(comparison of the work of several optimizers is shown in Figure 4).

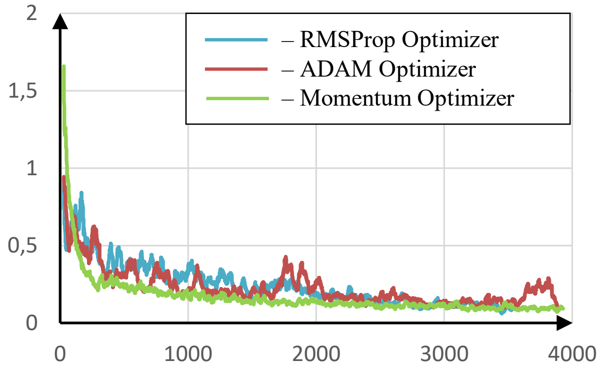

Figure 4: Graphs of changes in the value of the loss function when using various optimizers.

2.2 Rotation Operation

It is not enough to identify the object in the image, it is also necessary to define the robot position relative to the target object. First of all, the task of gripper rotation is solved. The solution of this task is to determine the angle of rotation for the correct orientation relative to the luminaire (target object) (Figure 5).

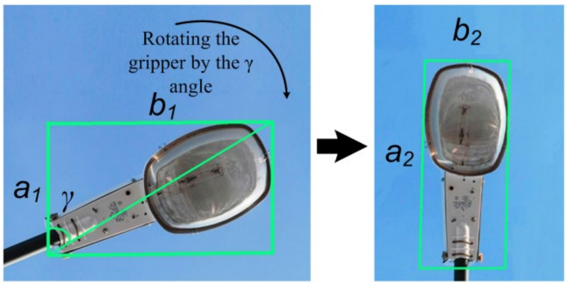

Figure 5: Determination of the rotation angle.

The solution of this task is performed using formulae (1) and (2).

$$\frac{b_1}{a_1} \neq \frac{b_2}{a_2}; \frac{b_2}{a_2} = \frac{B}{A}; \tag{1}$$

$$\gamma = \arctan\left(\frac{b_2}{a_2}\right); \tag{2}$$

where a_1, b_1, a_2, b_2 are the frame dimensions of a detected object (luminaire) in the image in pixels; A, B are the actual luminaire size characteristics in meters; γ is the manipulator gripper rotation angle.

2.3 Shift Operation

After the rotation operation and before approaching to the object, it is necessary center the object relative to the center of the image (Figure 6). This is necessary so that there is no gripper shift relative to the object when approaching it.

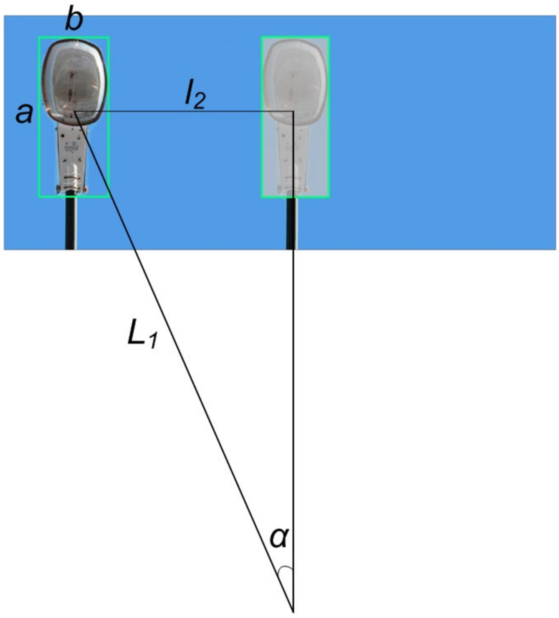

Figure 6: Determination of the angle of robot gripper.

To do this, it is necessary to determine the angle through which the robot should be rotated; this angle is determined by the Formula 3.

$$\alpha = \arcsin\left(\frac{L_2}{L_1}\right) = \arcsin\left(\frac{l_2 A}{L_1 a}\right); \tag{3}$$

where α is the angle through which the robot must be rotated; l_2 is the distance from the object to the center of the image in pixels; a, b are the frame dimensions of a detected object (luminaire) in the image in pixels; A, B are the actual luminaire size characteristics in meters; L_2 is the distance from the object to the center of the image converted into meters; L_1 is a measured distance from the gripper camera to the object in meters (approaching operation).

