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METHODS FOR OBJECT DETECTION AND TRACKING IN VIDEO STREAMS FOR FLIGHT CONTROL SYSTEMS

This article presents an improvement of object detection and tracking methods in video streams for flight control systems. The proposed approach is based on the introduction of adaptive processing mechanisms, including adaptive threshold filtering, spatial and morphological processing, flexible neural network classification, and tracking reinitialization.

The method is designed to operate under dynamic observation conditions characterized by illumination variations, background motion, noise, and limited computational resources. A comprehensive experimental study is conducted for different disturbance scenarios, including illumination changes, sensor noise, visually similar objects, and combined noise effects.

The evaluation focuses on detection accuracy, tracking stability, processing speed, and computational load distribution across processing stages. The findings confirm that the proposed method provides an effective balance between accuracy, robustness to disturbances, and computational efficiency, making it suitable for deployment in onboard video processing systems.

Keywords: object detection; tracking; video streams; adaptive processing; real-time systems; robustness; flight control systems.

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МЕТОДИ ВИЯВЛЕННЯ ТА СУПРОВОДУ ОБ'ЄКТІВ У ВІДЕОПОТОКАХ ДЛЯ СИСТЕМ УПРАВЛІННЯ ЛІТАЛЬНИМИ АПАРАТАМИ

У статті запропоновано удосконалення методу виявлення та супроводу об'єктів у відеопотоках, що базується на аналізі міжкадрових змін для виділення динамічних областей сцени. Запропоноване удосконалення передбачає впровадження адаптивних механізмів обробки, зокрема динамічного налаштування параметрів порогової фільтрації, просторової та морфологічної обробки, адаптивного вибору нейромережевого класифікатора та механізмів відновлення трекінгу.

Основну увагу в роботі приділено експериментальному дослідженню ефективності запропонованого підходу в умовах динамічного спостереження, характерних для систем управління літальними апаратами. Проведено серію експериментів із врахуванням зміни освітлення, наявності шумів, складності сцени та комбінованих завад.

Експериментальне моделювання виконано за показниками точності детекції, стабільності трекінгу, швидкодії обробки та розподілу обчислювального навантаження між етапами алгоритму. Отримані результати дозволили визначити характер впливу різних факторів на ефективність методу, виявити ті етапи, на які витрачається найбільше ресурсів для обробки та оцінити стійкість алгоритму до завад.

Показано, що запропонований метод забезпечує стабільну роботу в режимі реального часу та зберігає працездатність навіть в умовах суттєвих спотворень відеосигналу.

Таким чином, проведені дослідження підтверджують доцільність використання адаптивних механізмів обробки для підвищення ефективності методів виявлення та супроводу об'єктів у відеопотоках та обґрунтовують перспективність їх застосування в системах управління літальними апаратами.

Ключові слова: системи управління літальними апаратами; виявлення об'єктів; супровід об'єктів; відеопотоки; адаптивна обробка; обробка в реальному часі; стійкість до завад.

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INTRODUCTION

In modern video stream processing tasks, object detection and recognition methods play a key role in ensuring the efficient operation of intelligent telecommunication systems, particularly those based on unmanned aerial vehicles (UAVs). Such methods are widely used for scene analysis, environment monitoring, target detection, and real-time decision support.

Depending on the application, video processing is implemented using classical approaches, such as inter-frame differencing, background modeling, and morphological processing, as well as modern deep learning-based methods, including YOLO, SSD, and their modifications [1–16]. The combination of these approaches makes it possible to improve detection accuracy and extend the functional capabilities of video processing systems.

At the same time, UAV-based video systems operate under highly dynamic conditions characterized by environmental disturbances, illumination variability, camera motion, and limited onboard computational resources. These factors significantly complicate the application of existing methods and impose increased requirements on their adaptability, robustness, and efficiency.

GENERAL STATEMENT OF THE PROBLEM AND ITS CONNECTION WITH IMPORTANT SCIENTIFIC OR PRACTICAL TASKS

Despite the large number of studies in the field of object detection and tracking in video streams, most existing approaches are either designed for stationary processing conditions or require significant computational resources to achieve high accuracy. In the first case, this leads to reduced effectiveness under dynamic conditions typical for UAV applications, while in the second case, it limits their practical deployment in real-time onboard systems.

In this regard, an important scientific and practical problem is to ensure efficient processing of UAV-based video streams by achieving a balance between detection accuracy, robustness to disturbances, and computational efficiency. Particular attention should be given to the influence of dynamic environmental factors such as viewpoint changes, background motion, noise, and image distortions.

