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Sensor for Vehicles Classification

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***Abstract*—This paper focuses on problems of gathering parameters of a traffic flow using simple sensors. The first part of the paper describes properties of a sensor node based on a magnetometer. The influence of various parameters (vehicle velocity, sensor location and orientation) on sensor output has been evaluated. We found that the sensor is sufficiently sensitive to be located on the road verges. In the second part, the sensor is used for vehicles classification based on estimate of their length. Velocity of vehicles is measured by a speed trap. The results of classification are compared with measurements where the velocity of vehicles is just estimated.**

I. Introduction

TODAY we see ever increasing requirements for bigger throughput of the road network. This is not only true in large cities of developed countries, but also in relatively small (but growing) cities of less developed countries. Increasing competition among car producers, reducing production costs, increased standard of living, fall in prices caused by economic crisis and other factors caused that the number of cars in Eastern Europe has increased significantly in the last two decades. The transport infrastructure is not prepared for such number of vehicles. Increasing transport capacity between major cities is possible by expansion of existing roads and/or building new highways. The expansion of roads within cities is more difficult and sometimes even impossible. The problem is the density of buildings, limitations given by the protection of historical monuments or unwillingness of landowners to sell the land. These reasons can cause overcharge of the transport infrastructure projects. Moreover, decrease of government revenues due to economic crisis further aggravates the problems. Therefore, it is desirable to use existing infrastructure as efficiently as possible. Critical points in traffic control are the intersections. Inappropriate ways of managing the intersections can decrease the network throughput or even lead to congestion. Congestion causes direct economic losses in addition to the increase of harmful emissions and contributes to worsening air quality and thus public health.

The transport has stochastic nature, which makes the problem of intersections control even more difficult. Of course, it is possible to determine the approximate parameters of the traffic flows on various roads throughout the day and properly adjust the cycles of the traffic lights at intersections. However, intersections controlled by a fixed cycle cannot achieve, or at least approach, the optimal utilization of transport infrastructure [1]. This is only possible through adaptive algorithms based on information about traffic flows obtained in real time. The quality of information about the number of vehicles, their speed and possibly type is essential for optimal management of urban transport. Necessary information can be obtained by using different types of sensors. In some countries that face this problem for a longer time (USA, Canada and others), the main transport lines are usually equipped with an infrastructure that allows obtaining traffic data in real time. Among the most widely used systems belong induction loops. However, their retrofitting into the existing infrastructure is financially quite challenging and it is not reasonable to assume that this sensing system will be adopted in countries such as Slovakia. There are other ways to track the traffic: video system, radars, acoustic systems etc. [2]. However, each technology has its limitation: some are adversely affected by weather, other are unable to function properly under certain conditions (too slow or stationary vehicles). A very important factor are the costs of building and maintaining the system.

In recent years, systems based on wireless sensor networks (WSN) have become increasingly popular. Significant development of technologies in various areas (micro-electro-mechanical systems (MEMS), wireless communication, energy harvesting, power consumption of microprocessors) allowed the emergence of sensor networks that consist of a number of relatively simple elements that communicate through wireless technology. The main parts of a basic element (node) of such a network are described in [3]. The power supply for the node can be based on traditional batteries (that can provide energy for few years) or by using renewable energy sources in conjunction with ultracapacitors [4]. The small size of the node decreases the installation costs. The ease of installation of the WSN is further enhanced by the fact that there is no need to install cabling for power supply and communication between network elements. Of course, this technology has also its drawbacks. The nodes with constrained energy sources must be as energy-efficient as possible. The communication subsystem is usually the most significant energy consumer. Energy constraints limit data throughput and communication range. Therefore, it is necessary to use pre-

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processing of measured data with integrated microcontroller and to transmit only the necessary data.

This paper focuses on problems of gathering parameters of a traffic flow in real time using a magnetometer. The structure of the paper is as follows: the second chapter describes the sensor and three experiments focused on character of measured signals, the third section is devoted to the classification of the vehicles based on their length and the fourth part concludes the paper.

II. Experiments

A. Node prototype

Staff of the Department of Technical Cybernetics deal with different applications of wireless networks for years [4], [5]. Our current research is focused on WSN in traffic. We developed a node prototype based on a 32-bit microcontroller STM32F100RB. Sensing part of the node consists from the sensor LSM303 containing magnetometer with an accelerometer. The communication subsystem can be based on a module RFM70 or Xbee. The module RFM70 enables communication over short distances in the ISM 2.4 GHz band with data rates up to 2 Mbps. XBee module uses the same ISM band and has better communication range but slower data rate (up to 250 kbps) than the RFM70. Large capacity data storage is provided by micro SD card. The motherboard dimensions are 49 x 33 mm (Fig. 1).

