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INVESTIGATION OF THE EFFECT OF OBJECT SIZE ON ACCURACY OF HUMAN LOCALISATION IN IMAGES ACQUIRED FROM UNMANNED AERIAL VEHICLES

The use of unmanned aerial vehicles is gaining wide popularity in various areas of research and information acquisition. More and more often, unmanned aerial vehicles are used to obtain various types of images of the Earth's surface for its study. In particular, such data can be used in law enforcement, localization of crowds, etc. Typically, such systems operate independently of humans and provide information about objects in an automatic mode, with humans working only under the control of the aircraft. One of the main components of such systems is a neural network for localization and classification of objects, the parameters of which determine both the accuracy of the system as a whole and the design of the aircraft for shooting. In particular, the accuracy of the neural network determines the profitability of such a system, because if the accuracy is insufficient, the use of such systems will not make sense. Therefore, the main subject of research in this paper is a neural network for object localization, in particular YOLO v5, and its accuracy parameters on images obtained from unmanned aerial vehicles. The main focus of this paper is on the parameters of the neural network and the study of its metrics, which are important parameters of a trained neural network. Another important parameter for the further use of a neural network is its training parameters, as well as the data used for training. This study also pays attention to the details of the training process. The main goal of this study is to train a neural network on a selected dataset and to study the accuracy metrics of the trained neural network. The main goal of this study is to determine the dependence of localization accuracy on the area of the object, which will allow for more detailed development of unmanned systems with automatic object detection, as well as to assess the profitability of using such systems in task planning. On the basis of the data obtained, conclusions were drawn about the dependence of localization accuracy on the area of an object in images from unmanned aerial vehicles. These data can serve as a reference for unmanned aerial vehicle developers, particularly when selecting photo modules or planning the system architecture.

Keywords: *object localization; YOLO v5; human classification; human localization; UAV.*

Introduction

Motivation

Object localization tasks in images of various types are very common [1]. Many different neural network architectures are used to localize and classify objects. Also, such systems can work with different types of images, such as infrared [2], optical [3], radar [4] and sonar [5]. The most common are localization systems using optical systems. Infrared systems are also often used in localization tasks [6], for example, for video surveillance in darkness.

The localization of objects in images acquired by unmanned aerial vehicles (UAVs) is fairly new and is gaining widespread use. Such systems allow exploring the earth's surface without using direct access [7], which makes it possible to map and study remote areas of the earth's surface.

Systems for surveillance and localization of objects using unmanned aerial vehicles have also become widespread in law enforcement [8], search for missing [9] or dangerous objects. In particular, one of the areas of application of the above-described localization systems is the search and localization of people in UAV images [10]. Just this important application is of our main interest in this paper.

Many different architectures and objects can be used to find people in images, but there is little information on the accuracy of such networks for localizing people. There are also few available studies of trained neural networks that concern the accuracy of localization depending on the size of an object. Such information is quite important for real life systems, as it allows selecting the parameters (e.g., angular resolution and a carrier altitude) of the video module for an unmanned aerial vehicle for the task. It is the study of the accuracy of operation depending on the size of the object

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and the search for the minimum possible size of the object for localization that is the **main goal** of this paper.

State-of-the-art

Analyzing current research on the topic of object localization in images captured by unmanned aerial vehicles, we can notice several trends in this area [11, 12].

In particular, many works are related to the localization and classification of vehicles (cars, buses, trucks) in images, as well as their tracking [13]. These systems are also widely used in tasks relating to military equipment and homing. Many systems perform well enough for vehicles that occupy hundreds or thousands of pixels [14]. Meanwhile, humans are smaller objects.

There are also studies on remote sensing of the earth using unmanned aerial vehicles. The systems can be applied to the study of various types of objects, terrain, etc. that may be difficult to access by ground.

Studies of the accuracy of localization of people (humans) in images have been also carried out by several researchers [10]. One of possible tasks was to carry out counting of people in a given frame (image) [15]. The system performed well enough but again the imaging conditions were such that hundreds of pixels corresponded to each human. The study of the dependence of localization accuracy on the size of the object has not been carried out.

