Integration of Computer Vision and IOT Into an Automatic Driving Assistance System for "Electric Vehicles"

Sizhuo Du, Jiayan Zhang, Yubo Wang, and Zeyu Li

***Abstract*—The study resulted in the main trends of neural network training and an analysis of potential problems arising in the development of such networks. The research resulted in obstacle data harvesting algorithms and data transmission methods to a neural network, as well as an optimal learning algorithm. They trained the neural network using continuous data and time series data, sensor readings, image processing modules, machine learning and deep learning modules, local, peripheral, and cloud resources. The article presents a road obstacle detection and avoidance system based on a neural network. Testing the developed model resulted in a high identification level of pedestrians, reaching 88%. These values were 91%, and 94% for cars and roadways, respectively. The developed model had object recognition limits at distances up to 70 m behind and in front of the car and 6 m on its sides. The minimum distance was 1.6 m for image segmentation.**

***Index Terms*—Network performance evaluation, network performance modeling, networks.**

I. Introduction

According to World Health Organization[1] every year the lives of approximately 1.3 million people are cut short as a result of road traffic crash. Between 20 and 50 million more people suffer non-fatal injuries, with many incurring a disability as a result of their injury. Road traffic crashes cost most countries 3% of their gross domestic product. The main sources of road accidents are speeding, driving under the influence of alcohol and other psychoactive substances, nonuse of motorcycle helmets, seat-belts, and child restraints, distracted driving, unsafe road infrastructure, unsafe vehicles, inadequate post-crash care, inadequate law enforcement of traffic laws. Currently, more than 20% of cars have access to a communication system that combines safe driving and automotive safety functions. Using neural network technologies is advisable to recognize graphic objects and improve traffic safety. The literature contains many technologies to improve traffic safety, in particular, Driver Attention Monitoring Systems. In this regard, they use algorithms that consider the time of day, weather, global positioning system (GPS) coordinates, traffic congestions and drivers' physical conditions, sleep duration, blood pressure, and pulse. Petri nets provide with a solution. There are plans to integrate the proposed algorithm into mobile applications that allow sending notifications to focus drivers' attention. Of course, such a method cannot be used for unmanned road transport projects. Projects that involve the development of "smart driver assistants" are of greater interest. Such systems allow removing the human factor from driving. Therefore, the detection and avoidance of obstacles is an actual function of the vehicle automatic pilot systems. Many industries use special robotic devices that can recognize graphic objects. Unmanned robotic harvesters and drones use such devices as well. Calculating a safe vehicle path is the basis of their algorithms.

A. Literature Review

Ensuring safe robot cars is an urgent task concerning an automated driving assistant or for unmanned vehicles [12]. Reducing road collisions and accidents, ensuring the mobility of elderly and disabled people, improving road traffic, saving fuel and reducing emissions of harmful substances are the most important areas to derive benefit from using autonomous vehicles [20]. Many artificial intelligence and Internet of Things (IoT) researchers focus on edge computing. This technology aims at network overload handling, relaxation processes, etc. Edge computing allows processing computer vision data and video without uploading to cloud storage or file sharing, which significantly reduces the cost of data transmission [18]. The infrastructure of smart cities involves regulating traffic and improving road safety, reducing environmental problems, interacting with cloud platforms, supporting IoV services and automotive cloud platforms [13]. This system is especially relevant for developing countries

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[1][Online]. Available: https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries)

[16]. Integrated smart city network systems can use and process IoV data to provide intelligent traffic management. This system assumes feedback between IoV objects and drivers. In particular, the researchers discuss the application of such a system using Egypt as an example [2].

