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INFORMATION TECHNOLOGY OF VIDEO DATA PROCESSING FOR TRAFFIC INTENSITY MONITORING

Traffic jams are a huge problem for all road users and are caused by increasing traffic intensity and poor quality of traffic management systems. The systems that control traffic flows and decide to change parameters must receive reliable and up-to-date data on traffic intensity. In order to accurately determine the traffic intensity, a system of automated video data processing from video surveillance cameras of the traffic lane is developed. The traffic intensity is determined by the method of obtaining the traffic congestion coefficient (TLCR) according to the data, gained by processing the video frame using the U-Net neural network, and the following transformation of TLCR time series into traffic intensity time series. The new in formation technology implements an image processing algorithm to detect the presence of vehicles in a certain section of road, a method of determining the congestion of the lane (TLCR) and a method of determining the intensity of successive values of congestion of the lane. The experimental results show that the proposed information technology is able to identify traffic intensity with an accuracy of 99,35 percent.

Keywords: *image analysis, traffic intensity, traffic congestion index, TLCR, neural network.*

Introduction

Road congestion is a huge problem for all road users and is caused by increasing traffic intensity, low traffic capacity and, at the same time, poor quality of traffic management systems. Traffic intensity is the most important factor influencing road safety. Its value is used in planning and conduction of road construction works on highways, development plans and measures for the growth of the road network, determining the amount of investment in the road industry [1]. The systems that control traffic flows and decide to change control parameters must receive reliable and up-to-date data on traffic intensity. Therefore, one of the most important tasks is data collection, because the quality of the system as a whole depends on the correctness of the determination of traffic indicators.

The Road Design Guide indicates 10 percent growth rate for all national roads annually [2]. The correspondence of this value to the actual growth rate can be assessed only if the analysis of the growth rate is performed on the basis of actual traffic data, as the increase in traffic intensity is not constant in different areas. Therefore, the requirement of up-to-date traffic data and proper data analysis is necessary to achieve reliable traffic characteristics.

There are various methods for determining the traffic intensity on highways including contactmechanical, magnetic-inductive, visual, combined methods, etc. In Ukraine, visual accounting is used to determine the traffic flow intensity [3].

In work [4], the authors use GPS data to determine the intensity. The information received in real time was presented as a sequence of pairs of the physical coordinate and the serial number of the vehicle. The disadvantage of this method is the inaccuracy of determining the coordinates due to errors in navigation systems. As a result, the data obtained may not coincide with the location of the vehicle in reality and lead to incorrect determination of the intensity as a whole.

In work [5], a full-fledged INFOPRO Video Detector device was proposed for vehicle accounting. The device captures various characteristics of traffic, including the average speed of cars, traffic intensity and the interval between cars. The disadvantage of the system is the high cost and the need to install the device in the study areas at a specially designated height, instead of using cameras.

In work [6], the authors propose to use visual accounting, and only then based on the actual values of intensity to apply a mathematical model in the form of functional dependence, taking into account the month, day of the week, time of day and holiday. To assess the adequacy of the proposed method, the authors used Fisher's *F*-test. The disadvantage is the need to reconduct visual accounting in a short period of time, because the number of vehicles on the roads is constantly growing and the data obtained earlier will no longer be relevant. Emergencies, such as an accident or a traffic light malfunction, are also not taken into account.

In work [7], reverse parsing is used to determine cars from images obtained from the Earth observation satellite Radarsat-2 — a physical phenomenon in which light from a flash is repelled back into the lens, causing bright spots between the flash and the main object [8]. The authors state that this method allows to correctly detect up to 90% of vehicles, which makes it possible to use it to monitor traffic. However, the method has a significant disadvantage, namely, a vehicle whose size is smaller than the image expansion is difficult to detect.

In work [9], images from video cameras are used to determine the number and speed of vehicles. Image segmentation is performed using a method based on neural architecture [10].

