Monitoring of Transport Flow Emissions based on the Use of Convolutional Neural Networks

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Abstract: This paper studies the use of machine vision in the environmental monitoring of harmful traffic flow emissions. The purpose of the study is to develop a methodology for the high-quality and complete collection of data on the atmospheric emissions of harmful substances from traffic flows. The data is collected within the entire functional area of intersections and adjacent road sections falling within the video surveillance camera angle. Our solution is based on the use of the YOLOv3 (You Only Look Once) convolutional neural network architecture and SORT (Simple Online and Real-time Tracking) tracker. The system is based on the real-time collection and interpretation of the data obtained from street video surveillance cameras using convolutional neural networks. In this study, we focused on collecting the data on two substances: carbon oxide CO and sulphur dioxide SO_2. We chose these substances taking into account their stable properties, which allow them not to react with other substances. To assess the quality of the obtained data on harmful emissions, we verified their identity based on laboratory measurements of the Environmental Monitoring Centre Public Institution. An analysis of the data sample confirmed the absence of statistically significant differences in the calculations of the emissions using neural networks versus the laboratory measurements.

1 INTRODUCTION

Urbanization and an increase in the site development density of large cities are important features of the formation of modern society. The growing population density in cities leads to an increase in the number of cars, which ultimately determines the increased volumes of environmental pollution (Makarova et al., 2017).

Studies confirm that over 25% of (CO_2) emissions fall at urban transport, and it is projected that this share will likely rise if the policy does not change (Ko et al., 2011; Gately et al., 2013; Wen et al., 2017). Many administrative decisions, including transport taxes and charges, we used to reduce CO_2 emissions, but to improve effectiveness, it is necessary to better understand the current situation to make proper organizational and management decisions. Cities allocate more and more funds for the deployment of signal posts to monitor the environmental situation, but this approach does not allow one to determine the share of traffic flow emissions. In (Franco et al., 2013; André, 2004), the authors review the ways how

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the Emission factors (EFs) can be derived from the test data, with a clear distinction between the data obtained in controlled conditions (measurements on an engine and chassis dynamometer using standard driving cycles) and measurements in real operating conditions. To calculate CO_2 concentrations in cities, Gaussian-type diffusion simulation models are used depending on local meteorology and traffic distribution (Johnson et al., 1973).

In (Franco et al., 2013; Woo et al., 2016; Gokhale and Pandian, 2007), the authors studied the influence of the driving model (for example, acceleration, deceleration, and cruising speed) on the nature of emissions, and, therefore, on the resulting concentration of pollutants. At the same time, the considered numerical models based on solving the basic flow and dispersion equations are still too complicated. Alternatives are models, which are basically parametrized semi-empirical models using apriori assumptions about the flow and dispersion conditions. The Danish Operational Street Pollution Model (OSPM) belongs to this category of parameterized models. In the OSPM, exhaust gas concentrations are calculated using a combination of a plume model for direct input and a rectangular model for a recirculated portion of outdoor pollutants. The flow and dispersion conditions in street canyons were parametrized based on a profound analysis of the experimental data and model tests (Berkowicz, 2000).

However, the tasks of environmental monitoring can no longer be effectively solved using non-optimal heuristics due to the small amount of collected statistical data through the use of mobile laboratories or stationary posts. To collect and evaluate the data on the emissions caused by various groups of vehicles in the conditions of heavy traffic, we need operational and accessible systems for real-time monitoring of the traffic flow parameters (Johnson et al., 1973).

There is a need for an operational and permanent system to monitor the urban environmental setting caused by the traffic flow emissions, which would increase the efficiency of controlling the environmental situation, and subsequently would serve as the basis for making management decisions to regulate the urban traffic flow (Zhang et al. 2018; D'Angelo et al., 2018). In recent years, there has been a steady trend for the deployment of street video surveillance systems in cities. Some studies (Zhang et al., 2019; Zhang et al., 2017, Makarova et al., 2016) use these low-resolution video surveillance systems and deep neural networks to count vehicles on the road and estimate the traffic density. Examples of using traditional machine vision methods are the systems developed in (Rathore et al., 2018; Sun et al., 2017) analyzing the cargo carriage problems. Despite the obvious advantages of developing such systems, there are few studies aimed at collecting and analyzing the speed and nature of traffic flows in the tasks of monitoring vehicle emissions (Fedorov et al., 2019).

The purpose of this study is to consider the principles of building a real-time environmental monitoring system, as well as to analyze the quality of its readings as compared to real laboratory measurements of environmental emissions caused by the traffic flow.