These obstacles were the main motivation for researching this area of application.

Objectives and the approach

The paper describes the entire process of training a neural network for localization and classification of people, from the choice of dataset to the study of accuracy, using the YOLO v5 [16, 17] neural network. The neural network implementation from ultralitics was used for training, and their pipeline for training the neural network was also used. A benchmark for studying the accuracy of the model was developed using the pytroch library [18].

The main focus is on the accuracy of the neural model, in particular, on such metrics as intersection over union (IOU) [19], precision and recall [20], as well as the dependence of classification accuracy (model confidence) on the size of the object. As a conclusion, we present the statistics of the network, as well as possible further ways to develop and improve the accuracy of the neural network.

1. Selecting the dataset

The accuracy of a neural network directly depends on the data set used to train the network. For each of the tasks, you should use a data set that is most similar to the data that will be used in the network.

To train a neural network, it is important to choose a dataset that clearly and accurately labels objects. Also, the dataset should allow training using different image sizes, i.e., it should be of sufficiently high resolution. These parameters are important when choosing a dataset [21].

A high-resolution dataset [22] was chosen to train the neural network for people localization and classification, but the main training was performed using full HD (1920*1080) image quality. The dataset consists of 4095 images, including 3588 in the training set and 507 in the validation set. The training set contains 49075 objects of different sizes and positions. The statistics of the distribution of object size for the full HD image size is shown in Figure 1, with the yellow lines representing the boundaries of the main number of objects. The minimum object area in the images is 79 pixels, which is 0.003% of the image size. The maximum area of an object is 301627 pixels, which is 14.5% of the image size. 70% of the object areas in the dataset are in the range from $2*10^2$ to $2*10^4$, which is from 0.0096% to 0.96% of the image size. Also, the selected dataset is characterized by different shooting positions relative to the main object (a person), as well as different shooting conditions and object density, examples of different data in the dataset are shown in Figure 2.

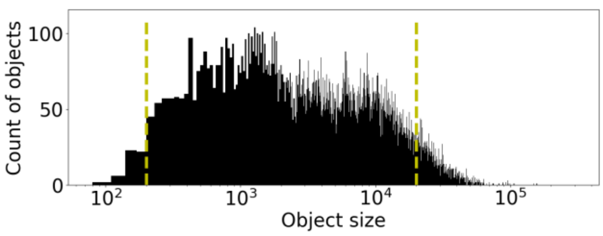

Fig. 1. Statistics of the distribution of the number of objects versus the size of the object in the training part of the dataset

The statistical characteristics of the test set are slightly different from the training set. The minimum area of an object is 514 pixels, which is 0.024% of the total image area. The maximum area value in the test set is 311040, which is 0.15% of the total image area. The distribution of the number of objects as a function of their area is shown in Figure 3.

The study on the dependence of the accuracy of object localization and classification on the size of the object was conducted using 10 videos from open sources. Each video is characterized by different shooting conditions according to the training dataset. The test set also contains objects of different sizes, which is necessary for the study.

Fig. 2. Examples of images in the training dataset

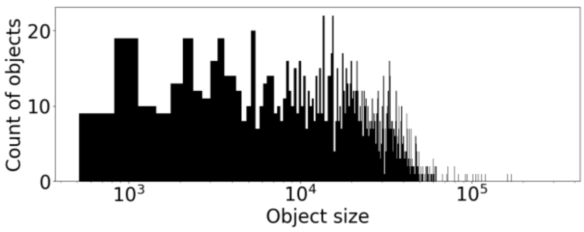

Fig. 3. Statistics of the distribution of the number of objects versus the size of the object in the test part of the dataset

2. Neural network training

The neural network was trained using the architecture from ultralitics using the original configurations for the YOLO v5s [16] neural network. This model is optimal in terms of network size, inference time, and prediction accuracy.