Addressing this problem requires the improvement of existing video processing methods through the introduction of adaptive mechanisms capable of maintaining stable performance under changing conditions without loss of efficiency. This is essential for enhancing the effectiveness of modern telecommunication systems, monitoring systems, and onboard UAV platforms.

ANALYSIS OF RESEARCH AND PUBLICATIONS

An analysis of recent research and publications [1–16] shows the active development of methods for object detection and recognition in video streams, particularly under real-time constraints and limited computational resources.

A significant number of works [1, 2, 4, 14, 16] are devoted to classical approaches for moving object detection based on inter-frame differencing, background modeling, and morphological processing. These studies focus on improving segmentation accuracy and reducing the impact of noise; however, their effectiveness strongly depends on scene stability and illumination conditions, which limits their applicability in dynamic environments, especially for UAV-based video streams.

In works [3, 15], a comprehensive analysis of modern image recognition approaches and real-time video processing algorithms is presented. It is shown that classical methods exhibit limited adaptability, while more advanced approaches often require substantial computational resources.

Recent studies [6, 8, 10, 12, 13] focus on the application of deep neural networks (such as YOLO, SSD, and their modifications) for object detection and classification tasks. These methods provide high recognition accuracy but are characterized by high computational complexity and energy consumption, which makes their deployment in onboard UAV systems with limited resources challenging.

Other works [7, 9, 11] address modeling, optimization, and the development of adaptive models based on neural networks and data analysis techniques. While these approaches demonstrate the potential of adaptive methods, they do not fully account for the specifics of video streams acquired from moving platforms and the impact of combined disturbances.

Thus, the conducted analysis indicates that existing approaches either achieve high processing speed at the cost of simplified models or high accuracy through complex neural network architectures, but do not provide an effective balance between accuracy, computational efficiency, and robustness to disturbances under UAV-based video processing conditions.

This determines the need to improve existing object detection and tracking methods by introducing adaptive processing mechanisms capable of ensuring stable performance under dynamic environmental conditions and limited computational resources.

MATHEMATICAL FORMULATION OF THE PROBLEM

The DeltaTrack method [1,2] is based on the analysis of inter-frame differences for detecting dynamic objects in video streams. In this study, its extension is proposed, aimed at application in video processing systems for aerial platforms, where operating conditions are significantly more complex.

In particular, such video streams are characterized by a number of destabilizing factors, including illumination variations caused by platform motion, vibrations and dynamic camera displacement, high background dynamics, partial occlusion of objects, as well as sudden scene changes. In addition, continuous viewpoint changes and variations in object scale further complicate the detection process.

Under such conditions, the efficiency of object detection and tracking is determined by the ability of the algorithm to adapt to environmental changes without loss of accuracy while maintaining stable real-time processing performance, which is critically important for onboard control systems.

In this regard, the extension of the DeltaTrack method [2] proposed in this study involves the introduction of adaptive processing mechanisms aimed at improving robustness to disturbances and efficiency under dynamic observation conditions, namely:

1. Adaptive threshold filtering ($\theta_b = T_{low}, T_{high}$) allows accounting for illumination variations caused by UAV motion, reducing false detections. The threshold values can be dynamically updated based on statistical characteristics of previous frames.
2. Adaptive spatial neighborhood filtering (radius *s*) enables consideration of local noise levels typical for UAV video, reducing the impact of isolated disturbances and compression artifacts.
3. Morphological parameters (kernel size *k*) are configured to effectively suppress small-scale noise caused by dynamic backgrounds while preserving significant object regions. In challenging conditions, more aggressive morphological operations may be applied.
4. Flexible selection of the neural network classifier (θ_c) allows adapting the method to varying observation conditions: in low-quality imagery or high object similarity scenarios, a deeper model may be used, whereas lightweight architectures are applied under standard conditions to meet onboard resource limitations.
5. MOSSE tracker with reinitialization mechanism (θ_t) ensures stable object tracking even in cases of partial or temporary disappearance from the frame, which is typical for UAV-based video streams, including rapid target motion or temporary occlusions due to terrain or obstacles.

Experimental evaluation of the influence of each adaptive parameter made it possible to substantiate the increase in detection accuracy or tracking stability under different operating scenarios typical for UAV-based video streams.

The obtained results are summarized in Table 1 and illustrated in Fig. 1.