The nodes can communicate with a personal computer using a special USB adapter that enables communication with both mentioned communication modules.

The developed sensor was used to carry out several experiments that were designed to determine the properties of the sensor and the impact of the sensor location on the measured data.

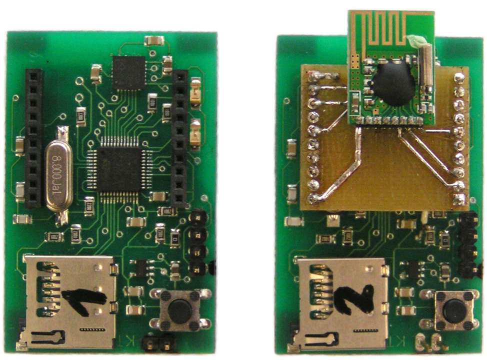

Fig 1. Node prototype

B. Experiment 1

The aim of the first experiment was to determine the sensitivity of the sensor. We also examined the effects of sensor location (relative to the vehicle) on the measured data. The experiment was based on repeated measurement of the magnetic field changes during the passage of the vehicle. After each measurement the position of the sensor was changed. There were 13 measurements made at a distance from -1.8 m to 1.8 m relative to the center of the vehicle. The speed of the vehicle was about 10 km/h during all measurements. The length of each measurement was 5 s while the sampling frequency was 220 Hz, thus total number of samples in each measurement is 1100. During the experiment, we used a personal car NISSAN Primera Wagon with dimensions of 450 x 160 cm (length x width) and weight of 1600 kg. The orientation of the sensor relative to the direction of movement of the vehicle and the magnetic field of Earth is shown in Fig. 4-A.

The waveform of the measured data is very dependent on the location of the sensor. A relatively small change in the sensor position can cause a large change in the data shape. This can be seen especially if the sensor is placed under the vehicle, particularly in channels Y and Z. On the other hand, the smallest impact on the data shape had sensor movement in the X direction. Fig. 2 shows the magnetic profile of the vehicle obtained by combining all the measurements in the X direction. When the sensor is located nearby the vehicle, the biggest changes in the magnetic field are in the Y axis. Changing the position of the sensor affects mainly the amplitude of the measured data, but not their shape. Presence of the vehicles can be detected with used magnetometer from relatively large distance, which depends on the amount of ferromagnetic materials in the vehicle. Of course, the sensitivity of the sensor affects the estimated length of the vehicle. For example, the length of the magnetic profile in Fig.2 is about 600 samples, which corresponds to 7.6 m. Actual length of the vehicle is just 4.5 m.

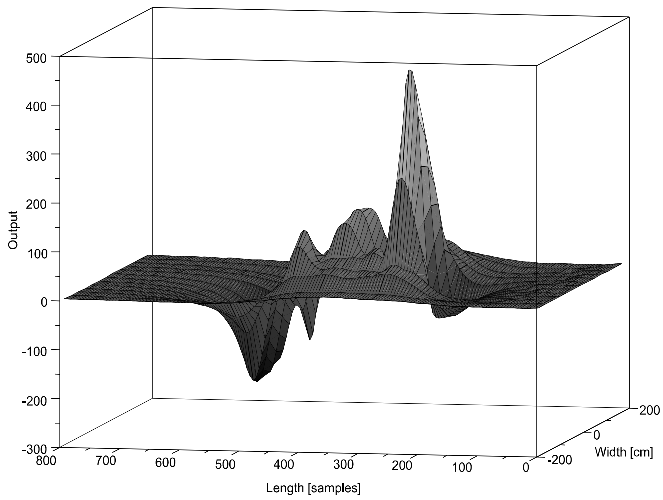

Fig 2. Magnetic profile of the test vehicle

C. Experiment 2

Next experiment was designed to determine the impact of vehicle speed on the shape of the recorded data. We conducted two series of measurements with different placement of the sensor: 0.3 m aside from the car and under the car. The vehicle was moving at the following speeds: 20 km/h, 40 km/h and 60 km/h. Fig. 3 shows obtained records.