2 A METHODOLOGY FOR COLLECTING AND INTERPRETING THE DATA

An autonomic tracking system based on neural networks was developed to collect the data on the traffic flow parameters (Khazukov et al., 2020). This system ensures detection and estimation of the number of vehicles and tracking their motion speed and path. The existing outdoor video surveillance systems with different distances from the road and mounting heights were used to obtain the data (Online broadcast, 2021). Our approach is based on the use of static cameras with a viewing angle providing visibility of the traffic lane to the right and the functional area of the pedestrian crossing. The data was collected at signal-controlled intersections using street video surveillance cameras located at a height of 14-40 m, with an elevation angle of 30° – 60° to the horizon (Figure 1).

Figure 1: An example of processing an incoming image by a neural network (Chelyabinsk).

The convolutional neural network ensured the processing of real-time frames (using the RTSP protocol) with a frame rate of at least 25 frames per second.

The problem of multiple object tracking is solved using the open-source SORT tracker. The SORT tracker is based on two methods: the Hungarian algorithm (Kuhn, 1955) and the Kalman filter (Kalman, 1960). Based on the data obtained from YOLO, we calculated the shortest distance from each detected object to all the predicted objects.

To train the neural network, we augmented 31,000 processed images, which allowed us to increase the initial data library up to 510,000 units. This approach allowed us to achieve high accuracy of recognition and tracking of the motion path and speed of the objects within 92 – 96%.

Besides using ultra-precise layers, the presented YOLOv3 architecture also contains residual layers, layers with an increased discretization, and skipped connections. CNN takes an image as input data and returns a tensor (Figure 2), which represents:

- coordinates and positions of the predicted bounding boxes, which should contain objects;
- the probability that each bounding box contains an object;
- the probability that each object within its bounding box belongs to a certain class.

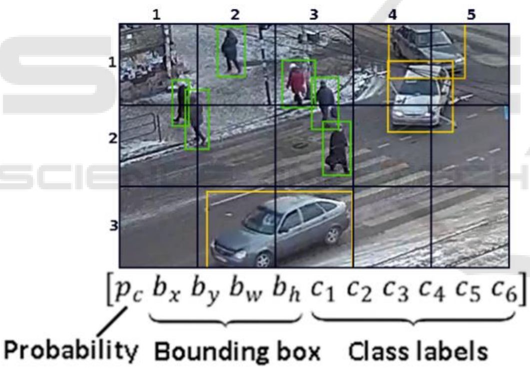

Figure 2: An output tensor.

Our method for determining the vehicle location is based on the use of a perspective transformation of mapping coordinates from cameras to a space of geographic coordinates. The developed approach allows us to detect and track the movement of vehicles in time.

2.1 A Methodology for the Summary Calculations of Traffic Flow Emissions based on Neural Network Algorithms

Polluting emissions in the exhaust gases of the vehicle flow are calculated according to the methods reflected in the national standard of the Russian Federation (GOST R 56162-2019, 2019; Order of the Ministry of Natural Resources and Ecology of the Russian Federation, 2019). According to this standard, the total one-time emission of the *i*-th pollutant (g/s) caused by vehicles moving in one direction over a 20-minutes period of an additional survey within the intersection is calculated by the formula:

$$M_{In_i}^{Tot} = \frac{1}{1200}\left(M_{In_i}^{red} + M_{L_i}^{green}\right) \qquad (1)$$

where: $M_{In_i}^{red}$ is the emission (in grams) of the *i*-th pollutant caused by vehicles moving in a specific direction within the intersection with the red traffic lights over a 20-minutes period of an additional survey, calculated, in turn, by formula (2); $M_{L_i}^{green}$ is the emission (in grams) of the *i*-th pollutant caused by vehicles moving in a specific direction within the intersection with the green traffic lights over a 20-minutes period, also calculated by formula (3).

$$M_{In_i}^{red} = \frac{P_{cyc}}{60}\sum_1^{N_{cyc}}\sum_1^{k}\left(M'_{In_{i,k}}\cdot G_{kIn}\right) \qquad (2)$$

where: P_{cyc} is the duration of the red traffic light during 20 minutes (s); N_{cyc} is the number of operating cycles the red traffic light over a 20-minutes period of time; $M'_{In_{i,k}}$ is the specific emission of the *i*-th pollutant emitted by vehicles of the *k*-th group in a queue at the red traffic light; G_{kIn} is the number of vehicles of the *k*-th group in a queue within the intersection at the end of each operating cycle of the red traffic light.

$$M_{L_i}^{green} = L^{In}\sum_1^{N'_{cyc}}\sum_1^{k}\left(M_{k,i}^{L}\cdot G_{k_{green}}\cdot r_{V_{k,i}}\right) \qquad (3)$$

where: L^{In} is the distance travelled by vehicles in one direction with the green traffic lights during 20 minutes, including the length of the vehicle queue and the length of the intersection area (km); N'_{cyc} is the number of operating cycles of the green traffic light during 20 minutes; *k* is the number of vehicle groups; $M^{L}_{k,i}$ is the specific running exhaust emission of the *i*-th pollutant caused by the vehicles of the *k*-th group; Gk_{green} is the number of vehicles of each *i*-th group passing through the intersection area in one direction at the green traffic light; $r_{Vk,i}$ is the correction coefficient taking into account the average speed of the vehicle flow on the road.