The following types of data exchange are used to optimize monitoring systems [5]: Vehicle-to-Vehicle (V2V) and V2I/I2V, where V2I is Vehicle-to-Infrastructure, and I2V stands for Infrastructure-to-Vehicle. Such communications significantly reduce the margin of error [8]. Since today the communication relies on many standards, research centres execute many projects to answer the question of which standard is the best or how to combine different systems to get the best effect [11]. It should be clearly stated here that unmanned vehicles do not use telecommunication systems. V2V or V2I/I2V data exchange research programmes appeared much earlier, both in the USA and in Europe. They are now commonly called "Connected Car" (USA) or "Cooperative Intelligent Transport Studies" [14]. The idea is connected with the development of active safety systems for cars. There are examples, which include navigation, early detection and accident prevention systems [15]. It is worth noting that the V2V and V2I/I2V communication should be focused not only on AV vehicles to use information more effectively. The communication system should also include nonautonomous vehicles if they use infotainment devices [23]. It will allow transferring information more effectively and quickly, and increasing the corresponding security. The concept of data transmission between vehicles is very important to develop autonomous vehicles, as well as between vehicles and the road infrastructure [6]. First, the idea of autonomous driving is based on an intimate knowledge of the space and topography of the terrain through which vehicles move. This requires updating information constantly in real time, and considering information received from other vehicles [23]. Thus, the researchers solve the problem of a static digital map, which often becomes outdated at the time of loading into a navigation system. Therefore, multilayer depth maps are widely used [7]. Based on a multilayer distance map, autonomous robots, in particular vehicles controlled by computer algorithms, can determine not only the location of objects directly in front of them, but also objects located further away [1]. Thus, it is also possible to enable a manoeuvre to evade another object simultaneously located at a greater distance than the first object to be evaded, for example, during an evasive manoeuvre [17]. It is also necessary to separate the frequency bands intended only for direct communication in V2V and V2I/I2V modes [24]. In addition to reducing the data transmission time, this allows reducing the number of errors in the vehicle environmental monitoring system [10]. Information can be obtained from sensors mounted on nearby vehicles, and it allows drivers keep on driving if external sensors fail [22], [25]. The problem of road safety also necessitates the need to update the software of on-board systems [21].

The motivation and novelty of this study are the following: based on the analysis of literature sources, it can be concluded that a sufficiently large number of applications for the automatic movement of cars have been developed at present. However, almost no one has dealt with the issues of the automatic movement of electric cars, especially when using self-learning programs.

B. Research Objective

There are driver assistance devices on the market, and some vehicles are equipped with automatic pilot systems and are used for passenger transportation. Nevertheless, electric vehicles must combine computer vision and the Internet of Vehicles (IoVs) into an automatic driver assistance system. This integrated system must be self-learning. Using sensors is important to locate obstacles in space more accurately, as well as image recognition tools from streaming video must be applied.

This article aims at integrating computer vision and IoT (IoV) to ensure the safety of electric vehicles. The researchers set the following tasks in the furtherance of this goal.

1) To develop a digital vehicle movement model for roads with obstacles.
2) To develop a neural network for recognizing obstacles using computer vision and IoT (IoV).
3) To carry out a statistical assessment of experimental and theoretical data.

II. Methods and Materials

To develop a crash avoidance system based on real-time IoV videos, the researchers planned to use images from infrastructure cameras, but we used only the scenario of vehicle movement in the article. They built a test vehicle using Unity Vehicle Physics to reproduce its behaviour. They used the Unity ML Agents plugin for our neural network, a test highway in the Unity Environment and the YOLO v2 neural network based on Resnet50 [3]. According to Lin et al. [26] although many tricks are used to improve the performance of YOLO v2, the detection effect on small objects is still not well improved.

YOLO is a new approach to object detection. Prior work on object detection repurposes classifiers to perform detection. Instead, it is necessary to frame object detection as a regression problem to spatially separated bounding boxes and associated class probabilities. A single neural network predicts bounding boxes and class probabilities directly from full images in one evaluation. Since the whole detection pipeline is a single network, it can be optimized end-to-end directly on detection performance.

This unified architecture is extremely fast. Base YOLO model processes images in real-time at 45 frames per second. A smaller version of the network, Fast YOLO, processes an astounding 155 frames per second while still achieving double the mAP of other real-time detectors. Compared to state-of-the-art detection systems, YOLO makes more localization errors, but is far less likely to predict false detections where nothing exists. Finally, YOLO learns very general representations of objects. It outperforms all other detection methods, including DPM and R-CNN, by a wide margin when generalizing from natural images to artwork on both the Picasso dataset and the people-art dataset [27].

