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IMPACT OF DISTORTIONS IN UAV IMAGES ON QUALITY AND ACCURACY OF OBJECT LOCALIZATION

The localization and classification of objects of different types in images is an important and actively researched topic because the designed methods and tools are exploited in a wide variety of fields, including remote sensing, security systems, and medical diagnostics. Imaging systems installed on-board unmanned aerial vehicles (UAVs) and drones have become popular recently, and they are potentially beneficial for numerous applications like mine detection, traffic control, and crowd control. Images acquired by such systems may suffer from low quality because of the use of rather cheap cameras and the necessity to transfer obtained data via communication lines with limited bandwidth, employing lossy compression. These factors can influence the quality and accuracy of object localization, which is typically negatively performed by trained neural networks. However, the intensity of the noise and distortions that can be considered acceptable, i.e. such that they do not lead to radical reduction of the performance characteristics are unclear. Given this, it is reasonable to investigate the impact of these effects on the quality of object localization and classification using a reliable data size and various noise/distortion intensities. Therefore, ***the research subject of*** *this paper is the performance of object localization and classification methods for color images acquired by UAV-installed sensors. The* ***primary focus*** *is on the dependence of localization and classification metrics on the noise intensity, where the simulated noise mimics not only noise but also distortions due to lossy compression by modern coders. The* ***aim of this work*** *is to obtain adequate statistics and analyze them to build dependencies of the metrics on the intensity of distortions.* ***The objective*** *is to obtain conditions for which the effects of noise and distortions can be considered negligible or acceptable in practice. The second objective is to analyze the sensitivity of several modern neural network models to noise/distortions.* ***The result*** *is a statistical assessment of the dependence of model performance on input data quality. The conclusions are based on the statistics characterizing the model performance for the noise/distortion intensity interval.* ***The conclusions*** *allow the selection of the best (most robust) neural networks and the establishment of appropriate performance conditions.*

Keywords: *object localization; classification; noise and distortions, UAV.*

Introduction

Motivation

Object (target) detection and estimation of spatial coordinates (localization) is a standard task in radar [1], hydroacoustics [2], optical [3], and infrared [4] imaging. There are numerous application areas where automatic localization and classification of objects can be required, including remote sensing [5], security systems [6], and medical diagnostics [7], etc.

Systems intended for object detection can be installed on land or onboard ships, satellites, or airplanes (e.g., fighters) [8, 9]. With the increase in UAV and drone technologies and applications, it has become popular to use different types of cameras installed onboard for solving various tasks [10, 11]. These can be forestry [12], mine detection [13], and digital elevation map reconstruction [14]. For these tasks and applications, high-quality images are required for processing and extracting useful information.

However, the quality of images acquired by UAV-based sensors and/or passed to on-land centers for data processing can be quite low [15, 16]. A question is how the acquired image quality can influence object detection and localization?

State-of-the-art

There are several basic factors that influence the quality of images acquired by UAV-based sensors and received after transfer via communication lines. Consider some of them in more detail.

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First, UAVs are usually equipped with small modules to reduce the weight of the vehicle and/or increase the payload. Therefore, camera modules installed on UAVs are often small and cheap. Thus, acquired images can be noisy [17].

Second, another challenge is the transmission of acquired images "to the ground", namely to the operator's device, for processing and blending. This requires good (broad enough) communication channels or a rather small amount of data to be transferred [18]. To reduce image size, compression methods and algorithms are employed, mostly with losses, which affect image quality and introduce distortions [19].

Thus, object localization and classification methods should be resistant to noise and distortion due to lossy compression. Note that the latter ones, under certain conditions, have properties very similar [20] to additive white Gaussian noise (AWGN), which is often used as the simplest noise model employed for initial stage studies [21, 22].