The purpose of this study is to increase the accuracy of determining the traffic intensity based on the analysis of video data in real time through automated processing of video data obtained from video surveillance cameras in the lane. The new technology is based on an image processing algorithm to detect the presence of vehicles in a certain section of road, a method of determining the congestion of the lane (TLCR) and a method of determining the intensity of successive values of congestion of the lane.

Methods and Tools

The following technical devices were used to implement the information technology for determining the intensity of traffic: a video surveillance camera and a computer connected to the Internet.

The process of determining the intensity of traffic in the video consists of the following stages:

- data collection from a video surveillance camera;
- convert video to a sequential set of images;
- image segmentation for vehicle selection;
- distribution of vehicles in traffic lanes;
- determining the TLCR load for each lane in each image;
- determination of traffic intensity from congestion indicators;
- determining the overall load;
- record indicators in the database.

The software consists of the following modules:

- Data collection module.
- Image processing module (segmentation).
- The module for determining the load index.
- Module for determining the intensity of traffic.

The following tools were used in software development: python programming language, SQLite database, and libraries tensor flow, OpenCV, NumPY, PySide.

Image Processing

Data from the website videoprobki.ua were obtained for the study. The U-Net neural network

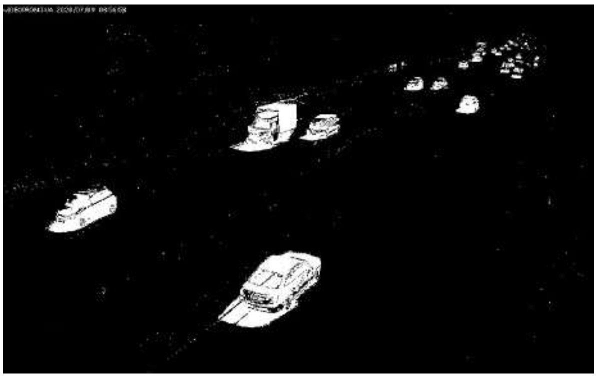


Fig. 1. The result of image processing of the U-NET lane

Fig. 2. The area selected to determine the congestion of the lane

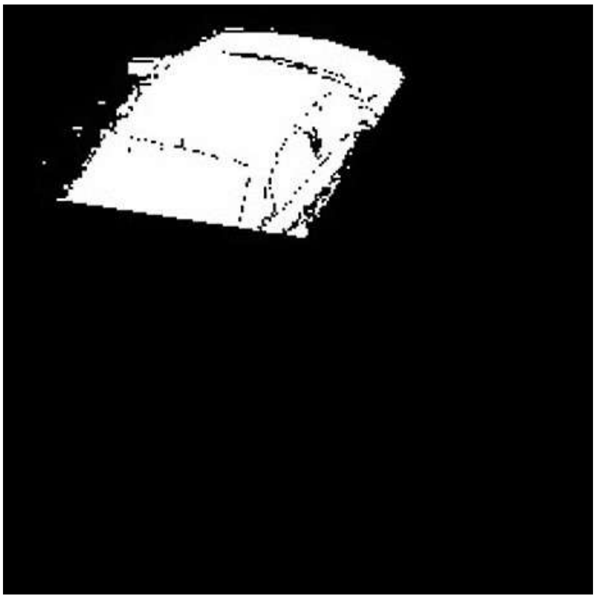


Fig. 3. The result of the conjunction operation

is implemented for image processing. The neural network solves the problem of segmentation, which allows you to select pixels that have common visual characteristics [12]. Typically, such neural networks are used to process biomedical images, because its training does not require a large amount of data [13]. The result of image processing of the lane by the neural network is shown in Fig. 1.

To determine the intensity of traffic, the congestion coefficient of the traffic lane (TLCR), determined by formula firstly proposed in work [12], should be found:

$$C = \frac{\sum_{i \in A} V_i}{255 \cdot |A|}, \quad (1)$$

where i is the pixel index of the region A; $|A|$ is the number of pixels of the region A, Vi is the value of the i-th pixel, C is determined in the interval [0, 1] through the coefficient 1/255.

