Comparative study on the effectiveness of various types of road traffic intensity detectors

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***Abstract*— Vehicle detection and speed measurements are crucial tasks in traffic monitoring systems. In this work, we focus on several types of electronic sensors, operating on different physical principles in order to compare their effectiveness in real traffic conditions. Commercial solutions are based on road tubes, microwave sensors, LiDARs, and video cameras. Distributed traffic monitoring systems require a high number of monitoring stations. In order to improve the accuracy of traffic monitoring, several modalities, complementing each other, may be used in the monitoring stations. In this paper, we propose a multimodal approach to traffic monitoring, using sensors and signal processing algorithms developed specifically for the described task. The aim of the work described here is to test each modality in a real-life scenario, assess their accuracy and to evaluate their usefulness for multimodal traffic monitoring stations. The modalities described in the paper are: Doppler sensor with custom signal processing, video analysis based on cameras and neural networks (employing deep learning algorithms), audio monitoring based on an acoustic vector sensor developed by the authors, as well as LiDAR and Bluetooth as supplementary means of traffic monitoring. Additionally, road tubes and a commercial video-based monitoring system were used in order to provide reference data. Consequently, we can present in this paper a comparative study on the effectiveness of traffic sensors operating based on different principles of work.**

Keywords*— traffic measurement; multimodal analysis; signal processing

I. INTRODUCTION

The research presented in this paper is a part of a broader project devoted to the development of intelligent road signs. The scope of the whole project is covered by another paper presented at the same conference, namely the paper entitled: “Development of Intelligent Road Signs with V2X Interface for Adaptive Traffic Controlling” authored by A. Czyżewski et al. The following chapters present a part of the research with focus to studying the effectiveness of various traffic intensity detectors. Sections II describes modalities, algorithms, and sensors that were used in the described work. Section III presents the results of the experiments in which the accuracy of each modality in traffic monitoring was evaluated.

II. MODALITIES

A. Road tubes

Pneumatic tubes are one of the most common means of measuring road traffic. A pair of rubber tubes is mounted in a road, separated by some distance, is used to measure the average speed of each vehicle within the measurement zone. Additionally, axle counting is performed, so that a vehicle class (given by its estimated width) may be determined. This method is simple and accurate, but it is also invasive, as the tubes obstruct the measured traffic. They are suitable only for short-term measurements, they can be used on roads with maximum two lanes in each direction, and they cannot be used on roads with high allowed speed (e.g. highways). They also do not work accurately in case of traffic jams. However, the road tubes may be used to collect the reference data, used to assess performance of other sensors. Therefore, data from the tubes were collected during the experiments described in this paper and compared with results obtained with other modalities.

B. Doppler radar

Doppler radars are the most common equipment used for traffic speed monitoring and enforcement. They operate on the basis of measuring the difference in frequency between the transmitted signal and the signal reflected by a moving object [1]. Professional radar equipment must comply to strict requirements which results in their high cost. For the purpose of collecting statistical data on road traffic in a distributed system, a high number of low-cost sensors is required. Therefore, we decided to employ consumer grade motion detection sensors for this task. Such sensors are characterized by a relatively low signal-to-noise ratio and are susceptible to electromagnetic (EM) interference. The proposed solution consists of a dual-channel (I/Q) motion sensor, a signal amplifier, analog-to-digital converter and Raspberry Pi microcomputer for signal analysis.

In order to make signal detection possible, noise and interference have to be suppressed. The solution to this problem developed by the authors is based on evaluating the difference between the phase spectra of signals recorded from two I/Q output channels of the sensor, computed with Fast Fourier Transform [2]. For signals reflected by moving objects, the phase difference should be about 90 or –90 degrees, depending on the direction of movement, while noise and EM interference should be concentrated around 0 degrees. Therefore, the phase difference is used to compute a weighting function which is then multiplied by amplitude spectra of the sensor signal. Thus, the level of noise and EM interference is decreased, making further signal analysis possible. Additionally, one of two directions (towards or away from the sensor) may be eliminated, which allows for

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separate detection of objects moving in each direction (Fig. 1).