2.4 Approaching Operation

The next operation to be performed is to define the value of the next step to approach to the object. For this, it is necessary to define the distance to the object (Figure 6).

Considering that the object can be photographed at each step of the algorithm (Figure 3), it is possible to compare the last two images, namely, to compare the geometric dimensions of the detected object and to estimate the distance to the object. For this, it is necessary to solve the system of equations (4) (Figure 7).

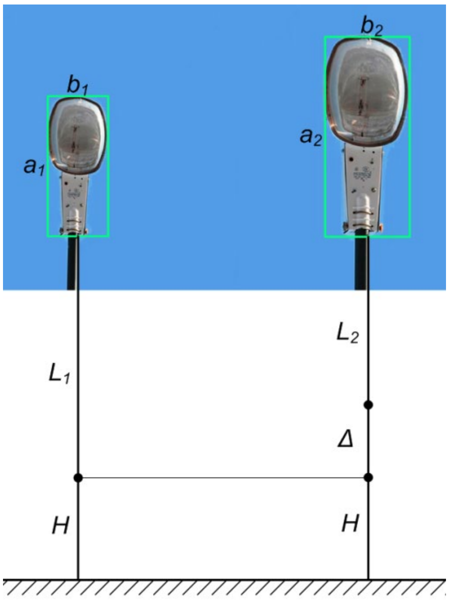

Figure 7: Determining the distance to the object.

$$\begin{cases} \dfrac{L_1}{L_2} = \dfrac{L_2+\Delta}{L_2} = k\dfrac{a_2}{a_1}; \\ \dfrac{L_1}{L_2} = \dfrac{L_2+\Delta}{L_2} = k\dfrac{b_2}{b_1} \end{cases} \tag{4}$$

where H is the camera height in meters; Δ is the distance travelled towards the object in meters; a_1, b_1, a_2, b_2 are the frame dimensions of the detected object (luminaire) in the image in pixels; k is the pixel-to-meter conversion factor (due to the use of two images, the values obtained from the system (4) are independent of the k value); L_1, L_2 are the required distances from the camera to objects in meters.

3 IMPLEMENTATION

Implementation of an algorithm to identify outdoor lighting luminaires requires neural network training.

To train a neural network, it is necessary to form a training sample of images with luminaires labelled on them. To label luminaires in the image, a rectangular area is selected, which coordinates are recorded in an XML file (Figure 8):

```
<annotation>
    <folder>train</folder>

 <filename>IMG_20191101_164622.jpg</fil
ename>

 <path>C:\tensorflow1.1\models\research
\object_detection\images\train\IMG_2019
1101_164622.jpg</path>
    <source>
        <database>Unknown</database>
    </source>
    <size>
        <width>195</width>
        <height>260</height>
        <depth>3</depth>
    </size>
    <segmented>0</segmented>
    <object>
        <name>luminaire</name>
        <pose>Unspecified</pose>
        <truncated>0</truncated>
        <difficult>0</difficult>
        <bndbox>
            <xmin>30</xmin>
            <ymin>44</ymin>
            <xmax>161</xmax>
            <ymax>144</ymax>
        </bndbox>
    </object>
</annotation>
```

To create labels, we use some tools (for e.g. *LabelImg*).

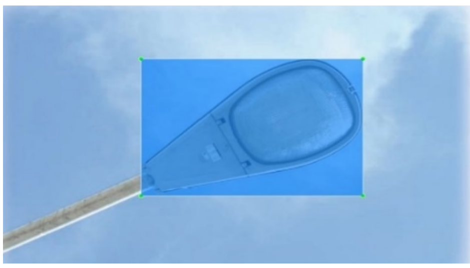

Figure 8: An example of labelling an object in an image.

After all images have been labelled, the coordinates of all selected areas are recorded to a ".csv" file, which contains the image names and coordinates of the selected areas in them.

