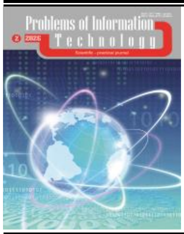

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Adaptive terrain-referenced vision system for autonomous multicopter navigation

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ABSTRACT

This paper proposes an onboard computer vision system with adaptive selection of recognition methods for autonomous multicopter navigation in Global Navigation Satellite Systems (GNSS)-denied environments. The approach represents terrain images as one-dimensional structural signals obtained through preprocessing, segmentation, grayscale conversion, and linearization. Recognition is performed using spectral, wavelet, and dynamic signal matching methods. An adaptive mechanism selects the most appropriate recognition method based on adequacy criteria describing the uniformity, symmetry, convergence, and sensitivity of the recognition process. The selected or combined methods are used for terrain recognition, checkpoint localization, trajectory reconstruction, and flight correction within a unified closed-loop navigation framework. The proposed architecture enables reliable autonomous navigation under spatial distortions, changing observation conditions, and limited onboard computational resources. Experimental results demonstrate that adaptive selection and weighted combination of recognition methods improve the robustness and accuracy of terrain image recognition for navigation in GNSS-denied conditions.

1. Introduction

Modern multicopters and other unmanned aerial vehicles are widely used for monitoring, remote surveillance, mapping, search and rescue operations, and autonomous navigation. One of the key challenges in the operation of such systems is ensuring stable spatial orientation and navigation when GNSS signals are unavailable.

GNSS signal loss can be caused by electronic countermeasures, urban infrastructure, multipath propagation, dense vegetation, and other external factors. Under such conditions, relying solely on inertial navigation systems leads to accumulated positioning errors and reduced multicopter navigation accuracy (Groves, 2013).

One promising approach to solving this problem is the use of onboard vision systems that provide navigation based on the analysis of images of the surrounding space and the Earth's surface. In recent years, visual odometry, Simultaneous Localization and Mapping (SLAM) approaches, and computer vision methods based on local features and neural network architectures have seen significant development (Scaramuzza and Fraundorfer, 2011; Cadena et al., 2016). Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF) methods (Lowe, 2004; Bay et al., 2006), as well as visual-inertial navigation methods (Weiss et al., 2012), are widely used to solve problems of visual localization and image matching.

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Despite the high efficiency of modern computer vision methods, their practical application in multicopter onboard systems faces a number of limitations. The main limitations include the high computational complexity of the algorithms, the need for significant amounts of training data, and their limited applicability in real-time systems with limited computing resources.

In this regard, computationally efficient methods for recognizing Earth surface images, designed for use in lightweight onboard machine vision systems, are of particular interest. Approaches to recognizing Earth surface images based on spectral analysis, wavelet decomposition, and dynamic signal matching methods were considered in (Rzayev et al., 2024a; Rzayev et al., 2024b). A system of recognition method adequacy criteria was proposed in (Rzayev et al., 2024c), designed to assess the robustness and sensitivity of recognition procedures with respect to artificially generated signal families.

Unlike traditional object-oriented computer vision approaches, this paper considers the Earth's surface as a structured source of navigational information suitable for localizing route checkpoints and reconstructing the flight path of a multicopter. The proposed approach is based on a structural-signal representation of landscape images, formed through preprocessing, segmentation, color space transformation, and linearization of Earth's surface images.

The key feature of the proposed system is the adaptive selection and weighted combination of recognition methods based on a system of adequacy criteria that characterize the stability, symmetry, convergence rate, and sensitivity of the recognition process for given families of Earth surface images.

The proposed architecture forms a closed-loop navigation and control system that integrates terrain recognition, checkpoint localization, flight path reconstruction, and multicopter motion correction into a single adaptive onboard vision system. The main objective of the work is to develop an adaptive onboard vision system for autonomous navigation of a multicopter in conditions of unavailability of GNSS signals based on the structural-signal representation of images of the Earth's surface and the adaptive selection of landscape recognition methods.

The main contributions of this work are as follows:

- development of an adaptive terrain-referenced onboard vision architecture that integrates terrain recognition, checkpoint localization, trajectory reconstruction, and flight control within a unified closed-loop navigation framework for autonomous multicopter operation under GNSS-denied conditions;
- development of a structural-signal framework for terrain image representation and adaptive recognition, based on artificial terrain signal families and a system of adequacy criteria for selecting the most appropriate recognition methods;
- experimental validation of the proposed adaptive recognition framework, demonstrating the applicability of adequacy-based method selection for robust terrain recognition under varying observation conditions and limited onboard computational resources.

The remainder of this paper is organized as follows. Section 2 reviews related work on terrain recognition and autonomous navigation. Section 3 presents the proposed adaptive terrain-referenced vision system and its methodological framework. Section 4 describes the experimental validation and discusses the obtained results. Finally, Section 5 concludes the paper and outlines future research directions.

2. Related work

The problem of autonomous navigation of unmanned aerial vehicles in conditions where GNSS-signals are unavailable is currently one of the most rapidly developing areas of research in the field of onboard intelligent systems. The most common approaches to solving this problem include inertial navigation, visual odometry, SLAM approaches, and navigation methods based on image analysis of the surrounding space and the Earth's surface.