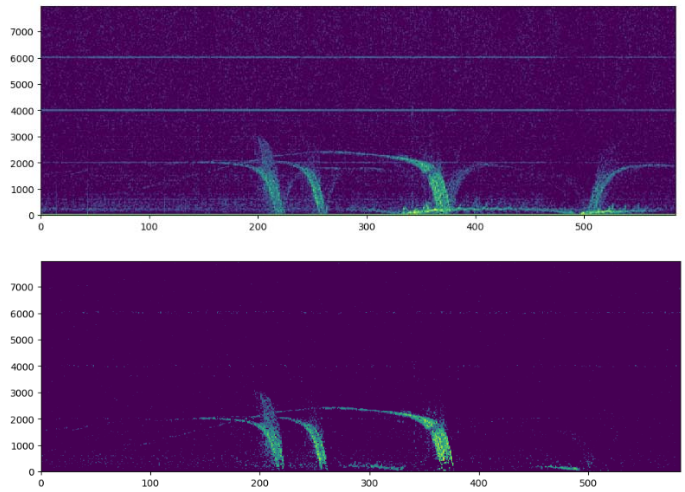

Fig. 1. Spectrograms of signal from the Doppler sensor (one channel): original (upper plot) and processed with the proposed algorithm [2] (lower plot) - only tracks of vehicles moving towards the sensor are retained. Plots show spectral amplitude (color) vs. time (horizontal axis) and frequency in Hz (vertical axis)

The remaining part of the algorithm is object detection and tracking. New objects are detected when a new strong spectral component is detected. This component is then tracked in the successive signal sections. Since the sensor measures only the radial component of the velocity vector, frequency of the track decreases as the object moves towards the sensor, also the track becomes wider, as the active length of the object increases (Fig. 1). After a track is finished (an object passed the sensor), the highest stable frequency of the track is found and converted to velocity using the Doppler equation [1]. A more detailed description of the algorithm can be found in [2] and the results of the experiments are presented in Section IIIA.

The main purpose of the sensor described here is to collect data on daily and hourly distribution of vehicle number and traffic speed. It is not necessary to detect each individual vehicle. There are several problematic cases in which the Doppler radar performance is suboptimal. If there are multiple lanes in the same direction, overlapping of object tracks and object occlusion occurs which results in misdetections. If the vehicles move very close to each other, the trailing vehicle is often undetected. Doppler radars are also unable to detect traffic jams. Therefore, it seems reasonable to supplement the Doppler detector with other modalities.

C. Video analysis

Classical approach to vehicle counting in video is based on using background subtraction methods [3]. Although these methods are easy to deploy, energy-effective and they do not require training, they may fail in difficult situations. Vehicles might not be detected in traffic jam, shadows and lights cause many false detections. Also, the background subtraction method requires a stable camera view, being sensitive to vibrations of the camera caused by the wind.

Current state-of-the-art methods of object detection are based on Convolutional Neural Networks (CNN) [4]. These methods are extremely data hungry and they require specialized processors to run. However, these requirements are no longer a holdback for vehicle detection, since specialized large datasets were published (i.e. UA-Detrac [5]), and recently, energy-efficient neural networks (SqueezeDet [6]) were developed. However, since CNN-based algorithms are black-box approaches, it is not known a priori what would be the accuracy of developed model when deployed, especially when there are significant differences between the source (train) and target (test) domains. There are some methods that allow for unsupervised learning, e.g. domain adaptation [7], however, these methods are not explored in this paper. The goal of this study is to measure how models trained on large datasets performed in real traffic monitoring scenario.

A tracking algorithm is required in order to perform vehicle counting. For this purpose, a simple online and real-time tracking (SORT) [8] is used. It is a state-of-the art tracking method that does not require training. In this algorithm, a Kalman filter is used for the prediction step and a Hungarian algorithm is used for associating new detections with existing tracked objects. This method is very efficient and accurate, its only drawback is the lack of handling long-term occlusions, which is not an important problem in our case.

Using video analysis for traffic monitoring presents several advantages and disadvantages. Counting vehicles on the basis of video analysis works also in multi-lane settings, which has a great advantage over other modalities, making it suitable for many real-world situations. While occlusions are challenging, it is also possible for such an algorithm to work in traffic jam situations. Video analysis can be also used for other complementary tasks, such as anomaly detection. However, these strengths come with some significant drawbacks. Firstly, such algorithms tend to fail in challenging illumination conditions, especially at night. Further, the accuracy of such a detector is dependent on the position where the camera was placed, because it determines the perspective with which the passing vehicles are observed. This also means that accuracy on each of the lanes may be slightly different. Finally, some manual calibration, such as selecting the region of interest where vehicles are counted, is usually required.

The goal of this study if to measure usefulness of CNN-based methods in traffic monitoring. For that purpose, a CNN-based detector (SqueezeDet) was trained on UA-Detrac dataset for vehicle detection. On top of that, vehicle counting is performed and the results are compared with Doppler radar and road tubes data. Also, 24h analysis is performed in order to measure the detection accuracy, also during the night. The results are presented in Section III.B.