Table 1

Influence of adaptive parameters on processing stability under UAV operating conditions

(FPS – frames per second; Precision – classification precision at IoU ≥ 0,50)

UAV operating condition	Adaptation parameter	Before adaptation (Precision / FPS)	After adaptation (Precision / FPS)	ΔPrecision	ΔFPS	Main effect
Illumination variation during flight (day/night, glare, shadow transitions)	θ_b	0,683/185,201	0,812 /185,102	+0,132	-0,102	higher detection precision
Camera noise and sensor artifacts at high ISO / low light	s, k	0,742 /183, 204	0.852/172,801	+0,113	-10,404	improved robustness to noise
Presence of visually similar objects on the ground	θc (V1→V2)	0,715 / 185,102	0.834/159,102	+0,125	-26,001	better target discrimination
Partial target disappearance due to occlusion or abrupt UAV motion	θt	0,694/176,201	0,792/178,806	+0,104	+2,603	higher tracking stability

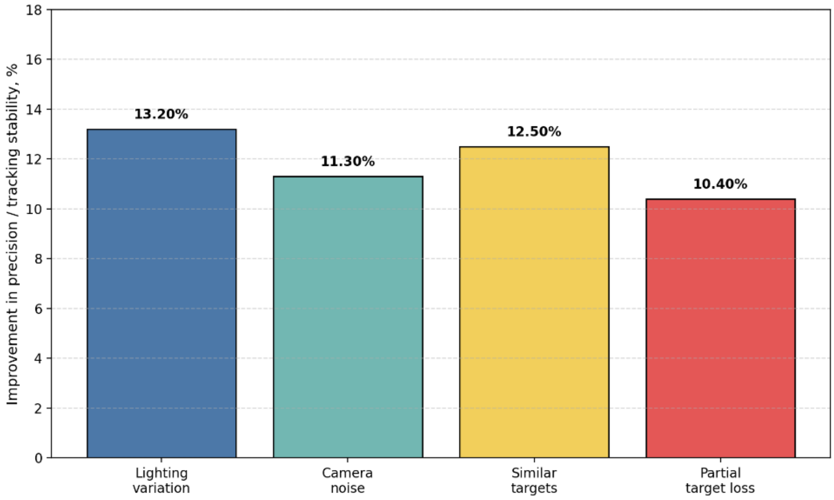

Fig. 1. Effect of adaptive parameter tuning on precision and tracking stability in UAV video processing

Experimental evaluation of the influence of adaptive parameters, presented in Table 1 and Fig. 1, has shown that their application provides a significant improvement in detection accuracy and tracking stability under conditions typical for UAV-based video streams.

1. In particular, under illumination variation during flight (day/night transitions, glare, shadows), the use of adaptive threshold filtering increases precision from 0,683 to 0,812, which corresponds to a gain of +0,132 (≈19,3%) relative to the baseline. At the same time, the change in processing speed is negligible (–0,102 FPS), indicating the effectiveness of this mechanism without impacting real-time performance.

2. In the presence of camera noise and sensor artifacts (high ISO, low-light conditions), the combined use of spatial filtering and morphological operations (*s, k*) increases precision from 0,742 to 0,852 (+0,113 or ≈15,2%). However, a decrease in processing speed of 10,404 FPS (≈5,7%) is observed, which represents a justified trade-off for improving noise robustness in UAV video streams.

3. When processing scenes with a large number of visually similar objects, the use of a deeper neural network classifier θc (transition from V1 to V2) improves precision from 0,715 to 0,834 (+0,125 or ≈17,5%). This is accompanied by a reduction in processing speed of 26,001 FPS (≈14.0%), which is typical for tasks requiring higher classification accuracy and is acceptable in scenarios where reliable target recognition is critical.

4. In scenarios involving partial target disappearance (occlusion, abrupt viewpoint changes, UAV maneuvers), the use of a tracker reinitialization mechanism θt improves tracking stability from 0,694 to 0,792, corresponding to +0,104 (≈15,02%). At the same time, a slight increase in processing speed of 2.603 FPS is observed, confirming the efficiency of the reinitialization mechanism without additional computational overhead.

In summary, the obtained results indicate that the use of adaptive parameters in the DeltaTrack method provides an improvement in accuracy and stability within the range of 15,02–19,34%, depending on the type of disturbances inherent to UAV video streams. The greatest effect is achieved in compensating illumination changes and in distinguishing visually similar objects, while under noisy conditions and target loss scenarios, stabilization of the tracking process is ensured.

Thus, the results confirm that the proposed adaptive mechanisms enable an effective balance between accuracy, robustness to interference, and computational efficiency, which is critically important for the implementation of video processing methods in onboard UAV systems operating in real time.