It is obvious that noise and distortion due to lossy compression have a negative impact on image/object classification [23, 24]. In particular, the effect of noise and its filtering was studied in [23], where it was shown that noise could lead to significant degradation of classification accuracy, whereas its pre-filtering could improve classification. The authors of the paper [24] demonstrated a negative effect of lossy compression on classification accuracy, although this effect was quite small for relatively small values of the compression ratio. In the paper [25], it was demonstrated that lossy compression sometimes results in improved classification accuracy. Thus, the effects can be rather complex and worth studying for each situation.

Currently, neural networks are widely used for object localization and classification [26, 27]. Some authors prefer to conduct training for high-quality image data [28]. In addition, many modern localization methods employ augmentation techniques such as noise, blur, and compression during training [29, 30]. This augmentation often improves the quality of model performance on different data types.

Objectives and the approach

Previously, we studied the accuracy of neural networks for localizing and classifying objects in UAV images [26]. However, when shooting under bad conditions, one may have a large negative influence of various factors, including interference from various kinds, mostly noise. Given the importance of obtaining accurate object localization and classification results, the main objective of this study is to analyse the impact of noise and lossy compression on the accuracy of neural networks. To investigate this topic, we generalized the types of noise and used the additive white Gaussian noise (AWGN) model as noise interference.

The proposed approach consists of creating a common benchmark for neural networks of different architectures. For this purpose, we used the VisDrone [31] dataset, which has high quality labeled data that meets our requirements. The dataset is also quite diverse in terms of lighting, natural conditions, shooting height, and other factors. Using the dataset, we have trained 5 models of different architectures under the same conditions on the same device and using the same data. The obtained neural networks were tested using the Intersection over Union (IoU) [32] and F1 scores [33]. These metrics allow us to determine the initial quality of the model and the subsequent impact of noise on the quality of the neural network.

The paper structure is the following. Section 1 describes the data used for training and testing. In Section 2, we consider the networks used and the peculiarities of their training. In Section 3, we discuss the impact of noise by distorting the test dataset with noise of varying intensity and estimating the aforementioned metrics. The obtained data were analysed, and conclusions were drawn regarding the magnitude of the metric drop and the immunity of neural networks to the influence of noise for each of the tasks: localization and classification. A short discussion, conclusions, and directions for further research are then presented.

1. Data for research

Recall that any neural network to be effectively used requires preliminary training using data that effectively represent possible practical situations. The VisDrone [31] dataset was chosen by us for model training and studying the effects of noise and distortion. There are several reasons for this choice. First, this dataset contains sufficiently high-quality images, which allows us to work with data without distortion. The size of the test part of the dataset was quite large (1610 images), which allowed studying the effect of noise and distortions at different angles, shooting conditions, and UAV flight heights. The objects in this dataset are divided into 11 classes, which makes it possible to evaluate the impact of noise on both small and large objects.

Using the training part of the dataset, several test models were trained and used in the research. The training dataset comprised 6471 images with 344737 labelled objects of different sizes and type (Class). The largest part of the dataset was represented by the Class "Car" (42%), followed by "Pedestrian" and "Motor". More detailed statistics about the class distribution are presented in Figure 1, a.

We also considered the statistics of the test sample, which was used to study the impact of noise on object recognition quality. The test (verification) dataset contains 1610 images, which were also divided into 11 classes. In line with the training data, the "car" Class has the largest number of labelled objects in the test data (37%). The statistics of data distribution between classes are shown in Figure 1,b.

Next, we take a closer look at the content of the images presented in the dataset to better understand the quality of the data and relevance of the results. The dataset contains images captured by UAV sensors at different flight heights, where the UAV height for each image is unknown. Examples of these images are shown in Figure 2. The images in the dataset also have high variability in terms of the position of objects (different vision angles, stationary and moving objects), as well as different shooting conditions and light and quality. Given the context of the images and their quality, we assume that the data are sufficient to test the impact of noise and distortion on the quality of object detection.

