UDC 629.735.33:004.93(045)
DOI:10.18372/1990-5548.88.20987

[1]Mykyta Soloviov,
[2]Mykola Komar

ANALYSIS OF MODERN APPROACHES TO AUTONOMOUS UAV NAVIGATION

Institute of Information Technologies and Systems of the National Academy of Sciences of Ukraine, Kyiv, Ukraine
E-mails: [1]19leviathan90@gmail.com ORCID 0009-0003-5131-7497,
[2]nickkomar08@gmail.com ORCID 0000-0001-9194-2850

Abstract—*The development of autonomous navigation methods for unmanned aerial vehicles (UAVs) is driven by the need to ensure reliable positioning, orientation, and trajectory planning without dependence on external infrastructure. This task is particularly critical in environments with partial or complete uncertainty—such as indoor, underground, or GPS-denied areas. Over the last decade, numerous approaches to autonomous UAV navigation have been proposed and implemented, ranging from traditional geometric and algorithmic techniques to intelligent systems and sensor fusion architectures. The objective is t analyze and systematize modern approaches to autonomous UAV navigation and to highlight the potential of correlation-extreme navigation methods in uncertain environments. The paper presents a structured overview of state-of-the-art navigation methods, their classification by operational principles, and their strengths and limitations in different use cases. Special attention is paid to correlation-extreme navigation methods, which rely on optimizing similarity functions between sensory data and reference maps. These methods demonstrate high potential for fully autonomous navigation in GPS-denied or signal-jammed environments. A comparative matrix highlights the trade-offs between accuracy, computational cost, robustness, and flexibility for each method. Correlation-extreme navigation is a promising direction for achieving robust autonomy in UAV systems operating in uncertain and complex conditions.*

Keywords—Autonomous navigation, unmanned aerial vehicle, correlation-extreme navigation, inertial navigation system, GNSS, SLAM, sensor fusion.

I. INTRODUCTION

In modern conditions of the rapid development of unmanned aerial vehicles (UAVs), the task of ensuring their full or partial autonomy is becoming increasingly important. The application domain of UAVs covers a wide range of fields, including reconnaissance, territory monitoring, environmental research, agriculture, mapping, and search-and-rescue operations, among others [1]. In all these cases, a critical requirement is the ability of the vehicle to orient itself in space and provide navigation solutions without operator involvement or with minimal external intervention. This creates a demand for reliable autonomous navigation methods capable of operating in complex and dynamic environments, often under conditions of uncertainty.

Traditionally, UAV navigation is based on the use of global navigation satellite systems (GNSS), inertial navigation systems (INS), as well as sensor suites (cameras, lidars, radars, etc.). However, such systems have significant limitations, including dependence on external signal sources (GNSS), error accumulation (INS), and reduced efficiency under adverse weather conditions or in the absence of visual features. In real-world scenarios – such as flights in canyons, in areas of radio jamming, or under electromagnetic interference – these methods lose effectiveness or may become completely unusable. Therefore, there is a need to develop new autonomous navigation methods capable of functioning under conditions of partial or complete uncertainty.

One of the directions that has attracted increasing attention in recent years is correlation-extreme navigation (CEN/CENS) methods [2]. These methods are based on the idea of determining an object's position by finding the extremum of a similarity function (e.g., correlation) between current measurements and reference information stored in the navigation system memory. This approach enables navigation without external signals and under conditions of significant noise. However, CENS also has several drawbacks, including high computational complexity, sensitivity to measurement errors, and dependence on the accuracy of the reference database.

In addition to CENS, a large number of other approaches to autonomous navigation have been developed in scientific and engineering practice – both classical and intelligent ones, including artificial neural networks, fuzzy logic, reinforcement learning methods, and hybrid models. Each of these approaches has its own strengths and weaknesses, and the choice of an optimal solution depends on the specific task, application conditions, computational resources, and available sensor data [3].

In this regard, there is a need for a systematic analysis of modern approaches to autonomous navigation, with particular attention to their effectiveness under conditions of uncertainty.