When determining the load index, it is important to correctly select the area corresponding to the lane. Cars passing on adjacent lanes, depending on the geometric properties and angle of the came-ra can be counted as cars moving in the study area. The angle of the camera does not always allow the use of a rectangle as an area corresponding to the part of the lane of formula 1. It was decided to improve the algorithm, using any quadrilateral instead of a rectangle. An example is shown in Fig. 2.

To determine the number and sum of pixel values in the selected lane area, the following algorithm is used:

- In the first step, an image of the same size as the original is created, and we place a figure on it that corresponds to the studied area of the lane.
- In the second step, the rectangle 1 around the shape is approximated using the boundingRect function of the OpenCV library [14] and the second rectangle 2 is cut out of the processed image using the neural network.
- The next step is the conjunction operation for rectangles 1 and 2, the result of which is the rectangle 3 (Fig. 3).
- The number of pixels in the selected area is determined in the fourth step by the number of non-zero pixels in the rectangle 1.

- The last step is summing pixel values in rectangle 3 using the sumElems function of the OpenCV library.

Fluctuations in the values of the TLCR load index are used to determine the intensity. The vehicle is credited if the TLCR value determined from the current frame is greater than the threshold value, and the TLCR value from the previous frame is less than the threshold value. To correctly determine the intensity, it is important that there is not more than one vehicle in the study area. Otherwise, fluctuations in TLCR values in a dense flow of cars will not be recorded. It is also important that the study area is not too small, because the asymmetry of parts of the vehicle can lead to erroneous fluctuations in a load. The intensity of traffic is determined by the formula:

$$I(A)=\frac{1}{T}\sum_{t=2}^{n}\begin{cases}1 \text{ if } & (c_t>k)\wedge(c_{t-1}\le k),\\ 0 \text{ other } & wise,\end{cases} \quad (2)$$

where T is the observation interval; c is the array of lane load factor (TLCR), k is the threshold value, c_t is one of the successive TLCR values over time.

To determine the threshold value, the root mean square error is calculated from the test sequence data, which is also known as the criterion of regularity [15]:

$$K=\frac{\sum_t\left(c_t^{real}-c_t^{model}\right)^2}{\sum_t\left(c_t^{real}\right)}, \quad (3)$$

where c_t^{real} is an actual value of intensity, c_t^{model} is a calculated value of intensity.

Determining the best threshold consists of the following steps:

- Carrying out visual accounting and determining the actual intensity of traffic for 2 hours. Each value is an intensity for 1 minute.
- Division of data into two parts: part A (data sequence) and part B (test sequence).
- Determination of the best values of k (threshold value) using the criterion determined on the training sequence of data in the selected interval by formula (3). The interval from 0,05 to 0,5 with a step of 0,005 is selected.
- Determination of the best value of k using the criterion determined on the test sequence of data.

For experimental data, the best threshold value k = 0,155 was obtained, the corresponding values of the criterion on the training and test sequences of data are 0,001375 and 0,000064, which indicates a fairly high accuracy of the model.

Evaluation Index

In [16], to assess the average performance of a video traffic system, the use of four indicators was proposed: Accuracy, Recall, Precision and *F-measure*. Accuracy is used to estimate the difference between the calculated value and the true value, which can be defined as:

$$Accuracy=1-\frac{|Counted-True|}{True}, \quad (4)$$

where ***True*** is the actual number of vehicles and *Counted* is the calculated number.