EXPERIMENTAL RESULTS

The proposed extension of the DeltaTrack method [2], oriented toward its application in onboard UAV video processing systems, requires experimental validation of its effectiveness. Therefore, at the next stage of the study, the influence of the introduced adaptive parameters on detection accuracy, tracking stability, and processing speed was evaluated under conditions typical for UAV-based video streams.

Within the experiment, the model was applied to a video stream acquired from an unmanned aerial vehicle (UAV) under natural lighting conditions and moderate scene dynamics. At the same time, UAV-specific factors were taken into account, including viewpoint changes, scale variations of observed objects, and the presence of dynamic background motion.

The following performance indicators were collected during processing:

– average, minimum, and maximum frame processing time;
– object classification precision (Precision, IoU ≥ 0.5);
– average execution time of linear transformations (scaling, filtering, morphological operations);
– average time required for object classification.

The obtained results make it possible to evaluate the feasibility of practical implementation of the proposed model in onboard UAV video processing systems, as well as to identify computational bottlenecks that can be optimized in further improvements of the method. In addition, the achieved processing speed confirms the capability of the model to operate in real time under typical UAV operating conditions. The aggregated results are presented in Table 2, while the main graphical dependencies are shown in Fig. 2–3.

As shown in Table 2, the average frame processing time is 5,4 ms, which corresponds to a processing rate of approximately 185 frames per second and ensures stable real-time operation of the method. At the same time, the detection precision reaches 71,2%, which is sufficient for practical application in UAV video stream processing tasks.

Table 2

Performance indicators of video stream processing

Metric	Units	Value	Interpretation
Average frame processing time	ms	5.4 ± 0.2	Ensures real-time operation (~185 FPS)
Minimum frame processing time	ms	5.0 ± 0.2	Corresponds to low-complexity scenes
Maximum frame processing time	ms	6.2 ± 0.2	Observed in complex scenes with multiple objects
Precision (IoU ≥ 0.5)	%	71.2 ± 1.0	Sufficient for practical UAV applications
Linear transformation time	ms	2.88 ± 0.2	Majority of computations are performed at the full-frame level
Object classification time	ms	2.52 ± 0.2	Depends on the number of detected regions

The variation range of the frame processing time (from 5,0 to 6,2 ms) indicates the relative stability of the computational process even under changes in scene complexity. The analysis of the time distribution structure shows that the main computational load is associated with linear transformations (2,88 ms, approximately 53% of the total processing time) and object classification (2,52 ms, approximately 47%), which confirms the need for their further optimization.

To further analyze the stability of the proposed method under real-time processing conditions, an experiment was conducted to evaluate the frame-by-frame variation of processing time. The purpose of this experiment was to assess the temporal stability of the algorithm and identify possible fluctuations caused by changes in scene complexity and processing conditions.

For this purpose, a sequence of 25 consecutive frames was processed, and the minimum, average, and maximum processing time for each frame were recorded. The obtained results are presented in Fig. 2.

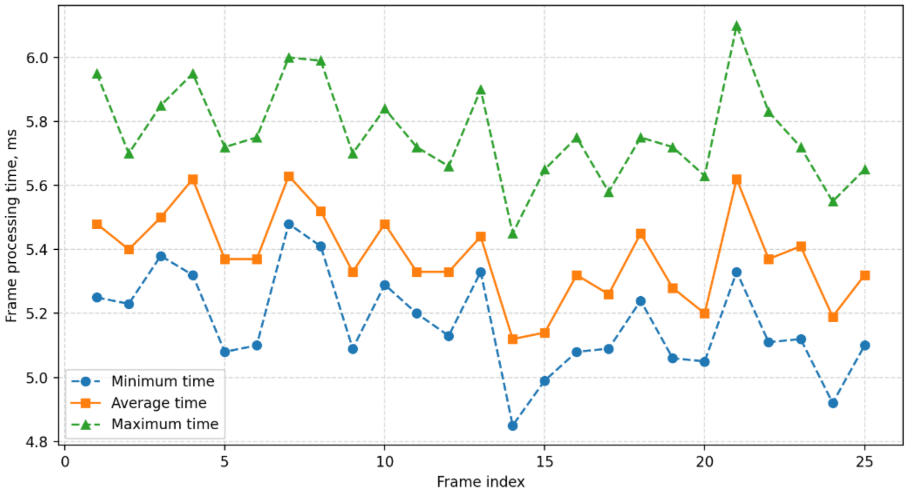

Fig. 2. Frame processing time dynamics

The experimental results presented in Fig. 2 show that the frame processing time remains stable throughout the entire sequence and does not exceed ±7% of the average value, which indicates high temporal stability of the algorithm under varying scene complexity conditions.