The purpose of this paper is to analyze modern approaches to solving autonomous navigation problems, to evaluate the advantages and disadvantages of existing solutions, to outline the unresolved part of the scientific problem, and to substantiate the relevance of further research in the field of correlation-extreme navigation.

Special attention is given to correlation-extreme navigation methods as a promising direction for overcoming existing limitations. The paper systematizes knowledge on autonomous navigation methods, provides their comparative analysis according to key criteria, and substantiates the further development of research in this field.

II. Classification of Approaches to Autonomous Navigation

Solving the problem of autonomous navigation of UAVs requires the selection and implementation of methods that enable the vehicle to determine its position, orientation, and trajectory without continuous operator involvement. Over the past decades, a large number of approaches to autonomous navigation have been proposed, which can be conditionally classified according to their operating principles and the type of data used. This section presents a systematization of the main methods applied in modern UAV navigation systems.

Geometric approaches are based on the direct use of geometric relationships between spatial objects, sensor data, and mathematical motion models [4]. Global navigation satellite systems (GNSS) (GPS, GLONASS, Galileo, BeiDou, etc.) provide high-precision positioning in open environments. However, their effectiveness decreases in urban areas, indoor environments, or under signal jamming. Inertial navigation systems (INS) use data from accelerometers and gyroscopes to compute position through the integration of accelerations and angular velocities. The main limitation of INS is the accumulation of errors, especially during long-duration missions.

Simultaneous Localization and Mapping (SLAM) is a method for simultaneously constructing a map of the environment and determining the vehicle's position within it. Visual (Visual SLAM), laser-based (LiDAR SLAM), and hybrid approaches have been developed. SLAM performs well in structured environments but has limited accuracy under disturbances or when the field of view is restricted [5], [6]. Visual odometry is based on analyzing changes in camera images to estimate motion [7]. This approach requires high-quality images and sufficiently textured environments [8].

Algorithmic and heuristic methods rely on mathematical algorithms for trajectory planning and obstacle avoidance. Search algorithms are widely used to construct optimal paths in known or partially known environments. These methods are effective for planning but often require a complete map or may become computationally expensive in complex environments. Kinematic and dynamic planning methods take into account the physical constraints of the vehicle when generating trajectories and are used in real-time autonomous navigation systems. Reactive methods are based on immediate responses to obstacles and environmental changes without constructing a complete map. A typical example is the artificial potential field method. Their advantage is high computational efficiency, while their main drawback is the risk of getting trapped in local minima.

Intelligent systems have been rapidly developing and involve the use of artificial intelligence for autonomous navigation. Neural networks and deep learning are used for object recognition, semantic segmentation of the environment, motion prediction, and decision-making. Their main advantages include generalization capability, the ability to work with unstructured data, and adaptability. However, they require large datasets and significant computational resources [9]. Fuzzy logic is used for navigation under uncertainty, where classical logical rules are not applicable, and performs well in hybrid control systems [10]. Bayesian networks, Monte-Carlo methods, and particle filters provide robust state estimation based on probabilistic posterior analysis and are key components in SLAM and sensor fusion systems. Reinforcement learning enables an agent to learn optimal behavior through interaction with the environment. It is highly promising for autonomous control in dynamic conditions but requires extensive training.

Sensor fusion involves combining data from multiple sensors (INS, GNSS, cameras, lidars, radars) to obtain a more reliable estimate of the vehicle's state [11]. Common approaches include the Kalman filter and its extensions (EKF, UKF), graph-based architectures, and neural networks for nonlinear fusion. Sensor fusion helps compensate for the weaknesses of individual sensors but requires complex processing and precise calibration.

Correlation-extreme navigation (CEN/CENS) constitutes a distinct class of methods due to its unique operating principle. It involves determining the spatial position of the vehicle by optimizing a similarity function between current observations (e.g., camera images or radar signals) and a reference map (pre-collected or synthetic). This approach does not require GNSS, demonstrates high robustness to interference, and can potentially provide high accuracy even in challenging conditions.