Recall is a measure of a method's success in identifying relevant objects in a set, that is, the percentage of relevant objects detected in all relevant objects, while Precision is the percentage of relevant objects detected in all projects. The *F-measure* is the weighted average harmonic mean of Recall and Precision, which combines the results of Recall and Precision. Three indicators can be defined as:

$$Recall=\frac{TP}{TP+FN},\quad Precision=\frac{TP}{TP+FP}, \quad (5)$$

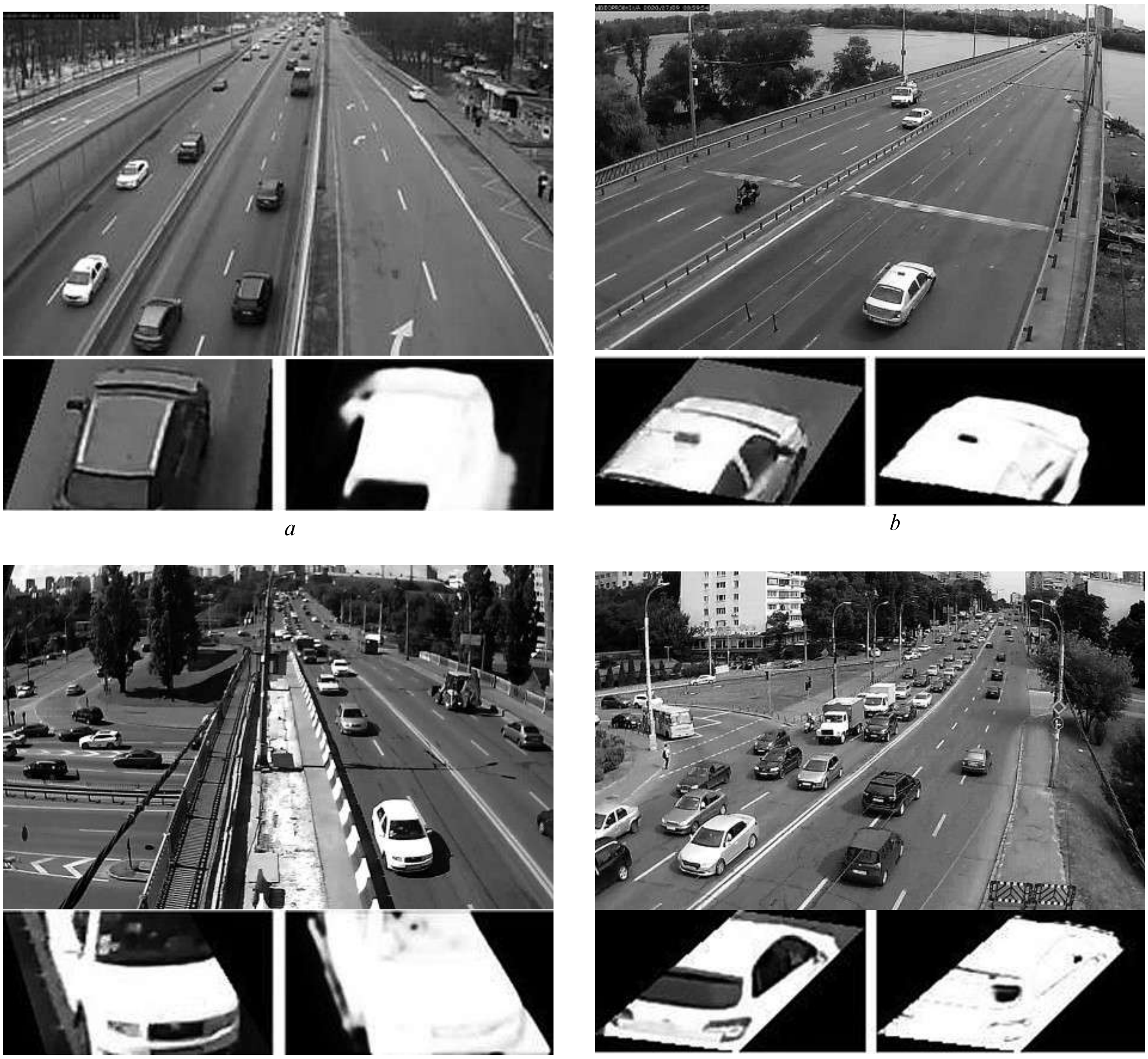
$$F\text{-}mesure=2\cdot\frac{Recall\cdot Precission}{Recall+Precission}, \quad (6)$$