For correct training of the neural network, it is necessary to use images of different types of luminaires from different angles, in different conditions in which we can observe them (examples in Figure 9).

The initial dataset for training of the neural network consisted of 250 images.

To test the object identification in the image, the convolutional neural network, the *TensorFlow* library to work with neural networks and its add-on for object detection in images (*Object Detection API*) were used.

Having prepared a set of images for training, select the previously prepared model [14]. *TensorFlow Object Detection API* provides a number of pre-trained models. The use of a pre-trained model significantly reduces training time. The model *"faster_rcnn_inception_v2_coco"* is selected for testing.

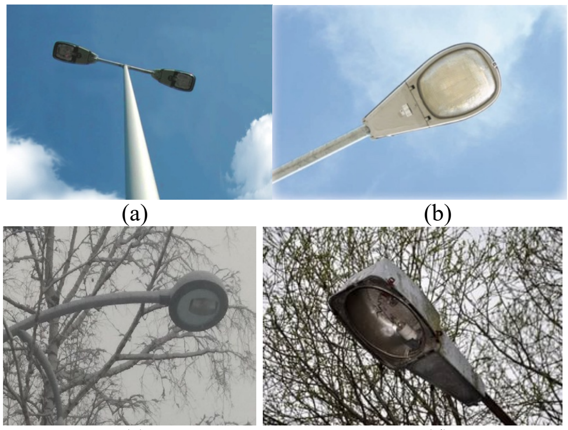

Figure 9: Examples of images from the training set.

As a result of the neural network training, rotation method implementation and approach-to-target method application, the algorithm shown in Figure 3 is implemented as a sequence of steps, an example of which is shown in Figure 10.

4 DISCUSSION

The task considered in this paper is an element of a complex solution consisting of two operations: the removing operation and installing operation of an outdoor lighting luminaire. Each of these operations consists of many subtasks, some of which can be invariant. For example, if we consider the luminaire removing operation, it can be decomposed into a number of algorithmic subtasks, as shown in Figure 11.

The solution of some tasks can be invariant. For example, the task of approaching to the target object in practice, using the proposed solution, can be performed in different ways. They will depend on the initial position, conditions affecting the quality of the images (for example, weather conditions and overlapping), and this does not take into account obstacles that may be in the way of the robot (for example, tree branches). Identification and grasping of objects by robotic systems are repeated many times. It means that the accumulated experience (photos and motion trajectories leading to successful results and failures) can be used for the training of the object detection model and improvement of the trajectory choice model based on machine learning methods or using intelligent algorithms.

Other tasks, which need to be solved for the luminaire removing operation, also have the property of invariance and the possibility of the algorithm modernization.

In this regard, at the moment, one can observe a variety of ways to solve these tasks, that combine attempts to create universal algorithms, the use of which will allow them to be used without relating to a particular object. One of the methods described in the literature when using neural networks for task recognition is the search for universal structures of such networks and use of Siamese networks [15].

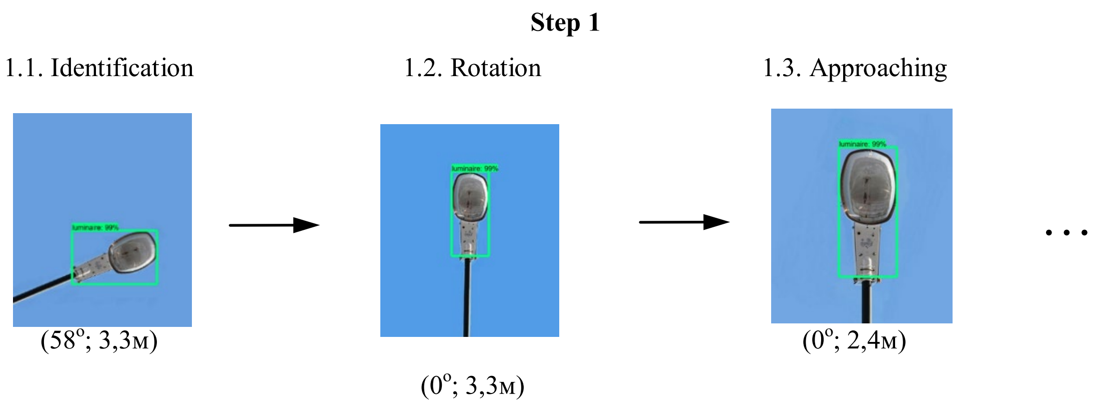

Figure 10: Identification and determination of the distance to the luminaire.