Thus, modern approaches to autonomous navigation can be classified, according to their operating principles, into geometric, algorithmic, intelligent, sensor fusion-based, and correlation-extreme methods. Each of these classes has both successful practical implementations and inherent limitations, especially under conditions of uncertainty.

III. Correlation-Extreme Navigation (CEN/CENS)

Correlation-extreme navigation (CEN, sometimes also referred to as CENS) is a class of methods that enables autonomous determination of an object's spatial position by searching for the extremum (maximum or minimum) of a similarity function between current sensor data and pre-known reference information about the environment. In most implementations, normalized cross-correlation or specialized similarity metrics are used, allowing robustness to noise, scaling, and other distortions.

In general form, the CEN problem is formulated as finding the coordinate r at which the similarity function C(r) between the current sensor observation and the corresponding fragment of a reference map (or template) reaches its extreme value [12].

In the case of image-based navigation, correlation is computed between the current camera image and a reference image (or terrain model) corresponding to a specific spatial position. In radar-based navigation, a similar procedure is applied to signals or their reflections [13].

Correlation-extreme navigation methods have a long history dating back to the 1960s. Initially, they were applied in rocketry and space technology—for example, in the DSMAC (Digital Scene Matching Area Correlation) system developed by NASA for trajectory correction of spacecraft through correlation-based terrain matching [14], [15]. Unlike GNSS, which require external signals, CEN provides full autonomy, making it suitable for operation in complex or isolated environments.

With the advancement of computational capabilities and the emergence of higher-quality sensors (high-speed cameras, radars, lidars), CEN methods have experienced renewed interest. In the 21st century, they are applied in unmanned aerial systems, autonomous ground vehicles, space landing missions (e.g., planetary probes), and other autonomous platforms [14], [16].

A typical navigation system based on CEN methods includes several key components. A sensor module provides current measurements (images, radar signals, altitude data, etc.) [16]. A reference database contains pre-collected maps, orthophotos, elevation data, magnetic maps, or other environmental templates. A preprocessing unit performs normalization, filtering, scaling, and other transformations to ensure comparability of current and reference data [17]. A correlation analysis module computes similarity function values for different candidate positions. An extremum search algorithm determines the most probable position through optimization techniques (e.g., gradient-based methods, stochastic algorithms, Monte Carlo methods). Finally, a state estimation and filtering module integrates correlation results into navigation filtering (e.g., using a Kalman filter), ensuring robust trajectory estimation [18].

The general operating scheme of a CEN system is shown in Fig. 1.