D. Audio analysis

Analysis of audio signals from passing vehicles is another method of traffic analysis. Compared with video analysis, it is not susceptible to difficult conditions (e.g. night). An Acoustic Vector Sensor (AVS) was used in the research described in this paper. The AVS delivers the following signals: acoustic pressure and three perpendicular particle velocity components. These signals are used for the calculation of three components of sound intensity on XYZ axes [9]. Every passing vehicle produces noise during its movement along the road, thus it can be considered to be a moving sound source. Therefore, analysis of sound intensity changes in time can be applied for counting vehicles and for determining their direction of movement. The sound intensity (SI) vector indicates the current position of the sound source. The SI vector is updated 46 times per second, thus it is possible to track the position of the sound source (vehicle). Based on this data, the presence of the vehicle and its moving direction may be detected in a passive way, without emitting any signals. This is the most important advantage of this technique over active methods such as radars ad LiDARs. In the presented research, the AVS based on MEMS digital microphones was applied. The detailed information about its design and properties can be found in [9]. The proposed method was tested in real traffic conditions. The obtained results are presented in Section III.C.

E. LiDAR

Registration of vehicles in road traffic can also be carried out using Light Detection and Ranging (LiDAR) devices which emit a beam in the infrared spectrum. These signals are series of very short light pulses which propagate in a straight line, bounce off the vehicles and return to the measuring device. Unlike radars, vehicle detecting via LiDARs is less prone to measurement errors. This device emits a more focused beam, which allows more accurate measurement at a given point. LiDARs can be used both during the day and at night, but they are more sensitive to weather conditions than regular radars, these devices must be also a static element of the system. In addition, the so-called cosine error, which is the inaccuracy of the measurement associated with the angle between LiDAR and the direction of the vehicle movement, has to be considered. Because of that, LiDARs are usually positioned alongside or perpendicular to the road. The possible uses of LiDAR include vehicle detection, lane occupancy, and frequency of vehicle flow

The main problem is that the beam is not directing towards the passing car. This kind of measurement is necessary to calculate the speed of the vehicle. Theoretically, two pulses of laser light allow the measurement of speed, where the difference between two measurements is equal to the distance divided by the time between two pulses is equal to the speed of the car. In the case of such scenarios, it is not possible to measure the speed due to the device's position perpendicular or at an angle in the direction of vehicle movement, which results in inaccurate measurement and calculation of the car speed is distorted by the cosine error. The speed measurement obtained by the Doppler radar and the occupancy time of the measurement point given by LiDAR may be combined, allowing calculation of the vehicle length. This data allows classification of the vehicle and indication of belonging to particular groups. A series of experiments were carried out and the results are presented in section III.D.

F. Bluetooth

Employing Bluetooth technology for vehicle detection becomes popular with a growing number of vehicles equipped with wireless communication systems. Depending on Bluetooth device class, the detection range may vary between 1 and 100 m [10]. Recent studies show that this technology makes a promising method of collecting real-time statistical traffic data and actual journey times from measurements on a long distances, e.g. 1 km, which is not possible or difficult with other modalities [11, 12]. The general idea is based on recording anonymous Bluetooth MAC addresses of devices together with a timestamp as they pass by each detector and then perform matching the addresses as vehicles pass through the next detector. Having such data, it is possible to estimate average speed on a given road section (e.g. a highway) and identify significant differences from the expected results, like these caused by congestions.

Technically, two approaches to MAC address monitoring can be distinguished, namely basic and advanced. The basic approach is utilizing standard hardware (Bluetooth adapter) and scanning for nearby Bluetooth devices using the HCI interface. The advanced approach requires a specialized hardware: a radio module with software implementing the Baseband controller and the Firmware Link Manager layers. With these components, one can create a monitoring application and optimize its temporal resolution. Following the advanced approach, we constructed a practical vehicle counter and performed field tests. The results of detecting vehicles equipped with Bluetooth devices are presented in Section III.E.

III. EXPERIMENTS AND RESULTS

In order to evaluate usefulness of the modalities described in Section II, a number of field tests have been carried out in real traffic conditions. The results of vehicle counting (all modalities) and speed estimation (only the Doppler device) are presented in this Section for all tested sensors and compared with the reference data. The experiments have been done at city streets located in the vicinity of Gdańsk University of Technology. The reference data was constructed from video recordings in which vehicles were marked and counted by a human, and also from the commercial device based on road tubes (Metrocount MC5600 Vehicle Counter System). The following traffic parameters were registered by this device for each vehicle: time, speed, direction, traffic volume, axle-based classification and gap between vehicles. The results obtained for particular modalities are described in the following subsections.