To train the neural network, they used publicly available data from GitHub and TensorFlow in the MATLAB deep learning Toolbox environment.[2]

To eliminate impulsive noise from the footage, we employed an adaptive video filter. The approach is based on estimating local orientation. By minimizing the equation for directional derivatives, the dominating orientation of the pattern in the immediate spatial neighborhood is estimated, and at the same time, its strength is calculated. The suggested technique is superior to other contemporary video noise reduction methods, according to experimental findings, both in terms of objective indicators and visual evaluation [28].

In order to create efficient transformations that transform distorted footage into a natural-looking sequence, we took an innovative technique. This technique offers a practical and effective means of removing distortion from a continuous video clip. The technique maintains straight features and conspicuous objects in a spatiotemporally coherent way, producing output video that looks natural and is simple to view and analyze [28].

We had no special color filters for the camera.

The learning environment presented a direct area with virtual obstacles, into which the car enters. They selected a departure point randomly. The car could move in the positive direction of the coordinate axes. The variables were the speeds of movement and wheel turning angles. The task of the studied neural network was to avoid obstacles on the road and not react to turns. The terrain model was without bends and distortions. The environment consisted of four main elements.

1) A test vehicle that must avoid obstacles. The vehicle was a conventional four-wheeled car with turning front wheels. They limited the wheel-turning angle to an angle of 45°.
2) Obstacles in the form of high cuboids with square bases. In this stimulator, they were static, and we positioned them corresponding to the environment.
3) Limiters that did not allow the car to leave the environment. They arranged the obstacles in a certain order. The car had to recognize them in the same way as ordinary obstacles, which allowed unifying the behaviour of the car without using additional logic to prevent it from leaving the environment.
4) Environmental coverage, which was a large single layer, served as the basis for all neighbouring objects. Each of these environments had the only one moving object, i.e., the test vehicle. The test vehicle contained a component responsible for data collection and control [4].

In this article, we used a method of synchronizing automatically the full-view image and GPS information which were recorded independently, respectively, for route map building. The full-view image sensor was composed of a pair of fisheye cameras. By synchronizing the two image streams of the pair of fisheye cameras a seamless full-view image was acquired; by synchronizing the full-view image with GPS information the full-view image stream was re-sampled uniformly so that the full-view image was registered to a digital map with approximately equal distance along routes [29].

[2] [Online]. Available: https://github.com/matlab-deep-learning

We used a DOMERA SDF6800DN Fisheye camera (8 MP resolution) with the variable mounting concept. This network camera has a fisheye lens specifically designed for the image sensor, allowing it to capture a complete half-space with a 360º panoramic view. DOMERA OS supports secure network authentication (IEEE 802.1X) and encrypted data transmission (TLS 1.2/AES-256). Camera has video compression H.264, H.265, and MJPEG.

Using the predicted tire-road friction coefficient, an AV route planning and tracking framework based on model predictive control were applied. Based on the safety distance between the host vehicle and the obstacle vehicle, which is influenced by both the tire-road friction coefficient and the vehicle speed, the desired path was created [30].

A. Data Collection Algorithms

They generated input data before training the neural network. For the obstacle avoidance system, they used compensation training according to the following algorithms:

$$.f_t = \sigma\left(X_t \cdot U_f + H_{t-1} \cdot W_f\right) \tag{1}$$

$$\bar{C}_t = tg\left(X_t \cdot U_c + H_{t-1} \cdot W_C\right) \tag{2}$$

$$I_t = \sigma\left(X_t \cdot U_i + H_{t-1} \cdot W_i\right) \tag{3}$$

$$O_t = \sigma\left(X_t \cdot U_O + H_{t-1} \cdot W_O\right) \tag{4}$$

$$C_t = f_t \ \left(C_{t-1} + I_t \cdot \overline{C_t}\right) \tag{5}$$

$$H_t = O_t \, tgC_t \tag{6}$$

where f_t is the front valve, I_t is the inlet valve; $\bar{C}_t$ is the candidate level; O_t is the off valve; C_t is the memory of the current LSTM cell; H_t is the output of the current LSTM cell; f_t is the front valve, I_t is the inlet valve; $\bar{C}_t$ is the candidate level; O_t is the off valve; C_t is the memory of the current LSTM cell; and H_t is the output of the current LSTM cell. To collect information about obstacles in a certain sector, we also collected LIDAR data and transmitted them to the neural network concerning the distance to the obstacles and their disposition angle relative to the car.