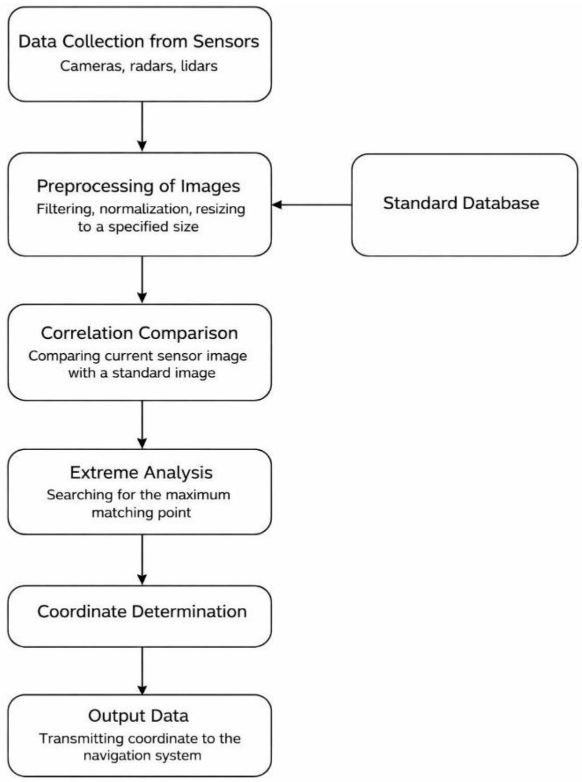

Fig. 1. CEN system operation scheme

The most significant advantage of CEN is its ability to operate without access to GNSS or any external infrastructure. This is critically important in conditions of signal jamming, underground environments, or beyond satellite coverage (e.g., during missions to the Moon or Mars). Correlation-based methods can operate with noisy, incomplete, or distorted data, making them suitable for use in harsh environments (smoke, dust, rain, signal interference). The CEN methodology can be applied to various types of data, including images, radar signals, magnetometric maps, gravimetric profiles, thermal imagery, and others. Reference information may be obtained experimentally or generated synthetically (e.g., using 3D terrain models or satellite imagery).

The computation of the correlation function over a large number of candidate positions is computationally intensive, especially for high-resolution data. This limits the applicability of CEN for real-time onboard processing in resource-constrained platforms. The effectiveness of the method directly depends on the accuracy, relevance, and completeness of the reference map. In the presence of significant discrepancies between the template and the actual environment (e.g., terrain changes, urban development, seasonal variations), the method may produce incorrect results. CEN also encounters difficulties in environments with rapidly changing objects (e.g., traffic flows, crowds, illumination changes), as the correlation structure of the signal varies. Depending on the selected similarity function and initial conditions, the extremum search may converge to a local maximum that does not correspond to the true position, requiring adaptive search strategies or integration with other navigation methods.

Correlation-extreme navigation has been applied in navigation systems for intercontinental ballistic missiles (ICBMs) and spacecraft, where GNSS is unavailable or unreliable. For example, NASA has used vision-based correlation landing systems for Mars missions. In UAV applications, CEN is used for autonomous terrain-following and navigation, especially in areas with unstable GPS signals (mountains, forests, tunnels), where terrain-referenced matching improves positioning accuracy. Underwater vehicles employ CEN based on bathymetric and magnetic maps, enabling navigation in complete absence of satellite communication. In combination with INS, CEN data can be used to correct navigation solutions through external referencing, thereby reducing inertial drift.

Thus, correlation-extreme navigation methods have strong potential for enabling autonomous UAV navigation under uncertainty. Their autonomy, robustness to interference, and independence from external systems make them highly valuable in many practical scenarios. At the same time, existing limitations – particularly high computational complexity and dependence on reference data – continue to motivate further research and development in this area.

Autonomous navigation of UAVs requires high reliability, robustness to external disturbances, flexibility, and adaptability under uncertainty. Therefore, a comparative analysis of the main navigation approaches discussed in previous sections is conducted to identify their advantages, limitations, and suitability for different conditions. Particular attention is given to correlation-extreme navigation (CEN/CENS) as a potentially key solution for navigation tasks under partial or complete uncertainty.

Advantages and limitations of different methods:

- Global Navigation Satellite Systems (GNSS).

Advantages: simplicity, high accuracy in open environments, widespread availability.

Limitations: complete dependence on external signals, vulnerability to jamming, unsuitability for indoor or tunnel environments [16].

- Inertial Navigation Systems (INS).

Advantages: autonomy, high update rate, ease of integration.

Limitations: error accumulation over time, need for periodic correction.

- SLAM.

Advantages: simultaneous mapping and localization, effectiveness in unknown environments.

Limitations: high computational requirements, poor performance in weakly structured or highly dynamic environments.

- Intelligent systems.

Advantages: ability to learn and adapt, high accuracy with proper training.

Limitations: large training datasets required, risks of overfitting or poor generalization, validation complexity [17].

- Sensor fusion.

Advantages: increased reliability through combining multiple data sources.

Limitations: complexity of tuning, requirement for precise sensor calibration.

- CEN/CENS.

Advantages: autonomy, robustness to signal loss, suitability for complex environments.

Limitations: implementation complexity, high computational cost, dependence on reference data quality [18].