A. Doppler radar

The aim of the experiment was to compare the performance of the Doppler sensor (DS), supplemented with signal processing algorithms developed by the authors, with the commercial detector based on road tubes (RT). Both the vehicle counting and the velocity measurement were performed. The DS was mounted in a box placed on a building wall at a height of 2.8 m, at the distance of 4.5 m away from the road, aiming at the moving vehicles at a horizontal angle of ca. 30 degrees. A total of 77 hours of continuous recordings from both sensors (from 12th to 15th October 2018) were analyzed. The data from RT were used as a reference in order to assess the performance of the custom detector based on DS (only vehicles moving towards the sensor were analyzed). The results of vehicle counting are summarized in Table I.

According to the obtained results, about 8% detections made by DS were false (they were not detected by RT) and about 3.8% detections made by RT were missed by DS. The accuracy of DS in vehicle detection is therefore about 90% which is sufficient for gathering the statistical distribution of the traffic in time, as shown in Fig. 2. However, not all FPs and FNs may actually be the detection errors. The RT performs the detection in a zone of the road (between two pairs of tubes), while the DS detects vehicles at a point situated near the entrance to the RT's detection zone. As a result, some vehicles (e.g. those that parked within the detection zone) may be detected by DS, but not by RT. It may explain the relatively high ratio of false positives for the DS. Such cases will be examined in more detail in future work.

TABLE I. RESULTS OF VEHICLE COUNTING BY DOPPLER SENSOR COMPARED WITH THE ROAD TUBES SYSTEM

Par.	Description	Total	Avg. per hour
ND	Number of vehicles counted by the Doppler sensor (DS)	4371	56.8
NT	Number of vehicles counted by road tubes (RT)	4182	54.3
TP	True positives (detected by both sensors)	4022 (92% of ND, 96% of NT)	52.2
FP	False positives (detected only by DS)	349 (8% of ND)	4.53
FN	False negatives (detected only by RT)	160 (3.8% of NT)	2.08

Comparing the results of speed measurements, it was observed that significant differences between both sensors exist, with DS providing smaller values than RT in many cases. The root mean squared difference was equal to 4.95 km/h. However, it should again be noted that RT performs a zone measurement, while DS does a point measurement at the beginning of the RT's zone. It was observed that vehicles do not move at a constant speed within the detection zone: many of them accelerate coming out of a corner, some decelerate approaching the crossroads while drivers are looking for a parking space. It may be a reason for the observed discrepancies in speed measurements, so the site used for experiments is not optimal for assessing DS's accuracy in speed measurement (a zone where vehicles move with approximately constant speed should be monitored, instead).

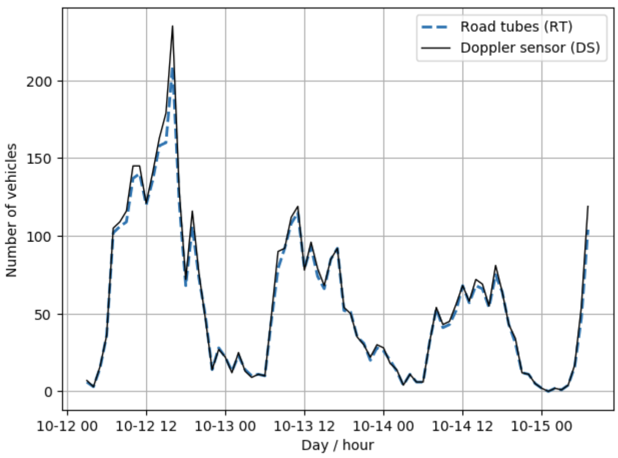

Fig. 2. Hourly distribution of the detected number of vehicles for Doppler sensor and for road tubes

B. Video analysis

For training of the classifier, the UA-Detrac dataset was used. There are more than 140,000 frames in the UA-DETRAC dataset, with 8250 vehicles that are manually annotated, leading to a total of 1.21 million labeled bounding boxes of objects. Data were collected by the dataset providers from 24 different locations in China. The videos are recorded at 25 fps, with resolution of 960×540 pixels. A set of 60 videos was split into the training and the validation set using 3:1 ratio. Training was stopped when the f1-measure on validation set converged. Training and tests were run on Intel Core i7, 2.6 GHz. Training on the UA-Detrac dataset took 2 days. Input to the classifier was resized to 480×270 pixels, as it provides a good compromise between accuracy and detection time. Detection speed was 10.7 fps.