where TP is the number of true positive results (vehicles that have been successfully counted), FN is the number of false negatives (vehicles that should have been counted but were't), and FP is the number of false positive results (false volumes). objects that were credited as vehicles). Using TP, FN and FP, *True*, *Counted*, *Accuracy* can also be expressed as:

$$True=TP+FN,\quad Counted=TP+FP. \quad (7)$$

$$Accuracy=1-\frac{|FN-FP|}{TP+FN}. \quad (8)$$

According to the work [16], Accuracy can only estimate the total difference between the calculated values and the actual values, and cannot reflect



a *b* *c* *d*

Fig. 4. The results of the experiments: *a* — Oleny Telihy Street; *b* — Pivnichnyi Bridge; *c* — Povitroflots'kyi Bridge, camera No. 1; *d* — Povitroflots'kyi Bridge, camera No. 2

errors in the interpretation of noise as a vehicle or errors in the detection of the missing ones. Worse situation would be that, the outcome of Accuracy may approach 1.0 when the numbers of these two mistakes are close to or even equal. Therefore, a comprehensive analysis of accuracy and *F-measure* may be more scientific to assess the effectiveness of the method.

The Experimental Results

The research results are presented in Table 1—4 and in Fig. 5. All four performance indicators *Recall*, *Precision*, *F-measure* and *Accuracy* for the camera on the Oleny Telihy Street is equal to 1,0, which means that all vehicles were correctly identified (Fig. 4,*a*, Table 1).

Table 1. **Calculation results of the Oleny Telihy Street**

Lane	True	Counted	TP	FN	FP	Recall	Precision	*F-measure*	Accuracy
Lane 1	207	207	207	0	0	1,0	1,0	1,0	1,0
Lane 2	161	161	161	0	0	1,0	1,0	1,0	1,0
Total	368	368	368	0	0	1,0	1,0	1,0	1,0

Table 2. **Calculation Results of the Pivnichnyi Bridge**

Lane	True	Counted	TP	FN	FP	Recall	Precision	*F-measure*	Accuracy
Lane 1	202	200	200	2	0	0,9901	1,0	0,9950	0,9901
Lane 2	223	219	219	4	0	0,9821	1,0	0,9910	0,9821
Total	425	419	419	6	0	0,9859	1,0	0,9929	0.9859

Table 3. **Calculation Results of the Povitroflots'kyi Bridge, camera No. 1**

Lane	True	Counted	TP	FN	FP	Recall	Precision	*F-measure*	Accuracy
Lane 1	266	265	265	1	0	0,9962	1,0	0,9981	0,9962
Lane 2	303	301	301	2	0	0,9934	1,0	0,9967	0,9934
Total	569	566	566	3	0	0,9947	1,0	0,9974	0.9947

Table 4. **Calculation Results for the Povitroflots'kyi, camera No. 2**

Lane	True	Counted	TP	FN	FP	Recall	Precision	*F-measure*	Accuracy
Lane 1	170	169	169	1	0	0,9941	1,0	0,9971	0,9941

For the camera on the Povitroflots'kyi Bridge, the value of the *F-measure* is 0,9929, and the accuracy is 0,9859. Six objects were missed among 419 correctly defined goals (Fig. 4,*b*, Table 2). For the camera No. 1 on the Povitroflots'kyi Bridge the value of the *F-measure* is 0,9974, and the accuracy is 0,9947.Three objects were missed among 569 correctly defined goals (Fig. 4,*c*, Table 3). For the camera No. 2 on the Povitroflots'kyi bridge one object was missed (Fig. 4,*d*, Table 4).