None of the analyzed methods fully satisfies all requirements for autonomous navigation under uncertainty. Therefore, hybrid navigation systems that combine the advantages of multiple approaches are actively being developed.

For example:

- INS + GNSS – a classical solution where GNSS corrects INS drift [18];
- SLAM + deep learning – improving mapping using neural networks;
- CEN + INS – periodic correction of accumulated INS errors using CEN [19];
- CEN + reinforcement learning – adaptation of navigation to changing environments in real time [19].

Such combinations improve system robustness, reduce dependence on individual sensors, and enable more reliable operation under partial information conditions.

Comparative analysis shows that no single technology is universal, but each has its own domain of optimal application [20]. CEN/CENS methods, despite their implementation complexity, possess unique properties that make them promising for navigation in challenging, noisy, and GNSS-denied environments [19].

However, to fully realize their potential, several engineering and scientific challenges must be addressed, including increasing processing speed, reducing computational complexity, and adapting algorithms to environmental changes.

Uncertainty in the context of autonomous UAV navigation refers to incomplete, inaccurate, inconsistent, or noisy information about the environment, the system state, or dynamic conditions. It arises due to:

- limitations or imperfections of sensors (e.g., low resolution, limited field of view, noise);
- loss of external signals (GPS, communication, maps);
- dynamic environmental changes (moving objects, weather, lighting, seasonal variations) [21];
- internal errors (inertial drift, software and hardware failures);
- unpredictable behavior of other agents (vehicles, humans, drones).

These factors reduce the reliability of classical positioning and orientation methods, especially in long-duration navigation tasks in unknown or poorly structured environments without GNSS.

Sensor uncertainty arises from noise, limited accuracy, or partial data loss. Structural uncertainty is associated with incomplete or inaccurate environmental knowledge (e.g., missing or outdated maps). Dynamic uncertainty results from time-varying conditions. Algorithmic uncertainty stems from limitations of computational models (e.g., local extrema, ambiguous interpretations). Contextual uncertainty relates to insufficient understanding of the operational scenario.

Inertial navigation systems are prone to drift accumulation, especially without external correction. In the absence of GNSS, positioning errors grow significantly, leading to trajectory deviations. Map-based correlation methods (including CEN) depend on the relevance and accuracy of reference data, which may degrade in rapidly changing environments.

Real-time methods such as CEN and SLAM require significant computational resources [22], limiting their use on lightweight UAV platforms. CEN methods also suffer from local extrema issues, particularly in repetitive environments (e.g., forests, urban grids) [22]. Moreover, real-world conditions are too complex for perfect modeling, making fully predictable navigation behavior unattainable.

Modern methods under uncertainty have clear limitations: GNSS is unusable under jamming or underground conditions; INS alone lacks long-term accuracy [23]; SLAM is limited in highly dynamic environments; intelligent methods may fail in unseen conditions [24]; sensor fusion depends on data availability; and CEN depends on map quality and optimization performance.

As a result, recent research focuses on adaptive navigation systems that adjust behavior based on available information, hybrid models combining multiple methods, reinforcement learning for adaptability, self-diagnostic systems, and integration of CEN with deep neural networks for improved robustness [25].

The analysis shows that among all methods, correlation-extreme navigation has the greatest potential for operation under high uncertainty. It does not rely on external signals, can utilize diverse sensor data, and is capable of operating in dynamic and adversarial environments.

Despite its limitations, further development of this approach – through optimization of similarity functions, integration with machine learning, and adaptive search strategies – can make it a key component of next-generation navigation systems.

Modern UAVs are increasingly used in military applications, agriculture, environmental monitoring, logistics, mapping, and rescue operations. The success of their missions directly depends on the accuracy and reliability of navigation systems, especially in complex or unpredictable environments where traditional positioning methods such as GNSS become ineffective.

Based on the analysis presented in previous sections, it can be concluded that none of the existing navigation methods provides a universal solution for autonomous positioning under uncertainty. This issue becomes particularly critical in the absence of external positioning sources, under high sensor noise, environmental variability, or when operating in previously unseen locations.