The dataset described in the previous section was used for training, with a resolution of 1920*1080 pixels. The input images were subjected to augmentation, which creates a mosaic image, to obtain a higher accuracy of the model by changing the environment and the size of objects.

The training process used binary cross-entropy (BCE) [23] with logit loss as a loss function that combines the sigmoid layer and BCE loss in one class. This loss function is used in classification tasks to measure the accuracy of object classification. For regression and box sorting, the intersection of union (IoU) [19] is used and the resulting predictions are employed to combine the target and predicted boxes. The BCE loss for object localization accuracy is presented as a function of the localization loss, a binary metric that does not pay attention to class. The BCE loss for classification is represented by the accuracy score for predicting the object's category. Equation (1) shows the original formula for measuring the binary cross-entropy loss:

$$l_n = w_n[y_n \log \sigma(x_n) + (1 - y_n)\log(1 - \sigma(x_n))], \quad (1)$$

where y is the predicted classification vector,

x is the target classification vector.

The Adam [24] complex optimizer with a learning rate of 0.01 was used as an optimizer. No weight decay was used for the bias and normalization layers, and weight decay with a value of 1×10-5 was used for the batch normalization layers. The model was trained for 300 epochs, and each epoch was evaluated using metrics. Figure 4 shows the dependence of the loss function for object detection accuracy during network training, and Figure 5 shows the dependence of the loss function for classification on the epoch.

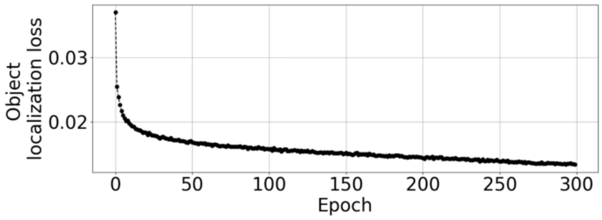

Fig. 4. Dependence of the loss function for localization on the epoch

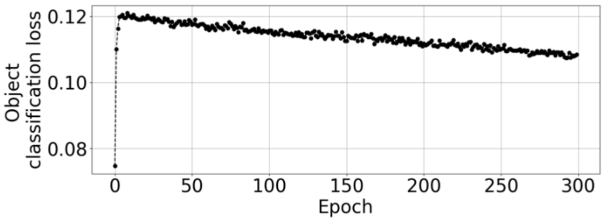

Fig. 5. Dependence of the loss function for classification on the epoch

3. Analysis of the results

3.1. Neural network accuracy metrics

To analyze the resulting neural network for localization and classification accuracy, we tested it on the test dataset described in Section 1. To determine the classification accuracy, we chose the precision and recall metrics, which reflect the memorization (retraining) of the neural network and its response. The calculation did not use an accuracy threshold, so all objects identified by the neural network were processed when calculating the metrics.

The metrics are calculated [25] by counting the number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) blocks. The precision metric is calculated using formula (2):

$$P = \frac{\sum_{i=0}^{nc} TP_i}{\sum_{i=0}^{nc} TP_i + FP_i}, \quad (2)$$

where nc is the number of classes.

The recall metric is calculated as follows (3):

$$R = \frac{\sum_{i=0}^{nc} TP_i}{\sum_{i=0}^{nc} TP_i + FN_i}, \quad (3)$$

where nc is the number of classes.

We also calculated the accuracy metric for the neural network, which looks like this (4):

$$Accuracy = \frac{\sum_{i=0}^{nc} TP_i + TN_i}{\sum_{i=0}^{nc} TP_i + FP_i + TN_i + FN_i}, \quad (4)$$

where nc is the number of classes.

For the precision and recall metrics, we conducted a study on the dependence of recognition accuracy on the threshold set for object classification accuracy. The study helped to determine the threshold value that is responsible for a fairly good localization accuracy and filters out incorrect results. Figure 6 shows that the curves intersect at 0.3, and the precision/recall ratio becomes positive, so 0.3 can be considered the minimum acceptable accuracy threshold for the resulting neural network.