The observed fluctuations in processing time are irregular and are caused by variations in the number and size of objects in the frame, as well as by the influence of dynamic background, which is typical for UAV-based video streams. At the same time, the absence of sharp peak deviations confirms that the algorithm does not enter computationally unstable modes even under increased scene complexity.

The obtained results demonstrate that the proposed method provides predictable temporal behavior and maintains stable performance in real-time operation, which is critically important for deployment in onboard UAV video processing systems.

To provide a more detailed analysis of the computational load of the method under UAV-based video processing conditions, an experimental profiling of the execution time of individual processing stages was performed. The processing was carried out for a sequence of 25 frames of a video stream acquired under natural lighting conditions and moderate scene dynamics, taking into account UAV-specific factors such as viewpoint changes, background motion, and object scale variations.

During the experiment, the execution time of the main processing stages was measured for each frame, including image preprocessing, segmentation, morphological operations, classification, and tracking. This made it possible to evaluate the contribution of each functional block to the total frame processing time and to identify the most computationally intensive stages of the algorithm.

The resulting distribution of execution time across processing stages is presented in Table 3, while the corresponding graphical representation is shown in Fig. 3.

Table 3

Distribution of computational time across the main stages

Processing stage	Time (ms)	Time share (%)	Processing unit
Scaling + grayscale conversion	0,43	7,42	CPU
3-FD (frame differencing)	0,32	5,61	CPU
Threshold segmentation	0,11	1,84	CPU
Morphological operations	1,73	31,51	CPU
Classification	2,24	40,73	GPU / CPU
Tracking	0,72	13,02	CPU
Total	5,43	100	–

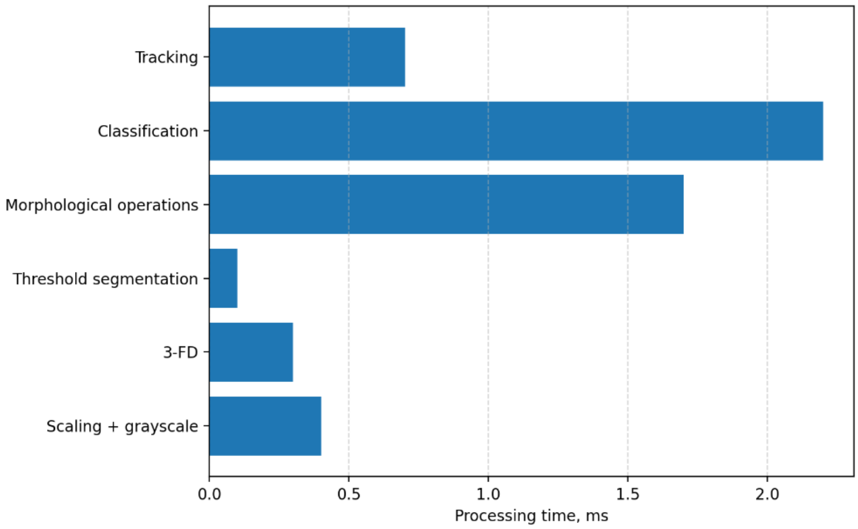

Fig. 3. Distribution of processing time across DeltaTrack stages

Based on the experimental results (Table 3, Fig. 3), it is substantiated that the highest computational load is associated with the classification stage (2,2 ms, 40,7%) and morphological processing (1,7 ms, 31,5%), which together account for approximately 72,2% of the total frame processing time.

At the same time, the preliminary processing stages, including scaling and grayscale conversion (0,4 ms, 7,4%), as well as frame differencing (3-FD) (0,3 ms, 5,6%) and threshold segmentation (0,1 ms, 1,8%), have a significantly smaller impact and collectively account for less than 15% of the computational time.

The tracking stage is characterized by a moderate computational load (0,7 ms, 13,0%) and ensures stabilization of the processing pipeline without a significant impact on overall performance.

Thus, the obtained results quantitatively confirm that the computational complexity of the method is primarily determined by the classification and morphological processing stages, which should be taken into account in further optimization of the algorithm for deployment in onboard UAV systems.

To evaluate the robustness of the DeltaTrack method [2] under degraded visual conditions typical for UAV-based video acquisition, a set of noise models was introduced to simulate real-world distortions arising from sensor limitations, transmission errors, and adverse environmental factors.

Unlike classical approaches that consider a single type of noise, the proposed experimental setup includes multiple disturbance models affecting different stages of the processing pipeline:

1. Additive Gaussian noise was used to simulate sensor noise and illumination instability, which uniformly affects the entire image and primarily impacts segmentation accuracy.