Therefore, autonomous navigation systems capable of self-localization based on internal data and reference information are of particular scientific and practical importance. One of the most promising directions in this field is correlation-extreme navigation.

IV. Conclusion

A systematic analysis of modern approaches to autonomous navigation of UAVs under conditions of uncertainty has been conducted. Navigation is a key component of UAV operation, as it ensures safe movement, accurate positioning, and adaptation to changes in the external environment.

In modern technical systems, there is a practical need to ensure reliable autonomous navigation under uncertainty. The application of UAVs in reconnaissance, search-and-rescue operations, environmental monitoring, agriculture, and logistics requires navigation systems capable of operating without continuous access to external signals (GNSS), under noisy conditions, dynamic environmental changes, and limited onboard computational resources.

To address these challenges, a wide range of approaches and methods have been proposed. These include classical GNSS-based and INS; geometric approaches and kinematic planning; simultaneous localization and mapping (SLAM) and visual odometry; LiDAR- and radar-based mapping methods; sensor fusion techniques using Kalman filtering; intelligent approaches based on machine learning, including deep neural networks, reinforcement learning, and fuzzy logic; as well as relatively recent CEN methods, which determine position by searching for extrema of similarity functions between measurements and reference maps. In practice, hybrid architectures combining several of these approaches are often employed to improve reliability and accuracy.

However, existing methods do not always meet the requirements of specific practical applications. The main limitations observed in practice include: dependence on GNSS and vulnerability to jamming; error accumulation in INS; reduced effectiveness of SLAM and visual odometry in low-texture, low-visibility, or dynamically changing environments; high computational demands of deep learning-based methods; and the dependence of CEN on the relevance and completeness of reference data, along with its computational complexity. These limitations reduce the effectiveness of existing solutions in real-world flight scenarios with constrained hardware resources.

Thus, a contradiction arises: there is a clear practical demand for autonomous navigation in real-world applications, yet existing methods do not fully provide the required universality, reliability, and efficiency. This contradiction defines the scientific problem: to develop and improve autonomous navigation methods – particularly through the optimization and hybridization of correlation-extreme approaches with inertial, visual, and intelligent methods – to ensure robust and efficient UAV navigation under conditions of uncertainty.

Therefore, research in this direction is highly relevant, both theoretically and practically justified, and opens new opportunities for the development of truly autonomous UAVs capable of operating without external references in real, dynamic, and uncertain environments.

References

[1] P. Yue, J. Xin, Y. Huang, J. Zhao, C. Zhang, W. Chen, and M. Shan, "UAV autonomous navigation system based on air–ground collaboration in GPS-denied environments," *Drones*, vol. 9, no. 6, p. 442, 2025. https://doi.org/10.3390/drones9060442

[2] I. Jarraya, A. Al-Batati, M. B. Kadri, M. Abdelkader, A. Ammar, W. Boulila, and A. Koubaa, "GNSS-denied unmanned aerial vehicle navigation: analyzing computational complexity, sensor fusion, and localization methodologies," *Satellite Navigation*, vol. 6, Art. 9, 2025. https://doi.org/10.1186/s43020-025-00162-z

[3] Y. Yang, J. Khalife, J. Morales, and Z. M. Kassas, "UAV waypoint opportunistic navigation in GNSS-denied environments," *IEEE Trans. Aerosp. Electron. Syst.*, 2022.

[4] H. Y. Lin and L. Y. Chen, "GNSS-denied UAV localization with satellite and aerial image matching," *SSRN*, 2024.

[5] C. Cadena, L. Carlone, H. Carrillo, Y. Latif, D. Scaramuzza, J. Neira, I. Reid, and J. J. Leonard, "Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age," *IEEE Trans. Robot.*, vol. 32, no. 6, pp. 1309–1332, 2016. https://doi.org/10.1109/TRO.2016.2624754

[6] H. Durrant-Whyte and T. Bailey, “Simultaneous localization and mapping: Part I,” *IEEE Robot. Autom. Mag.*, vol. 13, no. 2, pp. 99–110, 2006. https://doi.org/10.1109/MRA.2006.1638022

[7] T. Cozzens, “UAV navigation releases visual navigation system for GNSS-denied environments,” *GPS World*, 2022.