To study how the obstacle detection system will affect drivers during their interaction with the car, the road tests were carried out. Thirty-two people (17 males, 15 females; mean age: 34 years, range: 20–63 years; and mean annual mileage: 6271 km) were recruited to participate in the article. All participants were experienced drivers with more than two years of driving experience (and driving regularly). Participants were matched evenly by age, gender and driving experience. Participants began the test with normal driving (i.e., they performed their usual primary driving activities). The obstacle detection system became available to drivers ten minutes after the trip has begun. The participants were informed about it by a text message displayed on the system monitor. The drivers always completed the trip by driving as they normally would within the last five minutes of the trip. This driving mode was meant primarily to prepare participants for the driving test later that day.

In the test rides, drivers took the proposed test routes and drove for approximately 30–40 min per day during the working week (five days). Participants had no driving restrictions—they were simply asked to imagine how they might behave in a vehicle

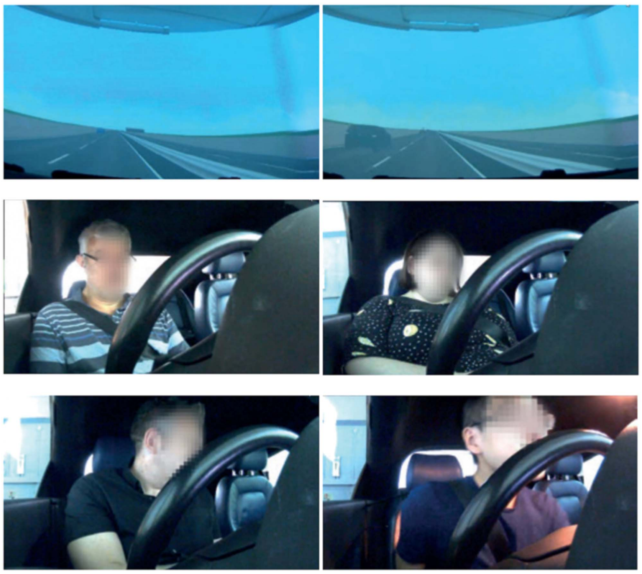

Fig. 1. Screenshot of the video fragment showing the road and the participants.

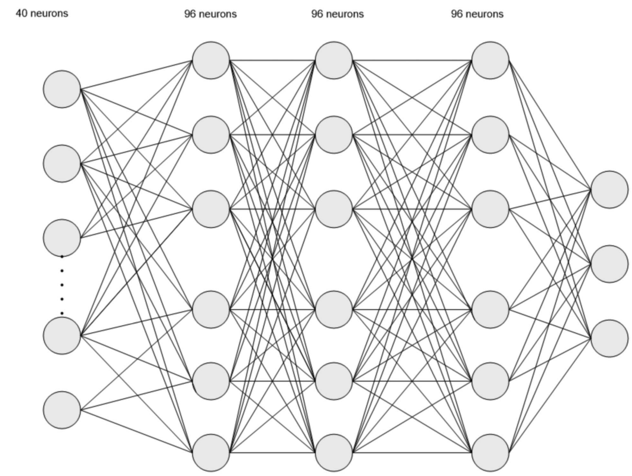

Fig. 2. Neural network diagram.

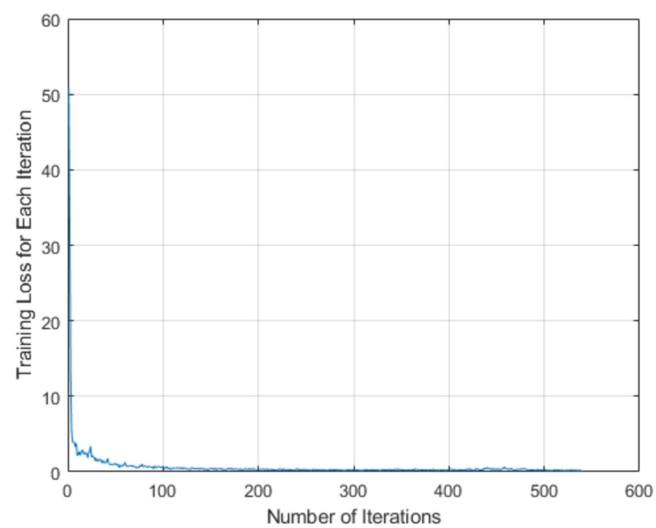

Fig. 3. Result of training the neural network to recognize obstacles.

while commuting or travelling. After each trip, the participants filled out a questionnaire where they rated the performance of the obstacle detection system. In addition, both external and internal video cameras have been recording throughout the study (see Fig. 1), providing insight into both driver behaviour and how it changed over the course of the trip and the week. The videos were also used to extract important visual indicators (road checking, mirror checking, etc.).