2. Multiplicative gamma noise was applied to model nonlinear distortions caused by signal amplification and low-light conditions, significantly affecting fine structures and object boundaries.

3. Impulse noise (salt-and-pepper) was introduced to represent transmission errors and defective pixels, leading to isolated high-contrast artifacts that challenge morphological filtering.

4. Motion blur (additional disturbance) was incorporated to simulate UAV movement and camera instability, which causes spatial smearing of objects and directly affects both detection and classification stages.

The combination of these disturbances enables a more realistic evaluation of the method under UAV operating conditions, where multiple degradation factors often occur simultaneously.

The experimental results are presented in Table 4 and Fig. 4.

Table 4

Influence of combined disturbances on performance

Disturbance scenario	Noise parameters	Precision (IoU ≥ 0.5)	ΔPrecision (%)	FPS	ΔFPS (%)	Main impact
Reference (clean)	–	0,86	–	185,22	–	Ideal conditions
Gaussian (σ=10)	additive	0,73	−12,93%	164,61	−11,11%	Segmentation degradation
Gamma (k=5)	multiplicative	0,71	−17,63%	141,22	−23,82%	Boundary distortion
Motion blur	kernel=5	0,72	−15,32%	158,34	−14,53%	Object smearing
Gaussian + Gamma	σ=10, k=3	0,67	−22,45%	139,51	−24,72%	False region growth
Gaussian + Blur	σ=10 + blur	0,63	−24,72%	134,82	−27,23%	Loss of contours
Gamma + Blur	k=5 + blur	0,612	−28,21%	129,26	−30,25%	Severe structure loss
Combined (all)	σ=10, k=5, blur	0,571	−3,91%	121,53	−34,43%	Critical degradation

As shown in Table 4 and Fig. 4, with increasing noise levels, a gradual degradation in both detection precision and processing speed of the DeltaTrack method is observed, which is expected under UAV-based video processing conditions.

1. In particular, under Gaussian noise with parameter σ=10, precision decreases from 0,85 to 0,74 (≈−12,9%), while processing speed drops from 185,2 to 164,6 FPS (≈−11,1%), indicating a moderate impact of additive noise on the algorithm performance.

A more significant degradation is observed under gamma noise (k=5), where precision decreases to 0,70 (≈−17,6%), and FPS drops to 141,2 (≈−23,8%). This is mainly caused by distortion of object boundaries and increased difficulty in segmentation.