[8] J. Engel, V. Koltun, and D. Cremers, “Direct sparse odometry,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 40, no. 3, pp. 611–625, 2018. https://doi.org/10.1109/TPAMI.2017.2658577

[9] O. Khatib, “Real-time obstacle avoidance for manipulators and mobile robots,” *Int. J. Robot. Res.*, vol. 5, no. 1, pp. 90–98, 1986. https://doi.org/10.1177/027836498600500106

[10] J. M. Mendel, “Fuzzy logic systems for engineering: A tutorial,” *Proc. IEEE*, vol. 83, no. 3, pp. 345–377, 1995. https://doi.org/10.1109/5.364486

[11] E. William, “UAV navigation in GNSS-denied environment using radio beacons and onboard sensor fusion,” Master’s thesis, Linköping Univ., 2024.

[12] R. Sydorenko, O. Sotnikov, Y. Kozhushko, and D. Babenko, “Substitution of optimization criteria for UAV information processing systems,” *Vyprobuvannia ta sertyfikatsiia*, vol. 4, no. 6, pp. 45–52, 2025. https://doi.org/10.37701/ts.06.2024.06

[13] V. Kharchenko and M. Mukhina, “Correlation-extreme visual navigation of unmanned aircraft systems based on speed-up robust features,” *Aviation*, vol. 18, no. 2, pp. 80–85, 2014. https://doi.org/10.3846/16487788.2014.926645

[14] A. I. Mourikis, N. Trawny, and S. I. Roumeliotis, “Vision-aided inertial navigation for precise planetary landing,” *IEEE Trans. Robot.*, vol. 25, no. 2, 2009.

[15] B. Van Pham *et al.*, “Vision-based absolute navigation for descent and landing,” *IEEE Robot. Autom. Mag.*, 2012. https://doi.org/10.1002/rob.21406

[16] I. Jarraya *et al.*, “GNSS-denied unmanned aerial vehicle navigation: analyzing methods, sensors, and algorithms,” *Satellite Navigation*, vol. 6, Art. 9, 2025.

[17] A. E. Johnson *et al.*, “Implementation of a map relative localization system for Mars Science Laboratory EDL,” *AIAA J.*, 2023.

[18] C. Wang, T. Ji, T.-M. Nguyen, and L. Xie, “Correlation flow: robust optical flow using kernel cross-correlators,” *arXiv preprint*, 2018. arXiv:1802.07078.

[19] H. Liu *et al.*, “A survey of sensors-based autonomous UAV localization techniques,” *Complex & Intelligent Systems*, 2025.

[20] F. Yao *et al.*, “GNSS-denied geolocalization of UAVs using terrain-weighted constraint optimization,” *Int. J. Appl. Earth Obs. Geoinf.*, vol. 134, Art. 104129, 2024. https://doi.org/10.1016/j.jag.2024.104129

[21] Y. Chang *et al.*, “A review of UAV autonomous navigation in GPS-denied environments,” *Aerosp. Sci. Technol.*, 2023.

[22] L. Zhang *et al.*, “Collaborative integrated navigation for UAVs: modeling and mitigating uncertainties,” *Sensors*, vol. 25, no. 3, Art. 617, 2025. https://www.mdpi.com/1424-8220/25/3/617

[23] Inertial navigation systems for UAV: uncertainty and error measurements, 2020.

[24] T. Elmokadem *et al.*, “Toward fully autonomous UAVs: a survey,” *Computers, Materials & Continua*, 2021.

[25] J. Rosen *et al.*, “Advances in inference and representation for SLAM,” *arXiv preprint*, 2021.