Regarding vehicle counting, a simple method of counting vehicles that pass through the region of interest was implemented. The specified region was manually selected (green area in Fig. 3). For each bounding box, it was checked whether its center lies within the region of interest. The vehicle count is increased if the object identifier (returned by the tracking component) was not counted before and if the trajectory length of the tracked vehicle is bigger than some (small) threshold. This way, it is possible to ignore some of the false positive detections caused mainly by low video quality and shadows caused by the sunlight. When the vehicle drives through the green area, the angle between its trajectory and the road direction is measured. If this angle is lower than 45 degrees, then the counter on the left side of the road is increased, if is between 135 and 180 degrees, then the counter on the right side of the road is incremented.

The video was recorded with 30 fps, however, for fair comparison, only every 5th frame is used (which gives 6 fps), as it is the estimated processing speed while the algorithm was deployed to embedded system Nvidia Jetson TX2.

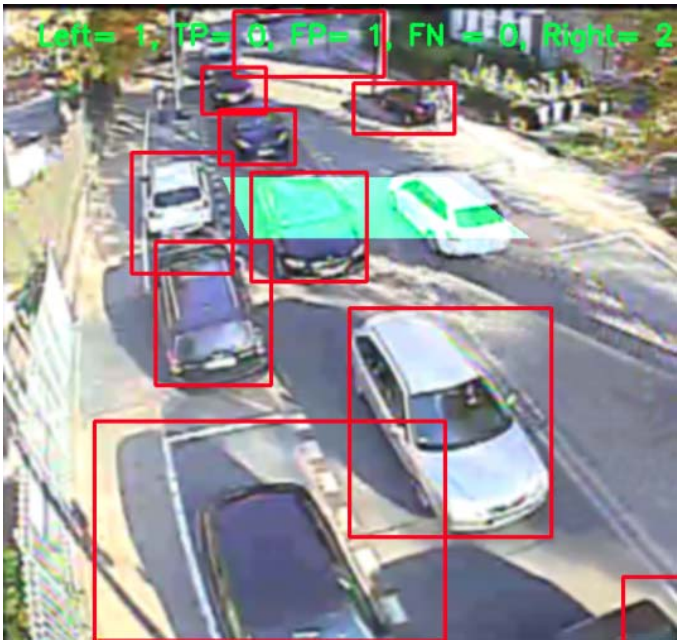

Fig. 3. View from camera and vehicle counting metrics

The goal of the experiment was to measure the accuracy of the vehicle counting system. The first challenge was the fact that the analysis was performed during 24-hour period, which includes nighttime detection known to be challenging for video analysis. Interestingly, the proposed detector achieved fair results also during nighttime, not a significant drop in accuracy was noticed. This is because the UA-Detrac dataset which was used for training contained few videos recorded at nighttime and because the scene was moderately enlightened by a street lamp. The second challenge came from the fact that the quality of the obtained video was very low, mainly due to strong compression used while recording the video. Gaussian smoothing was applied in order to remove the artifacts, but the quality of the video was still very low. Also, some dropouts were recorded in the video which prevented the detection of some vehicles. Nevertheless, similar technical challenges often occur in real-world conditions.

The presented model achieved 87% recall and 92% precision (Table II). Many of the false positives were caused by traffic jam situations where the passing vehicles were not counted by road tubes, but they still were mostly correctly counted by video analysis. Some of false negatives were caused by dropouts. It can be noted that strong sunlight and shadows caused many false positives. Some vehicles were recognized most accurately in the central part of the image, which is probably caused by the fact that cars viewed from such a perspective were frequent, i.e. cars recognition falls down as the car is closer to the camera and the perspective is vertical. This is one of the disadvantages of that system which requires a careful selection of a region of interest.