2. Neural network training

In this study, we have selected 5 popular neural networks for object detection. In particular, these are models from the YOLO (You Only Look Once) [34] structure, versions 5 and 8. Classical approaches have been also chosen, such as Faster Recurrent Convolution

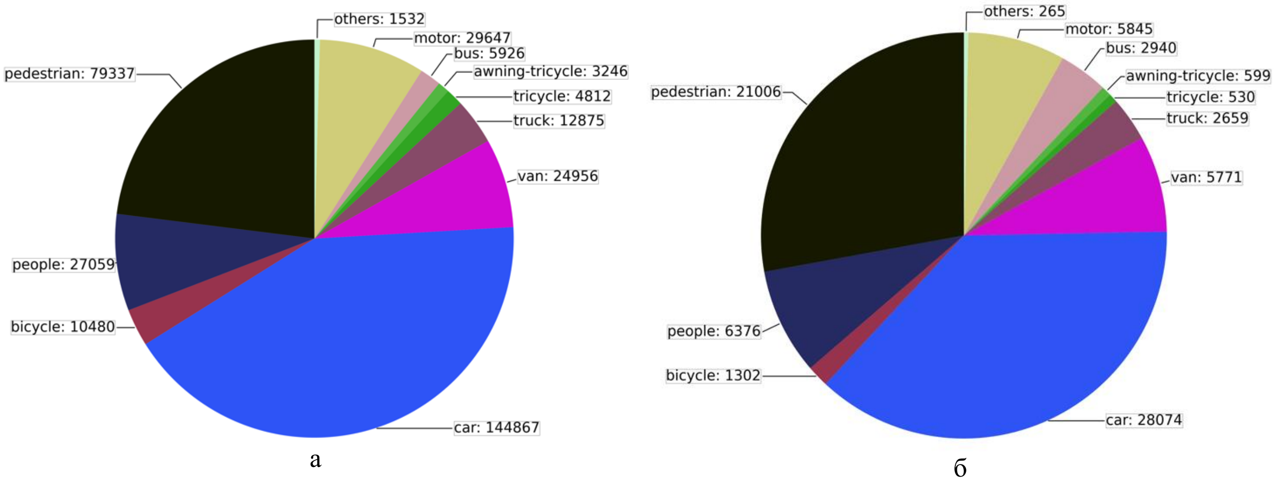

Figure 1. Distribution of classes in the training (a) and test (b) parts of the dataset

Figure 2. Examples of images in the VisDrone dataset

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Neural Network (Faster RCNN) [35], RetinaNet [36], and Single Shot Detector (SSD) [37]. Here, we briefly consider each model.

A Faster RCNN is a neural network that uses the Region Proposal Network (RPN) as a predictor of object boxes. This is a fairly classic object detection method. It has a relatively high accuracy in detecting objects of different sizes [38, 39].

SSD works by selecting and classifying boxes that are found based on anchors, which can be set manually according to the dataset and the task, or selected automatically based on the dataset. Accordingly, by using different variations of the anchors, the size of the objects to be recognized can be taken into consideration and studied. The architecture is classical and supports various backbones, which also affects the quality of the trained model.

RetinaNet is based on a multilevel model; thus, predictions are made at different levels and then aggregated. This structure allows for the recognition of objects of different sizes, particularly by controlling the number of levels and selecting their resolution. The proposed architecture also supports different backbones, thereby providing a wide variety of models.

The YOLO architecture represents the detection problem as a regression problem to spatially separated rectangles and their class probabilities. In this process, the entire image is considered, allowing the model to better understand the context [40].

To begin the study, all of the above models were trained using the noise/distortion-free images from VisDrone dataset analyzed in the previous section. The results obtained for the aforementioned models for the test dataset are presented in Table 1 and plotted in Figure 3, where the values of Intersection Over Union (IoU) [32] and F1 score [33] are given. Recall that, for both IoU and F1 scores, the larger the scores, the better.

Table 1

IoU and F1 score metrics of the trained models

Metric	F1 score	IoU
Faster RCNN	0.7078	0.736
RetinaNet	0.6855	0.6562
SSDLite	0.732	0.618
Yolo v5	0.825	0.763
Yolo v8	0.820	0.763

The results demonstrate that all five models performed reasonably well given the obtained metric values, where the YOLO networks provided the best results. The initial high-quality detection for training data allows studying the effect of image quality on object detection given the data obtained using the trained models.