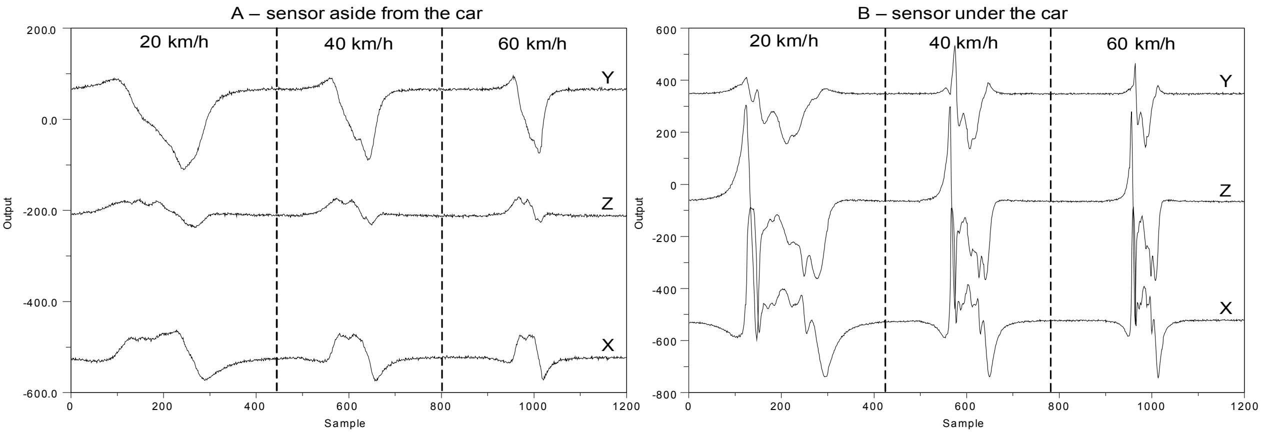

Fig 3. Records of vehicles with different speed

We evaluated the degree of similarity between the measured results using cross-correlation. Before calculating the correlation coefficient the measurements were normalized to the same number of samples using linear interpolation. The beginning and end of each record was determined using a defined threshold level. Table 1 shows the calculated values for all channels and both sensor locations.

The best results in terms of correlation coefficients are achieved for the Y channel and sensor located aside from the car. If the sensor is placed underneath the vehicle, the results are no longer as satisfactory, despite the apparent similarity of the measured waveform. This is probably due to difficulties in specifying the beginning and end of recording caused by the gradual change of the measured signal. In the future we will have to find a better algorithm to extract the vehicle record. Another problem is the already mentioned dependence of the measured values with respect to the position of the sensor. This problem can be solved by using multiple sensors located side by side in the monitored lane. However, this represents increased costs of the system implementation.

TABLE I.
DEGREE OF SIMILARITY OF MEASUREMENTS

Sensor placement	Channel	R_{20-40}	R_{20-60}	R_{40-60}
Aside from the car	X	0.9815	0.9408	0.9584
	Y	0.9831	0.9819	0.9972
	Z	0.9753	0.9415	0.9562
Under the car	X	0.9747	0.973	0.9888
	Y	0.8745	0.9357	0.9786
	Z	0.9017	0.9206	0.9432

D. *Experiment 3*

The third experiment was focused on the effect of vehicle orientation on the measured waveform. We have performed measurements with both sensor locations: aside from the car and under the car. Fig. 4 A, B shows the position of the sensor and the vehicle relative to the Earth's magnetic field in both cases.

Fig. 5 shows the measured waveforms for both directions of travel of the vehicle. The vehicle speed was 20 km/h. The waveform is virtually unchanged. The main difference is in the DC component of the signal. The value of the correlation coefficients confirms the similarity of the signals, especially for channels X and Y (R_x = 0.9955, R_y = 0.9887, R_z = 0.9463). The lower value of the coefficient R_z is mainly due to its small amplitude, making it difficult to determine the beginning and end of recording. It can be concluded that the orientation of the vehicle has no significant effect on the measured data.