The subtasks shown in Figure 11 are not unique. They constantly arise in the control and creation of robotic systems. Therefore, today there is a great variety of task solutions to find an object and grasp it, approach the manipulator to the target object and the gripping point. In literature, there are algorithms using stereo vision [16]; identification of objects based on the choice of primitives that they consist of [17]; search for objects in the image and their classification using neural networks [18]; performing operations related to inserting one object into another (insertion of wires in the terminals, in our case installation of a new luminaires) [19]; tasks related to the movement of the gripper with an object that are considered as tasks of bending around obstacles on the basis of predetermined trajectories [20].

The presence of a large number of algorithms indicates the relevance of solving these algorithmic subtasks. The solution of tasks is associated with compromises between quality and complexity of the hardware, complexity of the algorithms and the speed of their work. Today, there are solutions that demonstrate good results in laboratory conditions. However, they do not always work well in real conditions due to the factors of the environment in which they operate.

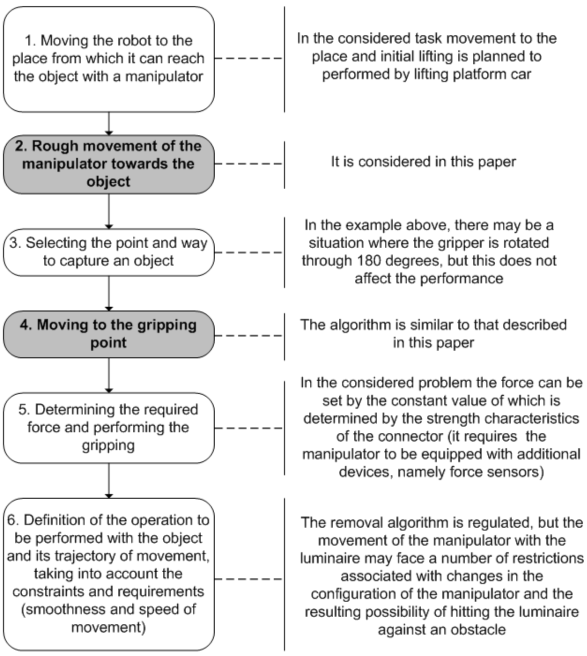

Figure 11: The scheme of dividing the luminaire removing task into algorithmic subtasks (the tasks considered in the paper are highlighted in gray).

5 CONCLUSIONS

The key task that was solved in the study described in the paper is the task of identifying objects. The use of neural networks is an effective tool that does not depend on a particular subject area.

The resulting model, trained on a dataset of 250 images, identifies the outdoor lighting luminaires in the images with high accuracy, but for some objects, much more images may be required to improve accuracy.

The approach considered in the paper relates to the subject area only through the object, the recognition of which takes place. In this regard, it can be considered universal and used to solve other applied tasks associated with the fact that an object must be taken and certain actions must be performed with it. Performing such manipulations is especially important when implementing humanoid robots capable of performing actions related to household and industrial activities. [21]. The creation of such robots is one of the priorities of robotics and is required to implement a complete Turing test [22].

REFERENCES

[1] A. Dudarev, "The Problem Sensitization Robotic Complex Drilling and Milling of Sandwich Shells of Polymer Composites," Proc. 4Th Int. Conf. Appl. Innov., vol. 4, no. March, 2016, pp. 15-19.

[2] N. Pavlov, A. Bachurin, and E. Siemens, "Analysis of Outdoor Lighting Control Systems and Devices for the Creation of Outdoor Lighting Automatic Control System Using the Traffic Flow Value," Proc. Int. Conf. Appl. Innov. IT, no. March, 2017, pp. 95-100.

[3] P. Slivnitsin and A. Bachurin, "A modern way of outdoor lighting maintenance," International Conference on Innovation Energy, 2019, J. Phys.: Conf. Ser. 1415 012010.