3. Case Study

In general, noise in images can be of different types and appearances. The most typical noise sources in optical images are read and shot noise [41]. As mentioned above, the AWGN was used as the initial step in our study.

Modeling different noise intensities allows studying the influence of noise intensity on classifier performance. For AWGN with zero mean and uniform power spectral density at all frequencies, it is possible to vary only the variance or standard deviation (STD). The images distorted by AWGN are shown in Figure 4 for different standard deviation values. We considered 10 values of the noise standard deviation: 3, 5, 7, 10, 15, 20, 25, 30, 35, and 50. Recall that noise with standard deviations 3 and 5 is usually invisible, whereas noise with standard deviations 30, 35, and 50 becomes annoying. Also note that noise in R, G, and B components is independent and has the same standard deviation values.

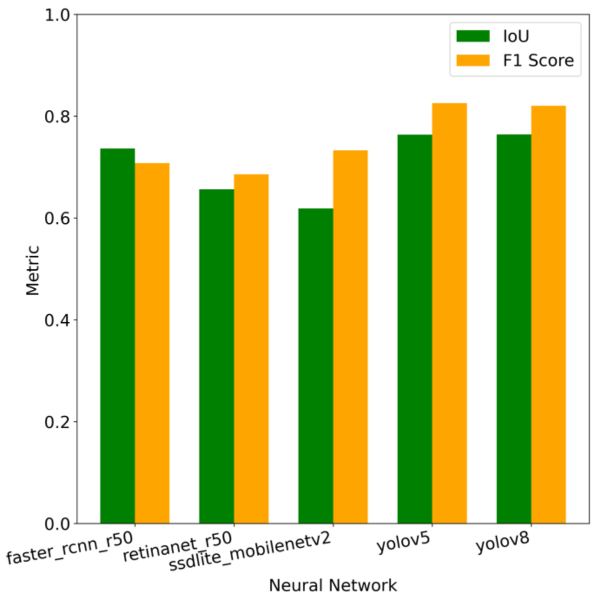

Figure 3. Metrics results of the trained models

Using the obtained noisy images, we studied the object localization and classification quality of previously trained models. For this purpose, we created a model testing environment, the so-called benchmark, to calculate metrics. This method of comparison obtains estimates of the accuracy of each model and compares the impact of image quality on localization quality.

Several criteria were selected as metrics, which are often used to characterize object localization accuracy. The Inersection over Union (IoU) [32] metric represents the ratio of the overlap of two frames to their total area. This metric estimates localization accuracy relative to markup in the dataset.

а б

в г

Figure 4. Noise-distorted images with standard deviation of 10 (a), 20 (b), 30 (c) and 50 (d)

The next comparison criterion was the F1 score [33]. It is calculated based on Precision and Recall [42]. The metric reflects the accuracy of the model's classification based on precision and recall. The metric is mathematically expressed as follows (1):

$$F1 = \frac{2*TP}{2*TP + FP + FN}, \quad (1)$$

where TP is the true positive rate, i.e. the number of correctly predicted objects, FP is the false positive rate (i.e., the number of objects that were marked but were not in the markup), and FN is the false negative rate (i.e., the number of objects that were in the markup but were not predicted by the neural network).

The studied criteria are standard indicators for object classification and localization models [32, 33], so their use in this case is appropriate and relevant to the study.

For each subsample (images with the added AWGN with certain standard deviation), we estimated the aforementioned indicators. Based on the obtained statistics, graphs showing the dependence of localization accuracy on noise intensity are plotted. The graph showing the ratio of the IoU metric to the intensity of the noise in the image (expressed in the STD) is shown in Figure 5.