TABLE II. RESULTS OF VEHICLE COUNTING BY VIDEO ANALYSIS COMPARED WITH ROAD TUBES

Par.	Description	Total	Avg. per hour
ND	Number of vehicles counted by video analysis (VA)	1853	77.21
NT	Number of vehicles counted by road tubes (RT)	1950	81.25
TP	True positives (detected by both sensors)	1701 (92% of ND, 87% of NT)	70.88
FP	False positives (detected only by VA)	152 (8% of ND)	6.33
FN	False negatives (detected only by RT)	249 (3.8% of NT)	10.38

C. Audio analysis

It was not possible to perform the experiments with the audio sensor at the same time as the previously described ones, because the road tubes produced noise that would distort signals recorded by the audio sensor. Therefore, a separate experiment was performed on a road with sparse traffic flow. The AVS was placed at a distance of 2 m from the road. An additional camera was used for collecting the reference data. Detection of vehicles and their moving direction was performed manually. The conditions were as follows: temperature 11°C, pressure: 1015 hPa, wind speed 8.5 m/s, wind direction: North, the road surface was dry. During the observation period of 53 minutes, a total of 192 vehicles passed the measurement point. Sound intensity signals were recorded from the AVS, then an algorithm for vehicle detection was applied. This algorithm analyzes sound intensity values and time dependencies between the intensity and the azimuth. The vehicle is detected when the sound intensity level exceeds a defined threshold and the azimuth crosses the zero line. Moreover, changes of the azimuth can be used for determining the vehicle movement direction (Fig. 4).

The algorithm was evaluated by comparing its results with the reference data (Table #SI). Some false positive results were observed (mostly on the further lane), no missed detections occurred for the closer lane. Based on the detection results, some metrics were calculated. Precision is the number of true positives divided by the number of true positives plus the number of false positives. The recall is the number of true positives divided by the number of true positives plus the number of false negatives. For the practical application, it is extremely important that the algorithm has a high recall (low number of false negatives – no detection while the expected event occurred). The presented algorithm has high recall and good accuracy. The obtained results are very promising. The proposed method will be tested in a longer period of time and under a different volume of traffic flow.

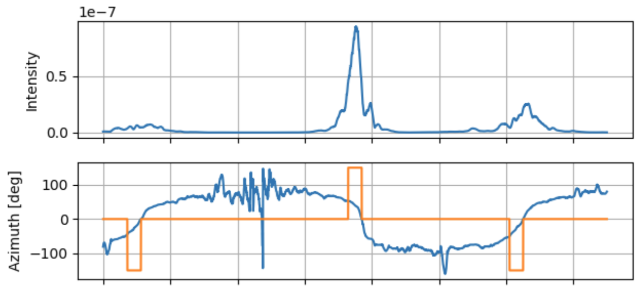

Fig. 4. Vehicle detection using the AVS: intensity vs. time (top) and azimuth vs. time (bottom), with detected vehicles and their direction of movement marked

TABLE III. RESULTS OF VEHICLE COUNTING USING AVS PROBE

Parameter	Lane 1	Lane 2	Total
True positive	98	92	190
False positive	6	9	15
False negative	0	2	2
Precision	94.2%	91.1%	92.7%
Recall	100.0%	97.9%	99.0%
Accuracy	94.2%	89.3%	91.8%

D. LiDAR

Two locations were selected for measurements. The first one was a single-lane, two-way city street with a speed limit of 50 km/h. The second location was a single-lane, two-way village road with a speed limit of 90 km/h. Firstly, road traffic measurements were made in three measurement scenarios, both in day and night conditions. Measurements were performed with the TF02 LIDAR device from Benawake, with the measurement rate 100 Hz which allows accurate readings of the passing vehicles, which is especially important during the occupation of two lanes of the road. The following experimental conditions were in force:

- measurement perpendicular to the road at the distance of 100 cm from the roadway; the height of the LIDAR fixation 40 cm from the surface,
- measurement of LIDAR set to 45-degree angle to the road axis also at a height of 40 cm and at a distance of 100 cm from the lane,
- measurement of LIDAR set to 45-degrees to the axis of the roadway and mounted at a height of 80 cm, and also at a distance of 100 cm from the lane.

The TMS-SA4 device (a microwave radar for traffic analysis) was used as a measurement reference, for counting the number of vehicles and for measuring their speed. According to the chosen reference, the effectiveness of each scenario was evaluated and the optimal one was chosen. The main collected data represented the number of detected cars. In addition, the measurements were recorded with a reference camera (Go Pro Hero 6 Black) and the vehicles were counted manually. The results are shown in Table IV, with false recognition rate (FRR) indicated.

TABLE IV. RESULTS OF THE MEASUREMENTS SCENARIOS

Scenario		Camera (ref.)	TMS-SA (ref.)	Correct detections	FRR [%]
DAY	90deg/ 40cm	48	48	46	4,17
NIGHT	90deg/ 40cm	69	69	69	0
DAY	45deg/ 40cm	43	43	42	2,32
NIGHT	45deg/ 40cm	61	61	59	3,28
DAY	45deg/ 80cm	45	45	40	11,11
NIGHT	45deg/ 80cm	51	51	51	0

The results indicate the unambiguity of the choice of the first scenario for subsequent measurements. During the second measurement session, 146 vehicles out of 151 identified by the camera (97%) were correctly detected by the LiDAR. Setting the sensor perpendicular to the axis of the road made it impossible to count vehicles in case of occlusion (vehicles present on both lanes simultaneously), which caused 5 missed detections (3%). No false positive detections were observed.