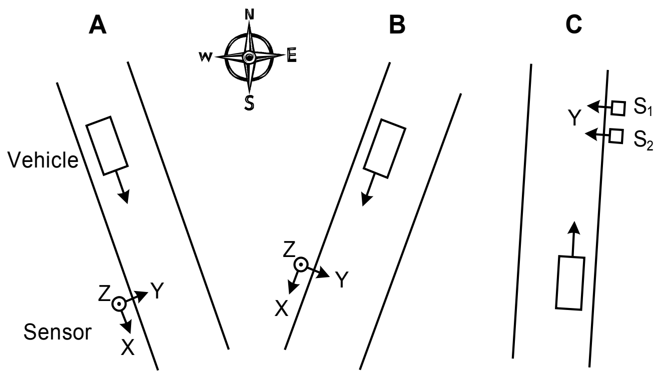

Fig 4. Orientation of the sensor and the vehicle

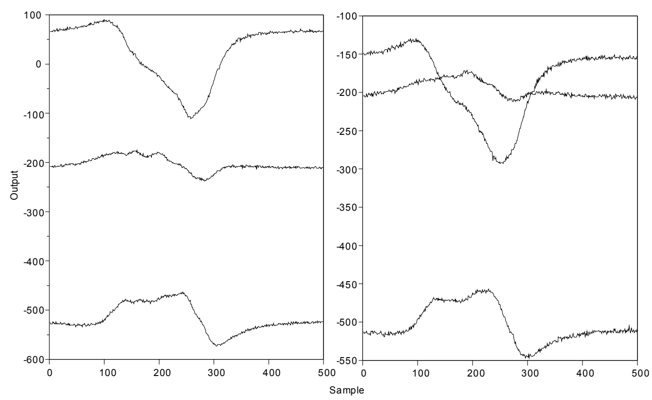

Fig 5. Various orientation of vehicle movement

III. Classification of vehicles

In the past, we conducted a preliminary measurement with a magnetometer for the purpose of vehicles classification [6]. The velocity of vehicles was estimated, since the measurement was performed with only one sensor. The result of classification was skewed with unknown speed of vehicles. We decided to repeat the experiment with a pair of sensors. Both sensors were placed on the verge of the road with spacing of 2 m. One module transmitted the measured data and the second module stored both measurements to the SD card. The sampling frequency was 220 Hz. Orientation of the sensor relative to the road is shown in Fig. 4-C. The measurement was made at the beginning of the village Nedožery-Brezany on 28th March 2012 at the time of 16:00 to 16:18. During the measurements, the vehicles were recorded by a camera. Analysis of the camera recording has provided the number and type of vehicles: 131 passenger cars, 4 vans, 4 trucks, 2 buses and a bicycle, altogether 142 vehicles.

The algorithm to classify vehicles according to their length consists of three steps. First, records of individual vehicles must be extracted from measured data. The second step is to determine the speed of vehicle by cross-correlation between records of the two sensors. The last step is calculation of the vehicle length and its classification. Let us look at each step in more detail. In accordance with the results of the first experiment, we used only channel Y to detect the vehicles. Output level of each channel is influenced by the orientation of the sensor due to the magnetic field of the earth and usually is nonzero. This DC component must be removed. Since the measured values are somewhat noisy, we used low-pass filter to suppress unwanted noise. The filtered data were only used for the extraction of the vehicle record. The beginning and the end of the vehicle can be detected by algorithm based on exceeding a certain threshold (zero zone). However, the recording of a vehicle can contain a number of zero-crossings. In order to distinguish whether it is a record of one or two vehicles, we had to evaluate the distance between the zero zone transitions. If the distance is less than the selected value, the transition is considered to be a continuation of the first vehicle record. Otherwise it is a recording of a new vehicle.

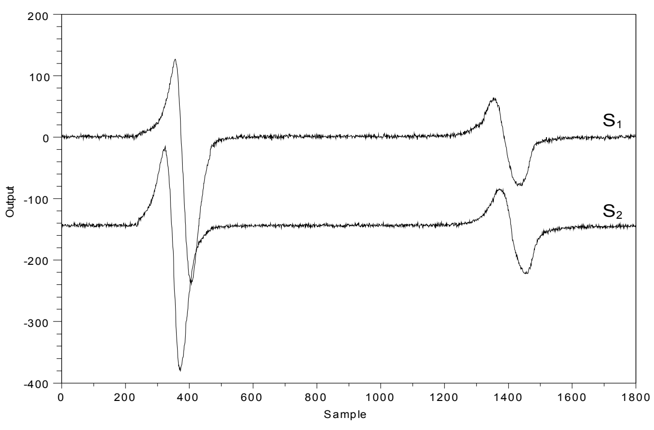

Fig 6. Record of vehicles with different direction of movement

The extracted record is then compared with record from the second sensor using cross-correlation. Given the proximity of the two sensors we assume a steady speed of vehicle and hence the same length of records. In the case of a greater distance between sensors, it is possible to use acceleration compensation [7]. Correlation coefficients are calculated for different values of shift between the first and second records. The shift, which corresponds to the largest coefficient, is directly proportional to the vehicle speed. The width of scan field depends on the lowest speed of the vehicle we want to capture. If the maximum shift is 100 samples, the sampling frequency is 220 Hz and the distance between sensors is 2 m, the minimum vehicle speed is about 16 km/h. Based on the sign of the shift (corresponding to the largest coefficient) it is possible to distinguish what is the direction of movement of the vehicle. Some vehicles, especially trucks, going in the opposite direction may cause a large enough change of magnetic field to confuse the detection algorithm. The sign of the shift makes it possible to eliminate most false-positives. Fig. 6 shows the record of the two vehicles captured by both sensors. The first part of the record belongs to a vehicle going in the right direction and the second part to a vehicle going in the opposite direction. We are not able to eliminate false-positives if we consider solely the level of signal change. Evaluating the shift between records is therefore very useful.