The system determines all the data necessary for the calculations by these formulas: categories, number, and average vehicle speeds, in real time with 20-minute averaging.

3 LABORATORY AND INSTRUMENTAL MONITORING OF POLLUTING EMISSIONS

Polluting emissions in Chelyabinsk (Russian Federation) are monitored by the Environmental Monitoring Centre of Chelyabinsk Region Public Institution, which periodically carries out measurements at any point in the city. The results are drawn up in the form of summary protocols recording the results of measuring atmospheric air samples for the presence of various pollutants, as well as the relevant meteorological situation. Measurements are carried out selectively - three measurements are generally taken in the morning, daytime, and evening during 24 hours. Table 1 presents an example of the summary data as of 08.12.2020.

The duration of a single measurement is 20 minutes. We used the following measuring equipment - WXT530 automatic weather station; Mettler Toledo XP205DR analytical scales; C012M Environment SA gas analyzer; AF22M Environment SA gas analyzer.

Notably, the measurement results generally record two groups of indicators - both exhaust pollutants of automobile engines (CO; SO_2) and suspended particles of various fractions determined not only by the exhaust gases but also by the operation of the brake pads of vehicles, the tire wear, the quality of the roadbed, as well as depending both on the average traffic flow speed and the meteorological situation.

As the initial data reflecting the true situation with the polluting emissions at the analyzed intersection, we took the measurement results of the Environmental Monitoring Centre (EMC) for three days - 25.11.2020; 02.12.2020; 08.12.2020. For our study, the Environmental Monitoring Centre provided the data only on the indicated working days, since the EMC has started working not so long ago and lacks a sufficient database for a more profound study: distribution of emissions by seasons, working days, and weekends, etc.

The data format and amount are analogous to Table 1.

The summary data on the calculation of several gaseous pollutants by the neural network algorithm as compared to the laboratory measurements of the EMC are presented in Figure 3 and Figure 4.

Table 1: Results of laboratory and instrumental emission monitoring.

Polluting emissions (mg/m^3)	Measurement time								
	07:20	**07:40**	**08:00**	**12:00**	**12:20**	**12:40**	**17:00**	**17:20**	**17:40**
Carbon oxide CO	0.352	0.66	0.341	0.3	0,3	0.3	0.385	0.377	0.3
Sulphur dioxide SO_2	0.009	0.009	0.009	0.009	0.015	0.009	0.009	0.009	0.009
Metrologic conditions									
Temperature (ºC)	-7.3	-6.9	-6.8	-5.1	-4.8	-4.7	-3.9	-4.3	-4.3
Relative humidity (%)	78	75	74	64	66	67	61	63	64
Atmospheric pressure (hPa)	1 000	1 000	1 000	1 001	1 000	1 001	1 001	1 001	1 001
Wind speed (m/s)	0.8	1.1	1.3	1.6	1.8	2.5	1.1	1.0	1.4
Wind direction (degree)	234	222	207	198	211	203	265	256	265

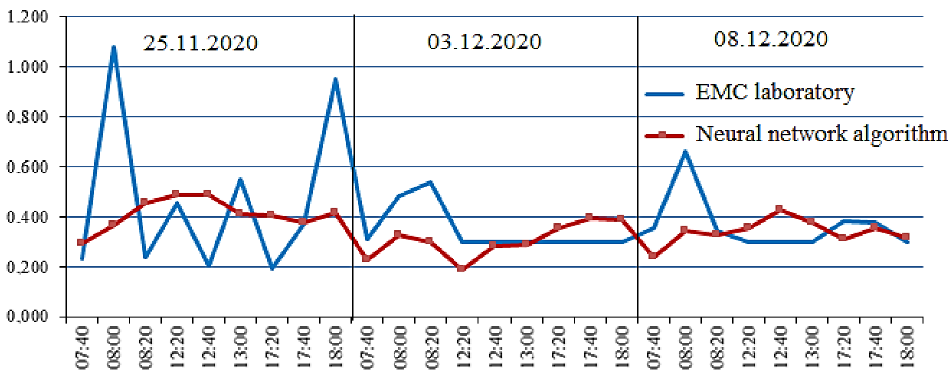

Figure 3: CO emissions (mg/m^3).