III. Results

To combine computer vision and the IoTs into a single system, the researchers used a neural network consisting of two subnets – a feature extraction network and a detection network. A pre-trained CNN ResNet-50 was the feature extraction network. A small CNN was the detection subnet, consisting of several convolutional layers and YOLO v2 specific layers.

It consisted of an input layer containing 40 *neurons* corresponding to data collected from their observations; three *hidden layers*, which used the ReLU activation function, each with 96 neurons, and an *output layer* consisting of the number of neurons corresponding to the number of actions of the three, with the linear activation function (see Fig. 2). This structure was based on some neural networks used for similar purposes. However, they adapted the test parameters to the research problem using empirical tests. Its basic version participated in determining the movements of vehicles, and we used it in the learning process as a neural network for predicting movements based on the current state. On the other hand, an additional model, called the target model, predicted actions based on readings from the second sensor. The analysed record contained readings stored in the movement memory. Overwriting the weight values from the base model to the target one updated this network each time. It happened after the end of an episode (it was an attempt of the robot to reach its goal, interrupted when it ran into an obstacle or exceeded the number of steps taken). Using the two neural networks to implement the deep Q-learning algorithm increased stability and efficiency of the learning process (see Fig. 3 and Table I).

It follows from Table II that the presented experimental data have high general performance. However, data clustering shows that the system poorly distinguishes several classes of images such as signs, pillars, and trees. The metrics for pedestrians, cyclists, and cars were accurate, as follows from Table III. They determine objects such as roadbed, sky, and buildings with a very high degree of accuracy. To increase the accuracy of the model, it is necessary to enrich the gallery of additional samples representing intermediate image classes.

The technology the researchers have developed will allow them to localize obstacles, recognize cars, pedestrians, especially in unexpected and forbidden places. Then, an application can warn drivers in advance, and they will be able to respond adequately to obstacles (see Fig. 4).

TABLE I
TRAINING THE NEURAL NETWORK TO RECOGNIZE OBSTACLES

No.	Iteration	Time Elapsed	Mini-batch RMSE	Mini-batch Loss	Base Learning Rate
1	1 1	00	7.13	50.8	1E-3
2	30	00:01	1.35	1.8	1E-3
4	60	00:14	1.13	1.3	1E-3
5	90	00:27	0.64	0.4	1E-3
7	120	00:39	0.65	0.4	1E-3
5	150	00:51	0.72	0.5	1E-3
10	180	01:04	0.52	0.3	1E-3
12	210	01:16	0.45	0.2	1E-3
14	240	01:28	0.61	0.4	1E-3
15	270	01:41	0.43	0.2	1E-3
17	300	01:52	0.42	0.2	1E-3
I8	330	02:05	0.52	0.3	1E-3
20	360	02:17	0.43	0.2	1E-3
22	390	02:29	0.43	0.2	1E-3
24	420	02:42	0.59	0.4	1E-3
25	450	02:54	0.61	0.4	1E-3
27	480	03:06	0.65	0.4	1E-3
29	510	03:18	0.48	0.2	1E-3
30	540	04	0.34	0.1	1E-3

TABLE II
IMAGE RECOGNITION AND SEGMENTATION RESULTS

	Accuracy	IoU	MeanBFScore	t-test	X^2	SSD
Bicyclist	0.8784545	0.60792	0.55089	0.000789	0.987827	0.589347
Building	0.784554	0.214577	0.914565	0.002002	0.989838	0.901307
Car	0.90956	0.70875	0.458402	0.0032	0.99978	0.649606
Fence	0.81507	0.76696	0.70919	0.007367	0.99983	0.58891
Pavement	0.884566	0.76799	0.45466	0.008338	0.999832	0.655089
Pedestrian	0.87629	0.458566	0.69244	0.013596	0.999845	0.626944
Pole	0.71586	0.70571	0.76424	0.03565	0.999985	0.523387
Road	0.940245	0.49409	0.45645845	0.032208	0.999985	0.635604
SignSymbol	0.79458	0.58511	0.514549	0.064288	1.00	0.492065
Sky	0.94112	0.90209	0.76098	0.203708	1.00	0.436496
Tree	0.87477	0.60829	0.8952	0.07367	1.00	0.43786