In all cases, the errors occurred due to the fact that the car was passing between the lanes and therefore two cars got into the frame at once. In this case, the TLCR does not fall below its threshold value and the system assumes that the previous car has not passed yet and therefore the vehicle is not erroneously credited (Fig. 5).

Discussion

We compared the basic indicators of our proposed system with the similar methods, which are presented in [16]. The obtained comparison results are presented in Table 5. With a comparable number of analyzed vehicles, it was found that the accuracy is higher in Y. Chen [16], although the total number of errors is 21 among which10 are missed vehicles and 11 are erroneously calculated. Thus, the values in formula (8) are compensated and as a result only one erroneous value will be taken into account. While the *F-measure*, which takes into account missing and erroneously calculated values, is more reliable for determining the accuracy of the system. In work [16] the *F-measure* is lower.

In total, 1522 vehicles were correctly identified in the experiment and 10 vehicles were missed. The only reason for missing cars is a traffic between lanes of the highway. [16] also mentions poor lighting and the movement of large and long cars, which can block smaller cars, as causes of errors. We did not find such causes in our study, although this may be the subject of future research. The obtained values of the *F-measure* 0,9967 and the Accuracy 0,9935 demonstrate the high reliability of determining the traffic intensity of the developed system.

a

b

Fig. 5. The examples of erroneously not included vehicles: *a* — Povitroflots'kyi Bridge, camera No. 1; *b* — Povitroflots'kyi Bridge, camera No. 2

Conclusions

In this study, a technology for determining the traffic intensity based on video data coming from a video surveillance camera is developed. The advanced algorithm for determining the congestion coefficient TLCR transport section makes it possible to take into account only cars moving in the studied lane. A method for determining traffic intensity based on congestion coefficient time seriesis developed.

The sequence of data processing and transformations constitute a new information technology for determining the intensity of traffic, and provides high accuracy in estimating the intensity of traffic on the road. The proposed system successfully calculated high-performance vehicles, for example, the average values of *F-measure* and accuracy reached 0,9967 and 0,9935, respectively.

Further research requires the development of a software module that implements an algorithm to predict the traffic intensity taking into account the entire data set.

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ІНФОРМАЦІЙНА ТЕХНОЛОГІЯ МОНІТОРИНГУ ІНТЕНСИВНОСТІ ДОРОЖНЬОГО РУХУ ЗА ДАНИМИ ВІДЕОРЯДУ

Вступ. Затори на дорогах є величезною проблемою для всіх учасників дорожнього руху і причиною їх є зростаюча інтенсивність руху та незадовільна якість систем управління транспортним рухом. Системи, що управляють транспортними потоками та приймають рішення про зміну параметрів управління, мають отримувати достовірні та актуальні дані про інтенсивність трафіку. З метою точного визначення інтенсивності транспортного руху було розроблено систему автоматизованої обробки даних відеоряду з камер відеоспостереження смуги дорожнього руху. Інтенсивність транспортного руху визначається розробленим методом отримання показника завантаженості транспортного руху (*TLCR*) за даними, отриманими в результаті обробки кадру відеоряду з використанням нейромережі *U-Net*. Результати досліджень демонструють, що запропонована методика здатна підраховувати транспортні засоби з точністю 99,35 відсотків.

Мета статті. Метою дослідження є підвищення точності визначення інтенсивності руху на основі аналізу відеоданих у режимі реального часу шляхом автоматизованої обробки відеоданих, отриманих від камер відеоспостереження у смузі.

Методи. Розпізнавання образів, моделювання, штучний інтелект, аналіз даних.

Результати. Розроблено інформаційну технологію визначення інтенсивності дорожнього руху за даними відеоряду, що надходять з відеокамери спостереження. Запропонована система успішно підрахувала транспортні засоби з високою продуктивністю, наприклад, середні значення *F*-міри та точність досягли 0,9967 та 0,9935 відповідно.