E. Bluetooth

The evaluation of the Bluetooth vehicle detector was done by comparing time instances of events detected by the Bluetooth sensor with the reference data from the road tubes. The maximum allowed time gap between the Bluetooth detection and the vehicle counter detection was 5 seconds. Hourly distribution of the number of detected Bluetooth devices and vehicle count is presented in Fig. 5 and Fig. 6.

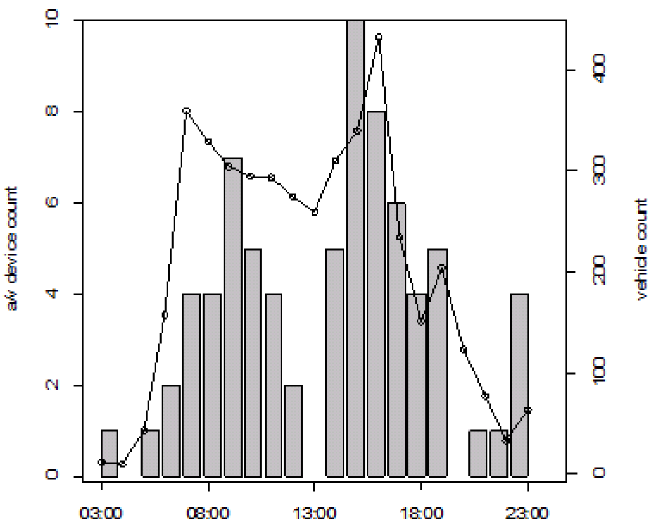

Fig. 5. Hourly distribution of number of vehicles and detected Bluetooth devices for weekday.

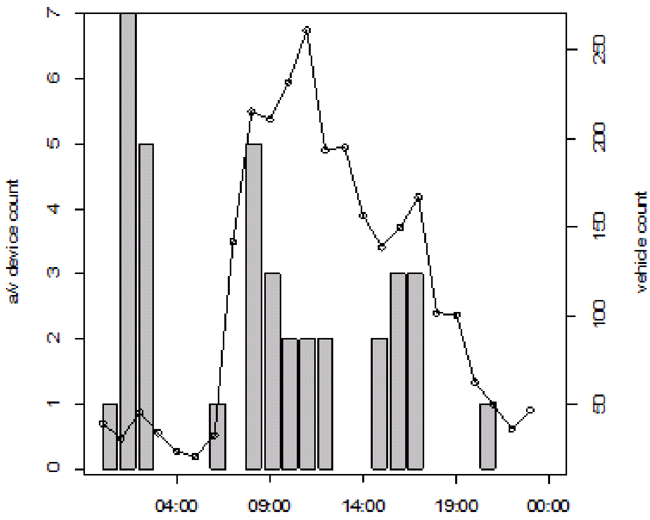

Fig. 6. Hourly distribution of the number of vehicles and detected Bluetooth devices for the weekend

The characteristic of the measurement localization implied careful Bluetooth data analysis. After data preprocessing (i.e. rejecting extremely weak signals), the total number of detected Bluetooth devices and vehicles was equal to 81. Complete results regarding time of day are provided in Table V, and the differences in observed mean RSSI value according to the lane are shown in Table VI.

TABLE V. RESULTS OF BLUETOOTH DEVICE DETECTION IN THE DAYTIME AND IN THE NIGHT TIME

	Days (7-22)	Nights (22-7)
Positive match	57	7
Total devices	76	7

TABLE VI. MEAN RSSI OF BLUETOOTH A/V DEVICES DETECTED IN CARS PASSED BY

Lane	mean RSSI [dB]
near	-82.5
far	-85.4

In the discussed scenario and localization, some drawbacks concerning Bluetooth should be pointed out. The first one is the case when a car maneuvers in the proximity of the Bluetooth sensor, and it is not detected by the tubes. Second, some strong signal emitting devices in vehicles traveling on nearby streets may be detected. Moreover, pedestrian walkway was along the road, so their hand-held devices such as Bluetooth headphones might introduce additional false detections.