[4] А.А. Бачурин и П.А. Сливницин, "Соедини-тельное устройство для монтажа и подклю-чения светильника наружного освещения," 2695631, 2019.

[5] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," Proc. - 2005 IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognition, CVPR 2005, vol. I, no. 16, 2005, pp. 886-893.

[6] P. Viola and M. Jones, “Rapid Object Detection using a Boosted Cascade of Simple Features,” in Proceedings IEEE Conf. on Computer Vision and Pattern Recognition, pp. 511-518, 2001.

[7] L. Mylnikov, B. Krause, M. Kütz, K. Bade and I. Shmidt, Intelligent data analysis in the management of production systems (approaches and methods), Shaker Verlag {GmbH}.

[8] V. Renò et al., “A SIFT-based software system for the photo-identification of the Risso’s dolphin,” Ecol. Inform., vol. 50, pp. 95-101, January 2019.

[9] N. Kumar et al., “Leafsnap: A computer vision system for automatic plant species identification,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 7573 LNCS, no. PART 2, 2012, pp. 502-516.

[10] H. Zhou, C. Yan and H. Huang, “Tree species identification based on convolutional neural networks,” in Proceedings - 2016 8th International Conference on Intelligent Human-Machine Systems and Cybernetics, IHMSC 2016, vol. 2, 2016, pp. 103-106.

[11] F. Al-Azzo, A. M. Taqi and M. Milanova, “Human related-health actions detection using Android Camera based on TensorFlow Object Detection API,” Int. J. Adv. Comput. Sci. Appl., vol. 9, no. 10, 2018, pp. 9-23.

[12] C. Szegedy et al., “Going deeper with convolutions,” Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., vol. 07-12-June, pp. 1-9, June 2015.

[13] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens and Z. Wojna, “Rethinking the Inception Architecture for Computer Vision,” Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., vol. 2016-Decem, pp. 2818-2826, December 2016.

[14] “Tensorflow detection model zoo.” [Online]. Available: https://github.com/tensorflow/models/blob/master/research/object_detection/g3doc/detection_model_zoo.md.

[15] S. Ravichandiran, Hands-On Meta Learning with Python: Meta learning using one-shot learning, MAML, Reptile, and Meta-SGD with TensorFlow. Packt Publishing Ltd.

[16] F. Chen, M. Selvaggio and D.G. Caldwell, “Dexterous Grasping by Manipulability Selection for Mobile Manipulator with Visual Guidance,” IEEE Trans. Ind. Informatics, vol. 15, no. 2, 2019, pp. 1202-1210.

[17] H. Dong, E. Asadi, G. Sun, D. K. Prasad and I.M. Chen, “Real-Time Robotic Manipulation of Cylindrical Objects in Dynamic Scenarios Through Elliptic Shape Primitives,” IEEE Trans. Robot., vol. 35, no. 1, 2019, pp. 95-113.

[18] C.H. Corbato, M. Bharatheesha, J. Van Egmond, J. Ju and M. Wisse, “Integrating different levels of automation: Lessons from winning the amazon robotics challenge 2016,” IEEE Trans. Ind. Informatics, vol. 14, no. 11, 2018, pp. 4916-4926.

[19] D. De Gregorio, R. Zanella, G. Palli, S. Pirozzi and C. Melchiorri, “Integration of robotic vision and tactile sensing for wire-terminal insertion tasks,” IEEE Trans. Autom. Sci. Eng., vol. 16, no. 2, 2019, pp. 585-598.

[20] Z. Cao, N. Gu, J. Jiao, S. Nahavandi, C. Zhou and M. Tan, “A Novel Geometric Transportation Approach for Multiple Mobile Manipulators in Unknown Environments,” IEEE Syst. J., vol. 12, no. 2, 2018, pp. 1447-1455.

[21] A. Billard and D. Kragic, “Trends and challenges in robot manipulation,” Science (80), vol. 364, no. 6446, p. eaat8414, June 2019.

[22] A.M. Turing, “Computing machinery and intelligence,” Mind, vol. LIX, no. 236, 1950, pp. 433-460.