Висновки. У даному дослідженні розроблено технологію визначення інтенсивності дорожнього руху за даними відеоряду, що надходять з відеокамери спостереження. Удосконалений алгоритм визначення показника завантаженості транспортної ділянки *TLCR* надає можливість враховувати тільки автомобілі, які рухаються по досліджуваній смузі. Розроблений метод визначає інтенсивність дорожнього руху на основі послідовних значень показника завантаженості.

Послідовність обробки та перетворень даних складають нову технологію визначення інтенсивності дорожнього руху, що забезпечує високу точність оцінки інтенсивності руху транспортних засобів на ділянці дорожнього руху. Запропонована система успішно підрахувала транспортні засоби з високою продуктивністю, наприклад, середні значення *F*-міри та точність досягли 0,9967 та 0,9935 відповідно.

У подальших дослідженнях необхідна розробка програмного модуля, який реалізує алгоритм прогнозування показника завантаженості з урахуванням усього набору даних.

Ключові слова: *аналіз зображень, інтенсивність транспортного руху, показник завантаженості транспортного руху, TLCR, нейромережа.*

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ИНФОРМАЦИОННАЯ ТЕХНОЛОГИЯ МОНИТОРИНГА ИНТЕНСИВНОСТИ ДОРОЖНОГО ДВИЖЕНИЯ ПО ДАННЫМ ВИДЕОРЯДА

Введение. Пробки на дорогах являются огромной проблемой для всех участников дорожного движения, и причиной их является растущая интенсивность движения и неудовлетворительное качество систем управления транспортным движением. Системы, управляющие транспортными потоками и принимающие решение об изменении параметров управления, должны получать достоверные и актуальные данные об интенсивности трафика. С целью точного определения интенсивности транспортного движения была разработана система автоматизированной обработки данных видеоряда с камер видеонаблюдения полосы дорожного движения. Интенсивность транспортного движения определяется разработанным методом получения показателя загруженности транспортного движения (*TLCR*) по данным, полученным в результате обработки кадра видеоряда с использованием нейросети *U-Net*. Результаты исследований показывают, что предложенная методика способна подсчитывать транспортные средства с точностью 99,35 процентов.

Цель статьи. Целью исследования является повышение точности определения интенсивности движения на основе анализа видеоданных в режиме реального времени путем автоматизированной обработки видеоданных, полученных с камер видеонаблюдения полосы.

Методы. Распознавание образов, моделирование, искусственный интеллект, анализ данных.

Результаты. Разработана информационная технология определения интенсивности дорожного движения по данным видеоряда, поступающим с видеокамеры наблюдения. Предложенная система успешно подсчитала транспортные средства с высокой производительностью, например, средние значения *F*-меры и точность достигли 0,9967 и 0,9935 соответственно.

Выводы. В данном исследовании разработана технология определения интенсивности дорожного движения по данным видеоряда, поступающим с видеокамеры наблюдения. Усовершенствованный алгоритм определения показателя загруженности транспортного участка *TLCR* позволяет учитывать только автомобили, которые движутся по исследуемой полосе. Разработан метод определения интенсивности дорожного движения на основе последовательных значений показателя загруженности.

Последовательность обработки и преобразований данных составляет новую технологию определения интенсивности дорожного движения и обеспечивает высокую точность оценки интенсивности движения транспортных средств на участке дорожного движения. Предложенная система успешно подсчитала транспортные средства с высокой производительностью, например, средние значения *F*-меры и точность достигли 0,9967 и 0,9935 соответственно.

В дальнейших исследованиях необходима разработка программного модуля, который реализует алгоритм прогнозирования показателя загруженности с учетом всего набора данных.

Ключевые слова: *анализ изображений, интенсивность транспортного движения, показатель загруженности транспортного движения, TLCR, нейросеть.*