Received: March 16, 2026
Accepted: March 30, 2026
Published: April 20, 2026

Soloviov Mykyta. ORCID 0009-0003-5131-7497. Postgraduate Student.
Institute of Information Technologies and Systems of the National Academy of Sciences of Ukraine, Kyiv, Ukraine.
Education: National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”, Kyiv, Ukraine, (2021).
Research interests: cybernetics, mathematics and system analysis, autonomous UAV navigation, embedded systems for UAVs.
Publications: over 5 publications.
E-mail: 19leviathan90@gmail.com

Komar Mykola. ORCID 0000-0001-9194-2850. Candidate of Science (Engineering), Senior Researcher, Deputy Director for Scientific and Organizational Work.
Institute of Information Technologies and Systems of the National Academy of Sciences of Ukraine, Kyiv, Ukraine.
Education: Institute of Information Technologies and Systems of the National Academy of Sciences of Ukraine, Kyiv, Ukraine, (2021).
Research interests: cybernetics, mathematics and system analysis, intelligent systems.
Publications: over 25 publications.
E-mail: nickkomar08@gmail.com

М. В. Соловйов, М. М. Комар. Аналаіз сучасних підходів до розв'язання завдань автономної навігації БПЛА

Розвиток методів автономної навігації для безпілотних літальних апаратів (БПЛА) зумовлений необхідністю забезпечення надійного визначення положення, орієнтації та планування траєкторії без залежності від зовнішньої інфраструктури. Це завдання є особливо критичним в умовах часткової або повної невизначеності, зокрема в приміщеннях, підземних середовищах або зонах із відсутнім чи пригніченим сигналом GPS. Протягом останнього десятиліття було запропоновано та реалізовано численні підходи до автономної навігації БПЛА – від традиційних геометричних і алгоритмічних методів до інтелектуальних систем та архітектур злиття сенсорних даних. Метою статті є аналіз та систематизація сучасних підходів до автономної навігації БПЛА, а також висвітлення потенціау методів кореляційно-екстремальної навігації в умовах невизначеності. Проведено порівняльний аналіз геометричних, алгоритмічних, інтелектуальних, заснованих на злитті сенсорних даних та кореляційно-екстремальних навігаційних підходів; виконано аналіз сучасних наукових публікацій; здійснено синтез критеріїв ефективності та сценаріїв застосування. У роботі подано структурований аналіз сучасних методів навігації, їх класифікацію за принципами функціонування, а також переваги та обмеження в різних прикладних сценаріях. Особливу увагу приділено методам кореляційно-екстремальної навігації, що ґрунтуються на оптимізації функцій подібності між сенсорними даними та опорними картами. Ці методи демонструють високий потенціал для реалізації повністю автономної навігації в умовах відсутності або пригнічення супутникових сигналів. Кореляційно-екстремальна навігація є перспективним напрямом для досягнення високого рівня автономності БПЛА в складних і невизначених умовах експлуатації.

Ключові слова: автономна навігація, безпілотні літальні апарати, кореляційно-екстремальна навігація, інерціальна система, GNSS, SLAM, sensor fusion.

Соловйов Микита Володимирович. ORCID 0009-0003-5131-7497. Аспірант.
Інститут інформаційних технологій та систем Національної академії наук України, Київ, Україна.
Освіта: Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського», Київ, Україна, (2021).
Наукові інтереси: кібернетика, математика та системний аналіз, автономна навігація БПЛА, вбудовані системи для БПЛА.
Публікації: понад 5 публікацій.
E-mail: 19leviathan90@gmail.com

Комар Микола Миколайович. ORCID 0000-0001-9194-2850. Кандидат технічних наук. Старший дослідник. Заступник директора з науково-організаційної роботи.
Інститут інформаційних технологій та систем Національної академії наук України, Київ, Україна.
Освіта: Інститут інформаційних технологій та систем Національної академії наук України, Київ, Україна, (2021).
Наукові інтереси: кібернетика, математика та системний аналіз, інтелектуальні системи.
Публікації: понад 25 публікацій.
E-mail: nickkomar08@gmail.com