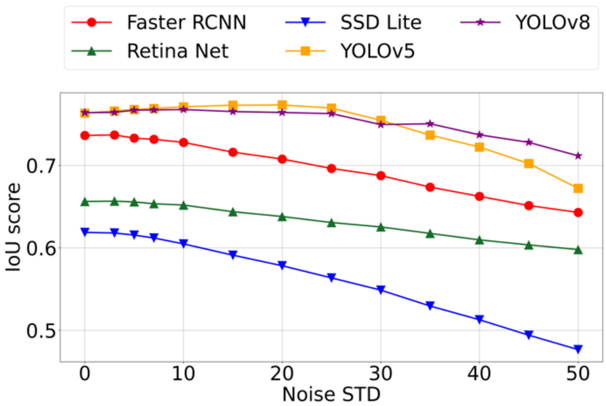

Figure 5. Graph of the IoU versus noise standard deviation

In general, the IoU metric reduced for all tested models, at least for noise standard deviations greater than 20. The reduction speed is also different. Some models are more susceptible to interference, such as the SSD Lite, where the metric drops by 35.7% for STD=50. Some are considerably less susceptible to interference, such as YOLOv8 and RetinaNet, which have drops of 9.4% and 9%, respectively. YOLOv5 is characterized by high immunity to noise and distortions for STD<25. Considering the obtained values of the metric drops, we can state that invisible noise (STD≤5) has practically no negative impact on the result of object localization.

By studying the effect of noise intensity on object classification using the same dataset, we also obtained the dependence of the F1 score on the noise intensity (Figure 6).

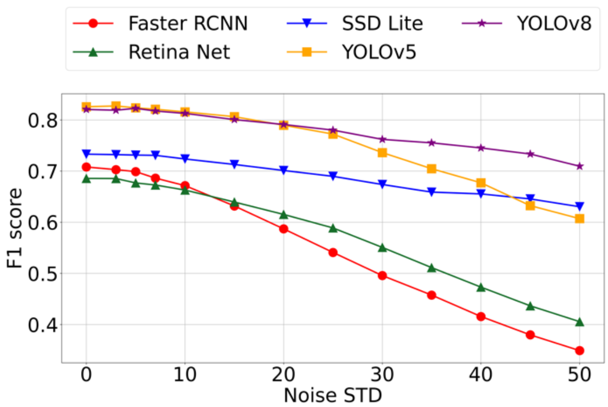

Figure 6. Graph of F1 score versus noise STD

The behavior of the classification quality metric is similar to the localization results. In this case, we observed a significantly faster drop in the metric value with the increase of the noise level. All dependencies decrease monotonically. Although the impact on the models is somewhat different, unlike localization, the SSD Lite has a 13.6% drop in the metric, which is the smallest among all the models studied. The largest drop in this metric was observed for the Faster RCNN model, which exhibited a 51.7% drop. The performance was the best for YOLOv8, which is more resistant to noise than YOLOv5, but only for STD≥25, i.e. for very intensive noise and distortions.

The reason for the poor immunity of the RCNN model is that with a higher number of localized blocks, there is also a higher probability that an object will be misclassified. The fact that the models that produce better localization (Faster RCNN, RetinaNet) ended up with worse classification results confirms this hypothesis.

Despite the differences in the behavior of the localization and classification metrics for different models, the dynamics of the metrics' values decreasing with increasing noise level remain. Classification is reduced more than localization, precisely because of the small size of the target objects and the specifics of the considered task.

4. Discussion

We studied the negative influence of AWGN in wide limits of its intensity. This was performed to understand the conditions when NN performance starts to deteriorate rapidly. In fact, noise with a standard deviation greater than 20 can be met in practice very rarely, or such distortions due to lossy compression might occur only for large compression ratios. This means that the best variants of the considered neural networks can perform well under typical conditions.

On the other hand, there exist methods of blind evaluation of noise characteristics [43, 44]. When applied to acquired images subject to further extraction of useful information, such methods can "characterize" image quality. In particular, methods [43, 44] can determine the dominant noise type, is the noise spatially correlated or no. This might help in further actions such as decision undertaking or producing pre-cautions (Be careful, original data of poor quality). Thus, intelligent systems with autonomous operation can be designed.