Fig. 5 shows an example of such an algorithm. The model considered three obstacles. It ignored the other four because it did not fit into the trajectory of the object. Thus, the trajectory and speed of the model will be adjusted to ensure safe movement.

The figure shows three projections of the display at time $\tau = 18$ s. The green lines indicate the contours of the models. Once an object comes onto the radar, the system identifies and highlights it with an orange outline. There are also orange dots inside the detections, representing a cloud of dots, indicating obstacles. The purple highlight is for segmented road sections. The system highlights in blue a set of points, which it does not consider.

The simulated model parameters showed the following values in MATLAB.

TABLE III
STATISTICAL EVALUATION OF IMAGE RECOGNITION AND SEGMENTATION RESULTS

	MEAN var 1-10	MEDIAN var 1-10	SD var 1-10	VALI D_N var 1-10	SUM var 1-10	MIN var 1-10	MAX var 1-10	_25t h% var 1-10	_75t h% var 1-10
Bicyclist	28.26	0.74	55.16	4.00	113.04	0.55	111.00	0.58	55.94
Building	25.98	0.85	50.68	4.00	103.91	0.21	102.00	0.50	51.46
Car	27.77	0.81	54.15	4.00	111.08	0.46	109.00	0.58	54.95
Fence	27.57	0.79	53.62	4.00	110.29	0.71	108.00	0.74	54.41
Pavement	26.78	0.83	52.15	4.00	107.11	0.45	105.00	0.61	52.94
Pedestrian	28.01	0.78	54.66	4.00	112.03	0.46	110.00	0.58	55.44
Pole	26.30	0.74	51.14	4.00	105.19	0.71	103.00	0.71	51.88
Road	26.47	0.72	51.69	4.00	105.89	0.46	104.00	0.48	52.47
Sign Symbol	27.22	0.69	53.18	4.00	108.89	0.51	107.00	0.55	53.90
Sky	25.90	0.92	50.07	4.00	103.60	0.76	101.00	0.83	50.97
Tree	27.09	0.88	52.60	4.00	108.38	0.61	106.00	0.74	53.45

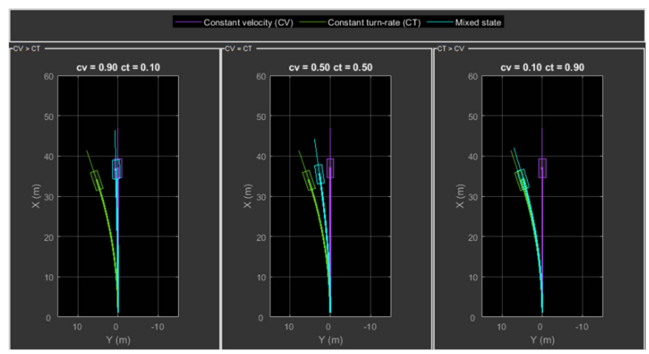

Fig. 4. Integral model with a constant speed of movement and a constant turning rate.

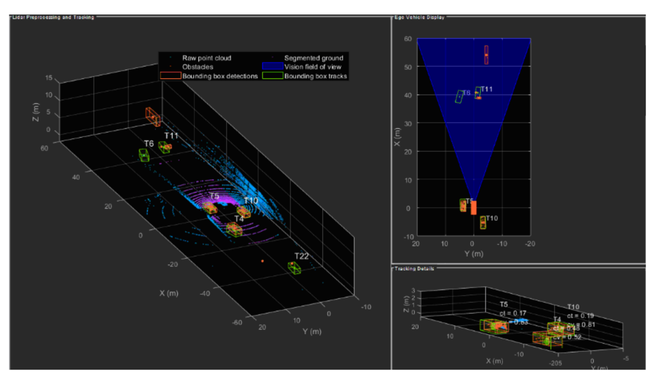

Fig. 5. Obstacle movement recognition and simulation in the path of the car based on the LIDAR data.