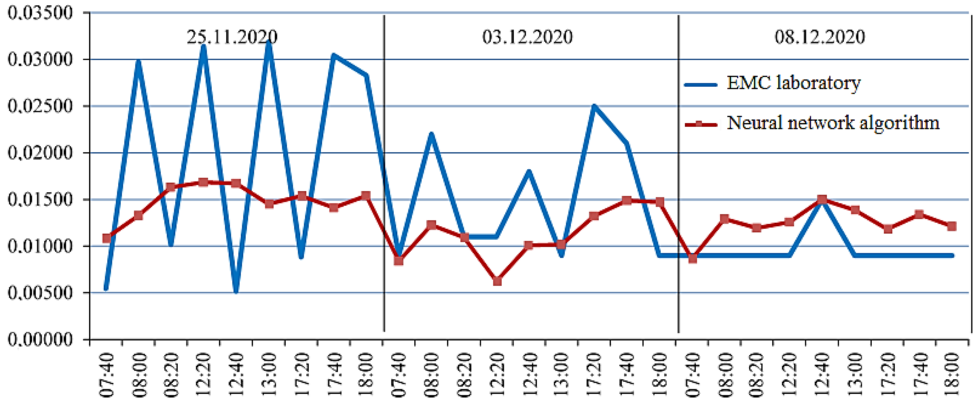

Figure 4: SO_2 emissions (mg/m^3).

According to the Figures, there is a clear visual identity of the calculated emissions obtained by the neural network method with the measurements of the EMC laboratory. Detailed differences, especially for 25.11.2020, are attributable to random disturbing influences in the EMC laboratory measurements, such as, for example, the passage of fully loaded freight vehicles; low-quality fuel; unbalanced car engines.

To assess the differences between the calculated and laboratory measurements of emissions, we advise determining the level of statistical confidence of the deviations in the measurements of these two fundamentally different systems presented in the Figures. In this situation, the most adequate analysis method is the parametric method for two independent samples - the variance analysis of average deviations.

A somewhat weaker approach, which does not require a normal distribution of the analyzed values, is the nonparametric Mann-Whitney method also suitable for the two independent samples. The results of assessing the differences using these two analysis methods are presented in Table 2, where cluster-1 corresponds to the EMC laboratory measurements and cluster-2 corresponds to the emission values calculated by the neural network method.

The conclusion about the statistical significance of the differences is formed at α_{calc} <0.05. However, both methods of analysing the differences – the parametric (variance analysis) and less rigorous nonparametric (Mann-Whitney) method affirm that the measurement differences are not statistically significant. This allows us to conclude about the statistically confirmed identity of the measurements of polluting emissions by the neural network method.

Table 2: Calculation of the statistical confidence of the differences between the EMC laboratory measurements and the calculations by the neural network method.

Cluster		CO	SO_2
1	Average	0.397235	0.014941
	N (number of measurements)	27	27
	Standard Deviation	0.2090833	0.0089034
2	Average	0.35827	0.012839
	N (number of measurements)	27	27
	Standard Deviation	0.0742809	0.0026343
Deviation of the average values (%)		-11.4%	-14.1%
Statistical significance level (α_{calc})			
Variance analysis		0.293	0.245
Mann-Whitney criterion		0.696	0.429

The lower variability level in the calculated emission values (standard deviation, cluster 2) is explained by the averaged approach to each recognizable vehicle, which does not take into account its individual characteristics. The lower level of the average calculated emission values follows from the focus only on the traffic flow, which does not take into account the emissions of the urban industrial enterprises.

4 CONCLUSIONS

The considered approach based on the use of neural network algorithms for identifying traffic flows and calculating its polluting emissions can serve as the basis for building a unified urban system of environmental monitoring determined by the traffic flows. In a local format, such a system is in high demand among several industrial enterprises that need to separate the polluting emissions of the enterprise itself and its surrounding traffic arteries to minimize “environmental” fines.

We confirmed the identity of the calculated estimates of polluting emissions by the neural network method and the laboratory measurements of the Environmental Monitoring Centre based on the statistical analysis of a small sample of data recorded during three working days of the winter weeks. In this case, the relative error of calculating the emissions by the neural network method is 12.0% for carbon oxide CO and 29.7% for sulphur dioxide SO_2.

Further improvement of the methodology based on the use of neural network algorithms ensures the expansion of its abilities to calculate all types of polluting emissions, especially the most pressing emissions of suspended particles of various fractions, integrally determined by several factors - brake pads, tire wear, average traffic flow speed, as well as the quality of the roadbed. An analysis of the influence of the current factors of the meteorological situation on traffic arteries on the polluting emissions is also a relevant area of further research.

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