Taking into account the results of the metrics, we also calculated the Mean Average Precision (mAP) [26] metric, which reflects the accuracy of search and classification. The metric is calculated using the threshold value IoU, changing which the number of correctly found blocks is calculated. For the obtained neural network, we calculated the values for the threshold of 0.5 and 0.95.

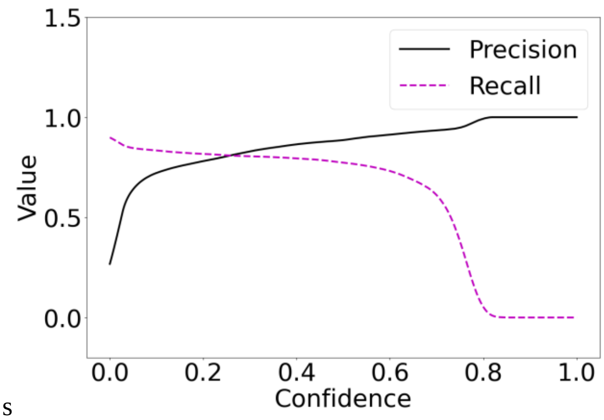

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Fig. 6. Dependence of precision and recall on the classification accuracy threshold

The results obtained from testing the neural network are presented in Table 1. Taking into account the results, the model accurately detects most of the objects in the images, we can say that about 79% of the objects were found by the network correctly. Also, taking into account the average IoU and mAP values, we can conclude that the network localizes objects with an average of 57% similarity to the original markup. Also, when the IoU threshold is raised, the number of correctly found objects drops significantly.

Table 1

Metrics results for the obtained neural network

Metric	Value
Precision	0.872
Recall	0.79
mAP 0.5	0.827
mAP 0.95	0.357
Accuracy	0.861
mean IOU	0.57

3.2. Studying the dependence of accuracy on the size of the object

Given the results obtained to determine the accuracy of the model in the previous subsection, we can assume that the resulting neural network is accurate enough to localize people. Therefore, in this section, we study the dependence between the size of the object and the accuracy of its detection.

The study used a set of videos obtained from open resources. Each video has a different location, number of objects, camera position relative to them, and different shooting heights. For each of the videos, the model was inferred, and the results below a given threshold, which was defined in subsection 3.1, were eliminated. Figure 7 shows examples of images with marked objects.

Fig. 7. Examples of object localization in a images

For the results obtained, we collected statistics on classification accuracy and object area. Using these data, we plotted the graph of classification accuracy versus the area of objects, which is shown in Figure 8. The results are as follows:

- when the size of the object is up to 100 pixels, the maximum classification accuracy is no more than 0.45;

- when the object size is up to 150 pixels, the maximum classification accuracy is 0.6;

- if the area of the object is more than 150 pixels, the classification accuracy is on average larger than 0.6.

The dependence graph also shows that even with a large object size, the classification accuracy can be low. The research has revealed that this is due to various reasons, such as illumination, human pose, and shooting angle.

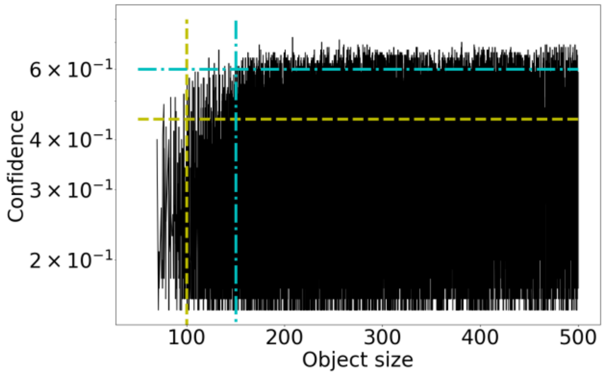

Fig. 8. Dependency of classification accuracy versus object size

Conclusions

By examining the resulting neural network for the dependence of localization accuracy on the area of the object, the following results were obtained:

- when the object area is less than 100 pixels, we have a rather low localization accuracy;
- with an area of up to 150 pixels, we get a medium accuracy that does not guarantee the presence of the desired object in the detected area;
- with an area of more than 150 pixels, we get a classification localization of larger than 60%, which is an acceptable minimum.