1) Limits: [−70 70].
2) YLimits: [−66].
3) ZLimits: [−210].
4) GroundMaxDistance: 0.3000.
5) GroundReferenceVector: [0 0 1].
6) GroundMaxAngularDistance: 5.

7) SegmentationMinDistance: 1.6000.
8) MinDetectionsPerCluster: 2.
9) MaxZDistanceCluster: 3.
10) MinZDistanceCluster: −3.
11) EgoVehicleRadius: 3.
12) MeasurementNoise: [6 × 6 double].
13) MeasurementParameters: [0 × 1 struct].

These results show that the developed application can adequately assess the road situation within a radius of 6 m and identify obstacles up to 70 m in front and behind the car.

The activities undertaken by the participants and their willingness to delegate control to the obstacle detection system gave a good indication of the level of trust that this technology had and its potential acceptance by the participants. The results showed that drivers changed a number of habitual visual control actions while the vehicle was under the control of the proposed system. A video record from day one shows that participants spent approximately 95% of their time with their eyes directed toward the roadway. By the fifth day, more than 20% of the time was devoted to secondary activities (radio or climate control, map viewing, etc). In other words, less than 80% of the time was spent looking directly at the road. These observations were also supported by the subjective assessments made by the participants themselves at the end of each day. Participants reported having a high level of confidence in the proposed obstacle detection system from day one. Moreover, the confidence in and the ratings of the technology increased during the week. Based on the situational awareness ratings, in the first half of the week (Monday to Wednesday), participants experienced a continued day-to-day decrease in demand for their attention and an increase in their understanding of how the obstacle detection system works.

In conclusion, we can say that the model can be trained in a more advanced environment and can make the neural network more statistical. Performance can be improved by introducing multiple sonars. For real life implementation more efficient and powerful sensors can be used. The model can be trained with more data to implement this in real life.

IV. Discussion

In this article, the researchers studied the neural pre-trained CNN ResNet-50 under the test conditions. Of course, real highways have turns and bends, which complicates the learning process of the network. In the future, they will use a database of images from three or more cameras and depth maps. Typically, images from two cameras generate depth maps based on stereoscopic vision. This article reports on the use of the neural network to implement an accident prevention system. The researchers built the car models and roads with obstacles. The study developed algorithms for processing obstacle data and transmitting them to the neural network. The proposed system can serve as a platform for a full-fledged road safety and vehicle accident prevention system that functions as a vehicle automatic pilot system. To test the neural network, one can use a video camera, a laptop with neural network-based software. The researchers used an already trained neural network, so the system recognized a new user substantially immediately. The neural network recognized contrasting sections of the road well and compared them using a series of video frames. They compared the frames using the method of projective geometry, which allowed them to recreate their coordinates in space. The system thus built a three-dimensional map. Many researchers also studied deep learning technologies for cars [14].

Connected and autonomous vehicles (CAVs) have witnessed significant attention from industries, and academia for research and developments towards the on-road realisation of the technology. State-of-the-art CAVs utilise existing navigation systems for mobility and travel path planning. However, reliable connectivity to navigation systems is not guaranteed, particularly in urban road traffic environments with high-rise buildings, nearby roads and multilevel flyovers. In this connection, Kamath et al. [31] presents traffic knowledge-based navigation (TAKEN) for enabling CAVs in urban road traffic environments. A traffic analysis model is proposed for mining the sensor-oriented traffic data to generate a precise navigation path for the vehicle. A knowledge-sharing method is developed for collecting and generating new traffic knowledge from on-road vehicles. CAVs navigation is executed using the information enabled by traffic knowledge and analysis. The experimental performance evaluation results attest to the benefits of TAKEN in the precise navigation of CAVs in urban traffic environments.