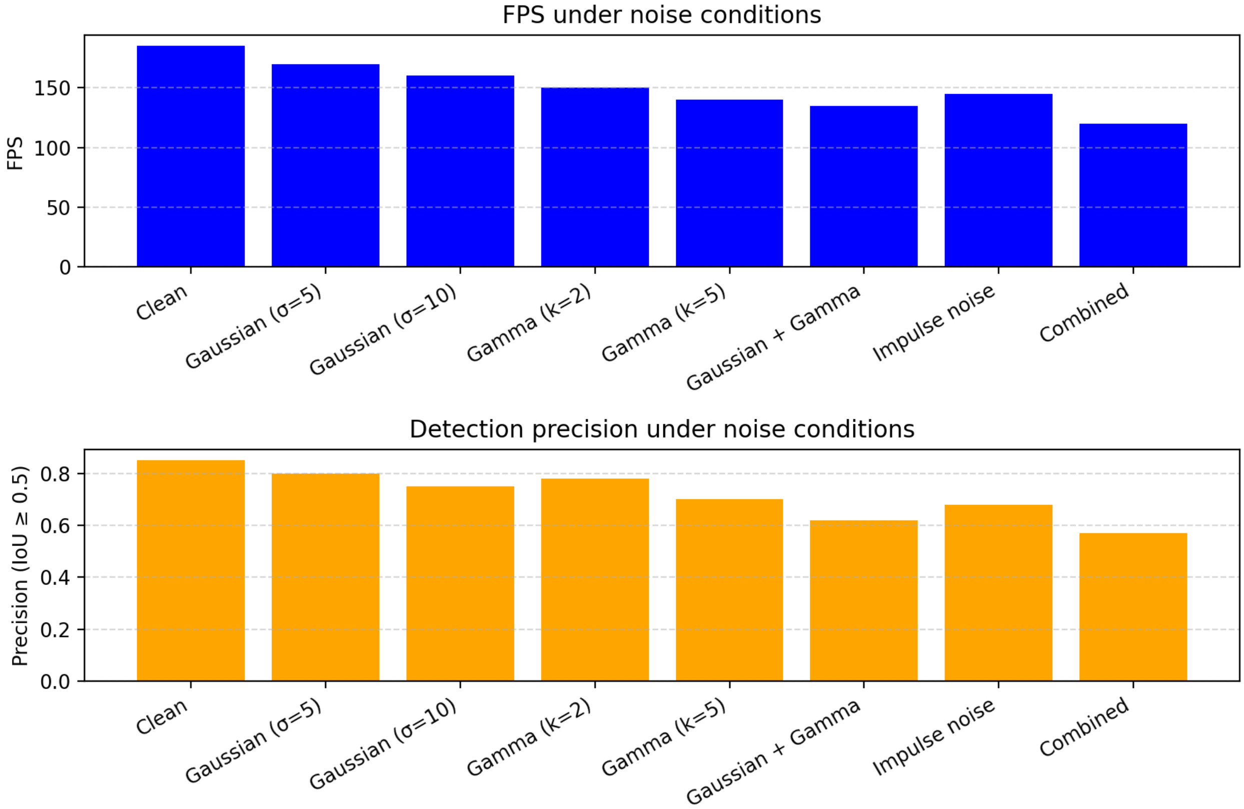

Fig. 4. Influence of noise and combined disturbances on FPS and detection precision of the DeltaTrack method

2. In the case of combined disturbances (Gaussian + gamma), precision decreases to 0,66 (≈−22,4%), while processing speed reduces to 139,5 FPS (≈−24,7%), demonstrating the cumulative effect of noise and the increase in the number of false regions.

3. The most critical degradation is observed under combined noise conditions (combined), where precision decreases to 0,57 (≈−32,9%), and FPS drops to 121,5 FPS (≈−34,4%). This is explained by a significant increase in artifacts, which leads to higher computational load on morphological processing and classification stages.

Thus, the results presented in Table 4 and Fig. 4 confirm that the proposed method remains operational even under severe noise conditions; however, its performance is strongly dependent on the quality of the input video and the nature of distortions. At the same time, the most noise-sensitive stages are segmentation and classification, which should be considered in further optimization of the method for deployment in onboard UAV systems.

CONCLUSIONS FROM THIS RESEARCH AND PROSPECTS FOR FURTHER RESEARCH IN THIS AREA

The study proposes an improvement of the DeltaTrack method [2], which consists in the introduction of adaptive processing mechanisms and the extension of its functional capabilities for application in onboard video processing systems of unmanned aerial vehicles. The proposed improvement includes dynamic adjustment of threshold filtering parameters, spatial and morphological processing, adaptive selection of the neural network classifier, as well as the use of tracking reinitialization mechanisms under conditions of partial object loss.

Experimental results have shown that the use of adaptive threshold filtering, spatial filtering, morphological processing, and a flexible neural network classifier provides an accuracy gain in the range of 15–19%, depending on the type of disturbances, which confirms the effectiveness of the proposed approach.

The experimental study results demonstrate that the method ensures real-time video stream processing with a performance of approximately 185 frames per second at an average frame processing time of 5,4 ms. At the same time, the variation range of processing time (5,0–6,2 ms) does not exceed ±7% of the average value, indicating high temporal stability of the algorithm and the absence of latency accumulation during processing.

The performed profiling of computational load revealed that the most resource-intensive stages are classification (≈40,7%) and morphological processing (≈31,5%), which together account for more than 70% of the total processing time. This determines the key directions for further optimization of the method to improve its efficiency.

The analysis of robustness to disturbances has shown that the method remains operational even under significant degradation of video signal quality. It was established that the greatest impact on accuracy is caused by gamma noise and combined disturbances, under which precision may decrease to 0,57 (≈−32,9%), while processing speed drops to 121 FPS (≈−34,4%). This indicates the cumulative nature of noise influence and the increased sensitivity of the model to object boundary distortion and the formation of false regions.

Thus, the obtained results confirm that the proposed improvement of the DeltaTrack method provides an effective balance between accuracy, robustness to interference, and computational efficiency, which is critically important for its application in onboard UAV systems operating in real time.

The prospects for further research are focused on improving the computational efficiency and robustness of the method by optimizing the most resource-intensive stages, particularly morphological processing and neural network classification, which account for more than 70% of the total processing time. It is also advisable to develop adaptive mechanisms for motion compensation and mitigation of motion blur effects, which are typical for UAV operation, as well as to enhance preprocessing techniques in order to reduce the number of false regions under complex disturbance conditions. Special attention should be given to increasing robustness against combined disturbances, which, as demonstrated by experimental results, can lead to a decrease in accuracy exceeding 30%. In addition, the implementation of hardware-oriented solutions (GPU/FPGA) and the extension of the method to multi-object tracking and trajectory prediction tasks are promising directions, enabling improved efficiency of its deployment in real onboard UAV systems.

