time Warping

The alignment method previously studied is definitely not analytical and deterministic, because it is mainly based on heuristics and empirical methods. So, we tried to identify and test a more analytical methodology, looking for any algorithm or more systematic methodology for the time sequences alignment. An interesting technique is represented by Dynamic Time Warping (DTW), originally developed in the context of speech recognition [4][5].

We have observed that in our case the estimate was not always consistent with the real case. The problem arises from the inherent nature of how our curves are constructed. First of all, in our case, the second curve will always be temporally shifted forward: the instants of beginning are never simultaneous, but the initial values of the second sensor will never have a correspondence with those of the first.

The second problem arises from the fact that ideally the DTW search for the alignment of a point of the first sensor at time T_i in the previous and successive instants. This implies that for some points of the second sensor the best alignment may happen with an apparently negative speed [6].

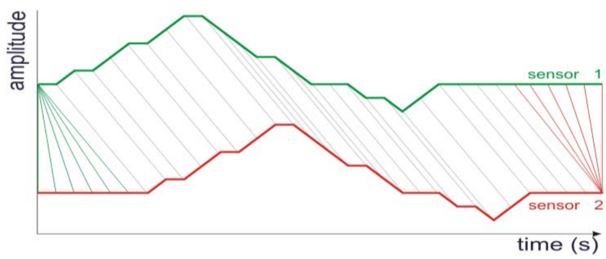

Figure 6: An ideal alignment of two magntic signals

After a series of tests we have observed that the use of the DTW does not provide significant improvements in the alignment of the curves. One possible development could be the customization of the algorithm DTW, by entering ad-hoc constraints to our case study.

E. Feature construction

Several combinations have been tested for the input features. As previously mentioned, the length of the vehicle is a feature that is easily detectable directly.

For other features we used the average values of the curves for each axis, in various portions of the curve.

For example, we can use the average value calculated on the Z axis in the first and in the second half of the curve. So an input feature can be described as follows:

$$F_1 = (Z^1_{AVG} ; Z^2_{AVG} ; length).$$

Similarly, we can use the average value of all axes:

$$F_2 = (X^1_{AVG}, X^2_{AVG}, Y^1_{AVG}, Y^2_{AVG}, Z^1_{AVG}, Z^2_{AVG}, length)$$

Otherwise we can divide each axis into a greater number of portions. Unfortunately, since there is no deterministic way to choose the most significant feature, it was necessary to repeat many configurations and multiple phases of training.

After that we choosed to use the average values of the Y and Z axes calculated of 5 portions of the curve, to which is added obviously the estimated length of the vehicle. Therefore:

$$F_3 = (Y^1_{t1}, Y^1_{t2}, Y^1_{t3}, Y^1_{t4}, Y^1_{t5}, Z^1_{t1}, Z^1_{t2}, Z^1_{t3}, Z^1_{t4}, Z^1_{t5}, length)$$

VII. Classification Test Results

Following our methodology, vehicle segmentation was reduced to about 2%. This allowed us to collect and use reliable correct data. It is possible to configure the system to perform predictions with different confidence ratio. Depending on user specifications it is possible to set different precision capabilities. Obviously a higher precision ratio involve more unpredicted vehicles.

In the last test performed on 332 samples were set two different confidence values.

A. Minimum confidence 30%

TABLE II. Confidence Matrix 30%

Output	*Car*	*Bus*	*Camper*	*Minibus*	
Car	88	0	0	1	99%
Bus	5	176	0	1	96,7%
Camper	6	1	9	5	43%
Minibus	3	3	3	31	77.5%
	86.3%	97.8%	75%	81.6%	91.6%

predicted: 332 unpredicted: 0 correct pred.:304 (91,6%) wrong pred.: 28 (8.4%)

B. Minimum confidence 50%

TABLE III. Confidence Matrix 50%

Output	*Car*	*Bus*	*Camper*	*Minibus*	
Car	87	0	0	0	100%
Bus	3	176	0	0	98.3%
Camper	2	0	6	0	75%
Minibus	2	2	3	23	82.1%
	92.6%	98.9%	85.7%	85.7%	96.7%

predicted: 302 unpredicted: 30 correct preds:292 (96.7%)wrong preds: 10 (3.3%)

C. Notes

Classification errors strongly decrease as we increase the minimum confidence percentage for assigning a pattern to a vehicle type. Accuracy increases up to 96,7%.

This is the configuration used for the Multi-Layer Perceptron (MLP) based machine learning classification:

- output layer neurons: 4 (output range 0 and 1)
- input layer neurons: 11
- hidden layer neurons: 4
- hidden layer's activation function: sigmoid

VIII. Conclusions

The prototype reaches good classification results greater than 90%. Better results can be reached with a large and more uniform dataset. The developed methodology allows us to use more complex and discriminant features. By adopting the Dynamic Time-Warping (DTW) algorithm introducing we improved vehicle length classification accuracy.

IX. Future works

We wish to add on the same hardware platform: camera streaming, a web server interface for visual traffic monitoring and control panel. We will evaluate multi-core embedded boards performance to find the best candidate for a large scale prototypation.

Acknowledgment

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