In most cases, image processing relied on neural networks and computer vision. The authors investigated the possibilities of influencing the movement to the right and left, reverse, brakes and acceleration. Computer vision applications allow identifying road signs, for example, a stop sign, as well as pedestrians. They can orient in space and communicate. The authors proposed AI applications based on deep learning algorithms that could be implemented in autonomous cars. In the article, Sharma and Zheng [2] investigated the possibility of using artificial intelligence tools, namely IoV, to ensure rational use of the battery charge of electric vehicles. They focused on both individual batteries and energy storage systems in terms of reuse. They analysed the dynamics of costs associated with the reuse of batteries. They also studied the environmental impact of using such vehicles. In the article, Liasi and Bina [5] proposed a neural network architecture that could be used for both driving a car, and testing the serviceability of autonomous cars. This development is interesting from the perspective of performance and the operation principle of controllers. A special feature is the ability to test the controller of transport technologies both online and offline. However, most developments involve the use of universal settings. The researchers developed the system, which allows personalizing a user to adjust seats, mirrors, climate, radio, etc. when integrated into a car. The car can recognize the driver when approaching the car. In the future, one can use front detection technology, which allows distinguishing between a person's face and its photo. Visual odometry presents data, which allows locating the car accurately even without additional sensors, such as GPS, LIDAR, radar, etc. The software runs using slam technology in the sensor fusion mode. Fourth and fifth generation autopilots can use the technology the researchers have developed. In the future, they will test this model in real conditions. In the article, Kumar et al. [9] present the possibilities of using numerous cameras to improve the accuracy of depth maps and allows determining the distance to obstacles. This article focuses on applications in autonomous vehicles or robotic mechanisms capable of moving independently in an urban environment. A facial recognition system allows drivers to adjust vehicle settings (for example, the settings of seats and mirrors, as well as the temperature in the cabin, etc.), considering the driver's personal preferences. The system works using ultrasonic sensors to record the movement of a controlled vehicle. The computer vision system works based on cameras and sensors. Environmental monitoring of the information about the vehicle and forwarding on the screens displayed by the front side of the vehicle body [19]. The vehicle can be accessed using a smartphone or a digital key. It will open the car automatically from a distance of 2 m. An automatic searching and parking system can also use this algorithm. This system can work using cloud technologies and record the movement of all vehicles or one of them in a certain area. Such robots include cars controlled exclusively by computer systems. In the article, Rohith and Sunil [3] present multilayer depth maps, which consider the distance to the objects behind them in addition to the distance to the foreground objects.

Taken together, the test data indicate an increase in the levels of complacency and confidence in the developed obstacle detection system among drivers. The time required to drive from home to work decreased by 6 to 14%. Drivers tended to increase their driving speed immediately after turning the obstacle detection system on. Despite these positive changes, one should also exercise some caution when drawing conclusions regarding the use of the system in real life, for the recorded behaviour of the participants also causes concern. Drivers may look forward to the predictable assistance of the obstacle detection system and thus be less prepared for an unexpected or sudden emergency.

V. Conclusion

The article presents the use of a neural network to implement a road obstacle detection and avoidance system. The researchers developed the simulator of cars and obstacles to demonstrate the capabilities of the neural network in practice, as well as to collect data on its various configurations in a convenient and fast way. The study identified the main training trends of neural networks, and analysed potential problems concerning the development of such networks. They considered the algorithms, which allowed this system to work, as well the principles of neural network training. The researchers found out that the neural network could recognize roads with 94% accuracy, cars with 91% accuracy and pedestrians—88%. In the developed model, the range capability limits of obstacles reached 70 m behind and in front of the car and 6 meters on its sides. The minimum range was 1.6 m for image segmentation. The statistical evaluation of the results showed that the standard deviation was from 0.43 to 0.63, the Pearson criterion χ^2 was from 0.98 to 1.00, and the Student's t-test was from 0.0007 to 0.02. To conduct the research, we developed the simulator based on a neural network consisting of ResNet 50 and a MATLAB-based simpler network. To determine the parameters of the road situation and the distance to obstacles, it was possible to use LIDAR data or images from two or more cameras. Using the simulator, we investigated the effectiveness of training and operation of this neural network in different configurations. The simulation was carried out based on the integral model, including the possibility of summing the constant movement speed and the constant turning speed to predict the direction of movement of the obstacles and to correct the trajectory of the controlled vehicle. The researchers developed the algorithms during the study to collect data on perturbations and ways of transmitting them to the neural network.

The proposed system, after additional research, in the future can serve as the basis for a full-fledged road safety system, in urban and other environments, and the prevention of vehicle accidents, functioning as a vehicle autopilot system.

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