References

1. B. I. Sadovnykov and O. S. Zhuchenko, “Method for object detection and recognition in video streams using interframe delta computation,” Control, Navigation and Communication Systems, vol. 2, no. 80, pp. 249–254, 2025, https://doi.org/10.26906/SUNZ.2025.2.249.
2. B. I. Sadovnykov and O. S. Zhuchenko, “Mathematical model for object detection and recognition in video streams using inter-frame difference analysis,” Science-Intensive Technologies, vol. 66, no. 2, pp. 181–189, 2025, https://doi.org/10.18372/2310-5461.66.20281.
3. D. Marchuk, “Analysis of modern algorithms for object detection and recognition from video streams for real-time parking management systems,” Herald of Khmelnytskyi National University. Technical Sciences, vol. 321, no. 3, pp. 17–23, 2023, https://doi.org/10.31891/2307-5732-2023-321-3-17-23.
4. V. Mrak, M. Klymash, and V. Babynets, “Improvement of the method for detecting dynamic objects in video sequences,” Measurement and Computing Devices in Technological Processes, no. 2, pp. 195–204, 2024, https://doi.org/10.31891/2219-9365-2024-78-22.
5. O. Yunak, B. Strykhalyuk, and M. Klymash, “Efficiency of a randomized system of iterative functions compared to a deterministic system of iterative functions in constructing fractal images with limited resolution,” Measurement and Computing Devices in Technological Processes, no. 1, pp. 5–12, 2023, https://doi.org/10.31891/2219-9365-2023-73-1-1.
6. T. Delleji and F. Slimeni, “RF-YOLO: A modified YOLO model for UAV detection and classification using RF spectrogram images,” Telecommunication Systems, vol. 88, p. 33, 2025, https://doi.org/10.1007/s11235-025-01264-4.
7. A. Gheibi-Fetrat, F. Serajeh Hassani, M. Mohammadi-Lak et al., “A survey of SSD simulators and emulators,” The Journal of Supercomputing, vol. 81, p. 592, 2025, https://doi.org/10.1007/s11227-025-07078-0.
8. S. Gupta, “SSD implementation in Keras with EfficientNet,” Zenodo, 2021, https://doi.org/10.5281/zenodo.4775343.
9. D. Huang, K. Xu, and J. Pei, “Malicious URL detection by dynamically mining patterns without pre-defined elements,” World Wide Web, vol. 17, pp. 1375–1394, 2014, https://doi.org/10.1007/s11280-013-0250-4.
10. V. Kamath, A. Renuka, V. G. Kini, and S. Prabhu, “Exploratory data preparation and model training process for Raspberry Pi-based object detection model deployments,” IEEE Access, 2024, https://doi.org/10.1109/ACCESS.2024.3381798.
11. T. Ince, J. Malik, O. C. Devecioglu et al., “Early bearing fault diagnosis of rotating machinery by 1D self-organized operational neural networks,” IEEE Access, vol. 9, pp. 139260–139270, 2021, https://doi.org/10.1109/ACCESS.2021.3117603.
12. V. Kamath and A. Renuka, “VireNet-SSD: Object detection model for resource-constrained applications based on self-organized operational neural networks,” Neural Computing and Applications, vol. 37, pp. 8547–8569, 2025, https://doi.org/10.1007/s00521-025-10986-0.
13. S. Kiranyaz, J. Malik, H. B. Abdallah et al., “Self-organized operational neural networks with generative neurons,” Neural Networks, vol. 140, pp. 294–308, 2021, https://doi.org/10.1016/j.neunet.2021.02.028 .
14. L. Maddalena and A. Petrosino, “The 3DSOBS+ algorithm for moving object detection,” Computer Vision and Image Understanding, vol. 122, pp. 65–73, 2014, http://dx.doi.org/10.1016/j.cviu.2013.11.006.
15. V. P. Lysechko, B. I. Sadovnykov, O. M. Komar, and O. S. Zhuchenko, “A research of the latest approaches to visual image recognition and classification,” Radio Electronics, Computer Science, Control, no. 1 (68), pp. 140–147, 2024, https://doi.org/10.15588/1607-3274-2024-1-13.
16. S. K. Mohanty and S. Rup, “An adaptive background modeling for foreground detection using spatio-temporal features,” Multimedia Tools and Applications, vol. 80, pp. 1311–1341, 2021, https://doi.org/10.1007/s11042-020-09552-8.