After removal of false-positives we evaluate the similarity of the records from both sensors. If the correlation coefficient is greater than the threshold 0.9, we consider the record to be reliable, and we classify the detected vehicle. Lower level of similarity is caused usually by a distortion of the measurement by a vehicle in opposite direction. From the whole measurement we extracted 148 vehicle records, of which 8 belonged to vehicles in opposite direction and 5 records had low correlation coefficient. Correctly detected were 135 vehicles, representing a 91 % success rate.

For each vehicle we can determine its speed. Assuming a uniform movement of the vehicle, the relation for vehicle speed is:

$$V = \frac{D.Fs}{S} \tag{1}$$

where Fs is the sampling frequency, S is the shift between the measurements detected by the correlation and D is distance between the sensors. Vehicle length L is proportionally dependent on the length of the vehicle record (N) by the relation:

$$L = \frac{N.V}{Fs} \tag{2}$$

In Fig. 7 are depicted the lengths of all detected vehicles. It is possible to distinguish between two groups of vehicles: smaller (personal) and larger vehicles (vans, trucks and buses). The reason why the calculated length of some passenger cars is unusually large has not yet been determined.

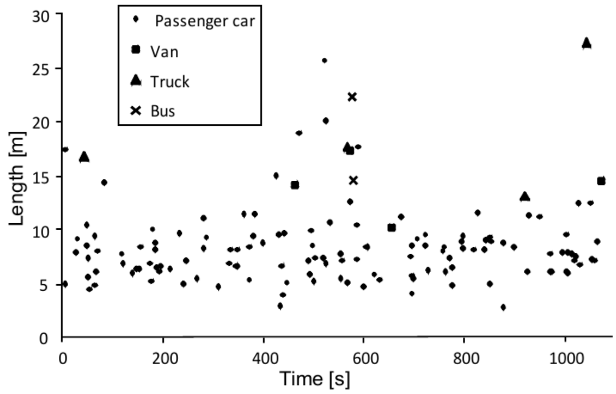

Fig 1. Length of vehicles (measured speed)

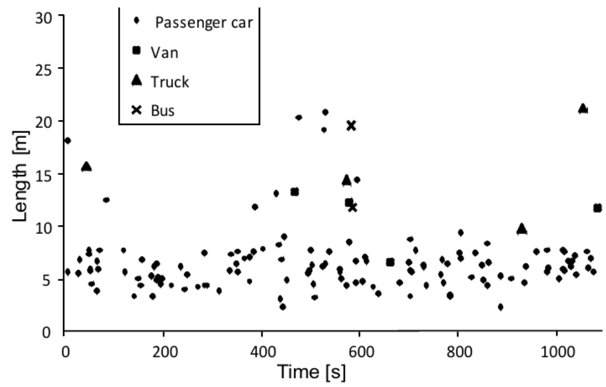

Fig 2. Length of vehicles (estimated speed)

Fig. 8 shows the lengths of the same vehicles if their speed is estimated to be 50 km/h as in [6]. Surprisingly, measuring the speed of vehicles does not yield significant benefits. This result is probably due to difficulties in determining the exact length of the vehicle using the magnetometer. The magnetometer measures only changes in the Earth's magnetic field and these changes depend strongly on the structure of the vehicle. The second source of problems is associated with the location of the sensor on the road verge. We are not able to ensure that all vehicles pass the sensor at the same distance. The amplitude of the measured signal is inversely proportional to the distance of the vehicle from the sensor.

I. Conclusion

This paper verifies the properties of the prototype sensor for vehicles classification (type and speed) based on a simple magnetometer. We found that the shape of the measured data is significantly influenced by a location of the sensor with respect to the vehicle. Based on the experiments we identified the channel of the magnetometer that provides data most suitable for further processing. The prototype sensor has been used in real traffic to measure the speed of vehicles and to estimate their length. Algorithm to extract records of individual vehicle from measurement was designed. Its success rate is 91 %. However, the results of the classification of vehicles are not significantly better than in the case of a simple estimation of the speed.

The measurements were evaluated off-line. In the future we would like to implement all algorithms directly to the node microcontroller and to transmit only necessary information using a wireless network. We would also like to carry out real-world measurements with sensor placed under the cars. Our research is also focused on the problem of re-identification of vehicles. We will develop efficient algorithms for compression of individual vehicle records to allow re-identification of vehicles even with a relatively low speed wireless network.

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