IV. SUMMARY AND CONCLUSIONS

At the current stage of advancement of the project, it was not possible to compare the data obtained from all types of sensors, simultaneously. However, achieving this possibility is expected at the next stage of the project implementation. So far, the main focus has been on assessing the effectiveness of individual sensors by comparing the received data with the ground truth data and on optimizing the operation principle and settings of individual sensors. However, it is now already possible to compare the effectiveness of individual sensors that work on the basis of different physical principles. It seems that microwave sensors and acoustic sensors have the best application prospects for measuring traffic.

For above reasons the modality employing LiDARs and Bluetooth should be treated as a complimentary functionality to be exploited in the presence of others, more reliable ones. Nevertheless, manufacturers of this kind of equipment, especially LiDARs which were used for measurements, announce the release of updated versions soon, therefore final decision concerning this modality employment in the intelligent road sign was not made, yet.

Undoubtedly, the modality worth devoting attention is video analytics supported by the process of deep training of neural networks. Despite the difficulties associated with proper lighting of the scene, possible soiling of camera lenses and the influence of bad weather, it brings interesting results, especially in the case where multiple lanes should be monitored, simultaneously.

Further tests of intelligent road signs under controlled conditions should aim to best reflect the real cases. However, many tests need to be carried out for different weather conditions, traffic, and visibility, and road infrastructure types to cover the entire spectrum of traffic situations.

ACKNOWLEDGMENT

Project financed by the Polish National Centre for Research and Development (NCBR) from the European Regional Development Fund under the Operational Programme Innovative Economy No. POIR.04.01.04-0089/16 entitled: INZNAK – “Intelligent road signs with V2X interface for adaptive traffic controlling”

REFERENCES

[1] G. Brooker, “Doppler Measurement,” In Sensors and Signals, Australian Centre for Field Robotics, University of Sidney, 2006, pp. 443-462.

[2] G. Szwoch: “Suppression of distortions in signals received from Doppler sensor for vehicle speed measurement,” 2018 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA), Poznań, 2018, pp.16-21.

[3] A. Bas, M. Tekalp, and F. S. Salman, “Automatic Vehicle Counting from Video for Traffic Flow Analysis," 2007 IEEE Intelligent Vehicles Symposium, Istanbul, 2007, pp. 392-397.

[4] S. Agarwal., J.O.D. Terrail, and F. Jurie, “Recent Advances in Object Detection in the Age of Deep Convolutional Neural Networks,”. arXiv preprint arXiv:1809.03193, 2018.

[5] S. Lyu et al., “UA-DETRAC 2017: Report of AVSS2017 & IWT4S Challenge on Advanced Traffic Monitoring,” 2017 14th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS), Lecce, 2017, pp. 1-7.

[6] B. Wu, F. Iandola, P. H. Jin, and K. Keutzer, “SqueezeDet: Unified, Small, Low Power Fully Convolutional Neural Networks for Real-Time Object Detection for Autonomous Driving,” 2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Honolulu, HI, 2017, pp. 446-454.

[7] S. Cygert, and A. Czyżewski, “Vehicle detector training with labels derived from background subtraction algorithms in video surveillance,” 2018 Signal Processing: Algorithms, Architectures, Arrangements, and Applications (SPA), Poznań, 2018, pp. 98-103.

[8] A. Bewley, et al., “Simple online and realtime tracking,” 2016 IEEE International Conference on Image Processing (ICIP), 2016, pp. 3464-3468.

[9] J. Kotus, and G. Szwoch, “Calibration of acoustic vector sensor based on MEMS microphones for DOA estimation,” Applied Acoustics 141 ,2018, pp. 307–321, DOI: j.apacoust.2018.07.025.

[10] R. Friesen, and R. D. McLeod, “Bluetooth in intelligent transportation systems: A survey,” International Journal of Intelligent Transportation Systems Research, vol. 13, no. 3, pp. 143–153, Sep 2015, doi: 10.1007/s13177-014-0092-1.

[11] A. Haghani, M. Hamedi, K. F. Sadabadi, S. Young, and P. Tarnoff, “Data collection of freeway travel time ground truth with bluetooth sensors,” Transportation Research Record, vol. 2160, no. 1, pp. 60–68, 2010, doi: 10.3141/2160-07.

[12] E. Sharifi, M. Hamedi, A. Haghani, and H. Sadrsadat, “Analysis of vehicle detection rate for bluetooth traffic sensors: a case study in Maryland and Delaware,” in Proceedings of the 18th world congress on intelligent transport systems, 2011, pp. 16–20.