Conclusions

The study of the impact of image quality, namely the level of noise in the image, on the quality of object localization and classification demonstrated that this dependence is quite strong. Thus, with an increase in AWGN STD, we obtain worse localization metrics that drop by 10-20% on average. Taking into account the classification metrics, we have a 25-35% drop for different models for the largest STDs. In addition, for STD≤10, the performance reduction was negligible, especially for YOLO-type networks.

The classification result is highly dependent on image quality, which is also a specific feature of the task. A large number of small objects in UAV images are poorly classified when the noise level is high. This is primarily due to distortions, which is a main problem in small object detection tasks.

Two directions of work with noise-distorted data should be investigated in future research. The first approach relates to filtering UAV data and its subsequent processing [45]. In this case, there may also be some loss of information about small objects due to filtering. The second direction is to study the impact of adding noise to the data when training the neural network. Such an approach can improve the accuracy of neural networks and reduce the impact of various types of interference on the quality of work.

Financing

The study was conducted without financial support.

Data availability

The manuscript contains no associated data.

Use of Artificial Intelligence

The authors confirm that they did not use artificial intelligence technologies in their work.

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

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ДОСЛІДЖЕННЯ ВПЛИВУ ШУМОВИХ ЗАВАД РІЗНОГО ТИПУ НА ЗОБРАЖЕННЯХ ОТРИМАНИХ ЗА ДОПОМОГОЮ БПЛА НА ЯКІСТЬ ТА ТОЧНОСТІ ЛОКАЛІЗАЦІЇ ОБЄКТІВ

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Локалізація та класифікація об'єктів різних типів на зображеннях є важливою темою, що активно досліджується, оскільки ці методи та засоби використовуються в найрізноманітніших сферах, включаючи дистанційне зондування, системи безпеки, медичну діагностику тощо. Останнім часом стали популярними системи обробки зображень, встановлені на борту безпілотних літальних апаратів (БПЛА) і дронів, які потенційно можуть бути корисними для багатьох сфер, таких як виявлення мін, контроль за дорожнім рухом і натовпом. Зображення, отримані такими системами, можуть мати досить низьку якість через використання відносно дешевих камер і необхідність передавати отримані дані через лінії зв'язку з обмеженою пропускною здатністю із застосуванням стиснення з втратами. Ці фактори можуть негативно впливати на якість і точність локалізації об'єктів, яку зазвичай виконують навчені нейронні мережі. Однак, незрозуміло, яку інтенсивність шуму та спотворень можна вважати прийнятною, тобто такою, що не призводить до радикального зниження робочих характеристик нейронної мережі. З огляду на це, доцільно дослідити вплив цих ефектів на якість локалізації та класифікації об'єктів, використовуючи достовірні обсяги даних та широкий діапазон інтенсивності шуму/спотворень. Тому основною **темою** цієї статті є дослідження ефективності методів локалізації та класифікації об'єктів на кольорових зображеннях, отриманих за допомогою сенсорів, встановлених на БПЛА. Основна **увага приділяється** залежності метрик локалізації та класифікації від інтенсивності шуму, де генеровані завади імітують не тільки шум, але й спотворення, спричинені стисненням з втратами сучасними кодерами. **Метою** роботи є отримання адекватних статистик та їх аналіз, побудова залежностей метрик від інтенсивності накладених спотворень. **Завдання** полягає в тому, щоб отримати умови, для яких вплив шуму та спотворень можна вважати незначним або прийнятним для практики. Інша мета - проаналізувати чутливість декількох сучасних нейромереж до шуму/спотворень. **Результатом** є статистична оцінка залежності ефективності моделі від якості вхідних даних. **Висновки** ґрунтуються на статистичних даних, що характеризують роботу моделі на інтервалі інтенсивності шуму/спотворень. Висновки дозволяють вибрати найкращі (найбільш стійкі) нейронні мережі та встановити умови їхньої належної роботи.

Ключові слова: локалізація об’єктів; літальні апарати, класифікація техніки, шумові завади, БПЛА.

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