Also, the metrics of object localization and classification obtained in the process using the trained neural network are quite high and indicate that the model was correctly selected and trained.

The data obtained can be useful in further studies of localization and classification of people, as well as other types of objects. This data may also be useful for designing unmanned aerial vehicles, including their photo (video) modules and flight altitude planning.

Contributions of authors: conception – **Vladimir Lukin**, **Rostyslav Tsekhmystro**; methodology – **Vladimir Lukin**, **Rostyslav Tsekhmystro**; problem formulation – **Vladimir Lukin**; analysis – **Rostyslav Tsekhmystro**; model development – **Rostyslav Tsekhmystro**; software – **Rostyslav Tsekhmystro**; validation – **Vladimir Lukin**, **Oleksii Rubel**; analysis of results – **Rostyslav Tsekhmystro**, **Oleksii Rubel**, **Vladimir Lukin**; visualization – **Rostyslav Tsekhmystro**; writing – **Rostyslav Tsekhmystro**; revision and editing – **Oleksii Rubel**, **Vladimir Lukin**.

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Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship, or otherwise, that could affect the research and its results presented in this paper.

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Data availability

The manuscript contains no associated data.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

All authors have read and agreed to the published version of this manuscript.

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ДОСЛІДЖЕННЯ ВПЛИВУ РОЗМІРУ ОБ’ЄКТА НА ТОЧНІСТЬ ЛОКАЛІЗАЦІЇ ЛЮДИНИ НА ЗОБРАЖЕННЯХ БЕЗПІЛОТНИХ ЛІТАЛЬНИХ АПАРАТІВ

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Використання безпілотних літальних апаратів набирає широкої популярності в різних сферах досліджень та отримання інформації. Дедалі частіше безпілотні літальні апарати використовуються для отримання різного типу зображень земної поверхні для її дослідження. Зокрема такі дані можуть бути використані в задачах забезпечення правопорядку, локалізації скупчення людей, тощо. Зазвичай такі системи працюють незалежно від людини та надають інформацію про об’єкти в автоматичному режимі, людина працює тільки з управлінням літального апарату. Однією з головних частин таких систем є нейронна мережа, для локалізації та класифікації об’єктів, від параметрів якої залежить як і точність роботи системи загалом, так і конструкції літального апарату для зйомки. Зокрема точність нейронної мережі визначає рентабельність такої системи, адже при недостатній точності використання таких систем не матиме сенсу. Саме тому основним предметом дослідження в даній роботі є нейронна мережа для локалізації об’єктів, зокрема YOLO v5, та її параметри точності роботи на зображеннях, отриманих з безпілотних літальних апаратів. Основна увага в роботі зосереджена на параметрах нейронної мережі та дослідженні її метрик, які є важливим параметром навченої нейронної мережі. Також не менш важливим параметром подальшого використання нейронної мережі є її параметри навчання, а також дані що використані для навчання, в роботі приділена увага також і до детальності опису процесу навчання. Основна ціль роботи полягає в навчанні нейронної мережі на обраному наборі даних та дослідженні метрик точності навченої нейронної мережі. Основна мета дослідження - це отримання залежності точності локалізації від площі об’єкту, що дозволить детальніше розробляти безпілотні системи з автоматичним виявленням об’єктів, а також оцінювати рентабельність застосування такого роду систем при плануванні задач. На основі отриманих даних зроблено висновки про залежність точності локалізації від площі об’єкту, на зображеннях з безпілотних літальних апаратів. Ці дані можуть слугувати опорними для розробників безпілотних літальних апаратів, зокрема при виборі фото модулів чи плануванні архітектури системи.

Ключові слова: локалізація об’єктів; YOLO v5; класифікація людей; локалізація людей; UAV.

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