Classic inertial navigation systems provide autonomous movement for unmanned aerial vehicles; however, they are characterized by the accumulation of positioning errors over time, which significantly limits the accuracy of spatial orientation during prolonged periods of GNSS signal absence (Groves, 2013). To reduce such errors, visual odometry and visual-inertial navigation methods based on the analysis of image sequences obtained by onboard optical sensors are actively used (Scaramuzza and

Fraundorfer, 2011; Weiss et al., 2012).

SLAM methods, which enable real-time position estimation and environmental reconstruction (Cadena et al., 2016), have made significant advances. Kim and Sukkarieh (2007; Bryson and Sukkarieh, 2008) explored approaches to implementing visual-inertial navigation and SLAM for unmanned aerial vehicles. However, the use of SLAM approaches in multicopter onboard systems is associated with high computational complexity and significant dependence on the quality of the observed scene.

SIFT and SURF methods, based on local image descriptors (Lowe, 2004; Bay et al., 2006), are widely used to solve image matching and robust feature extraction problems. These methods demonstrate high robustness to scaling and partial geometric transformations of images; however, they require significant computational resources when processing high-resolution images and do not always ensure robust operation under the limited computational capabilities of onboard systems.

In recent years, computer vision methods based on deep neural networks and convolutional architectures have seen significant advances. Despite their high image recognition accuracy, these methods require significant amounts of training data and are characterized by high computational complexity, limiting their use in lightweight, real-time onboard vision systems.

One alternative approach is to use recognition methods based on spectral analysis and signal processing. Such approaches include recognition methods based on the Fourier transform, wavelet decomposition, and dynamic signal matching methods (DTW – Dynamic Time Warping and DDTW – Derivative Dynamic Time Warping) (Mallat, 2009; Oppenheim and Schafer, 2010; Sakoe and Chiba, 1978; Keogh and Pazzani, 2001).

The use of adaptive analytical models for selecting computational procedures under uncertainty is also consistent with earlier studies on neuro-fuzzy decision support and intelligent data analysis (Rzayev, 2012), where adaptive model selection was considered as a general methodological principle rather than being restricted to a specific application domain.

The advantage of such methods is their relatively low computational complexity and the ability to adapt them to real-time systems with limited computing resources.

In the works (Rzayev et al., 2024a; Rzayev et al., 2024b), methods for recognizing Earth's surface images were proposed based on a structural-signal representation of the landscape, spectral analysis, and wavelet decomposition. In these works, Earth's surface images were converted into one-dimensional signal representations through preprocessing, color space transformation, scaling, and image linearization.

In the work (Rzayev et al., 2024c), a system of recognition method adequacy criteria was proposed, designed to assess the robustness and sensitivity of recognition procedures based on artificially generated signal families. The use of uniformity, symmetry, convergence rate, and sensitivity criteria allowed for a comparative evaluation of recognition methods for different signal types and observation conditions.

Despite a significant amount of existing research, the integration of structural-signal landscape recognition methods, adaptive selection of recognition methods, and navigation-oriented processing of Earth's surface images within a single onboard machine vision system remains understudied. Furthermore, existing approaches insufficiently address the need to create a closed-loop interaction between landscape recognition, navigation, and multicopter motion control under conditions of limited computing resources and real-time requirements.

Therefore, this paper proposes an adaptive onboard machine vision system based on a structural-signal representation of Earth's surface images, adaptive assessment of the adequacy of recognition methods, and the integration of recognition, navigation, and multicopter motion control procedures into a single closed-loop autonomous navigation system.

3. Proposed approach

An analysis of existing approaches shows that current methods of autonomous multicopters navigation do not sufficiently address the need for adaptive recognition procedures based on the observed landscape and the Earth's surface imaging conditions. Furthermore, existing systems are limited in their focus on integrating recognition, navigation, and motion control procedures within a single, closed-loop, real-time system. In this regard, this paper proposes an onboard technical vision system with an adaptive choice of recognition methods, based on the structural-signal representation of images of the Earth's surface and the use of a set of criteria for assessing the adequacy of recognition procedures.

3.1. General concept of the proposed system

An analysis of existing approaches to autonomous navigation of unmanned aerial vehicles reveals that modern machine vision systems insufficiently address the need for adaptive selection of recognition methods based on the observed landscape and the conditions under which Earth's surface is imaged. Furthermore, existing approaches are primarily focused on solving either local image recognition problems or visual localization tasks, failing to integrate recognition, navigation, and motion control procedures within a single, closed, real-time loop.

In this regard, this paper proposes an onboard vision system with an adaptive selection of recognition methods, designed for autonomous multicopter navigation in conditions where GNSS signals are unavailable.

The conceptual architecture of the proposed system is shown in Fig. 1. The system includes layers of sensor interaction, landscape imaging, structural-signal representation of Earth's surface images, adaptive recognition, navigation analysis, and multicopter motion control.

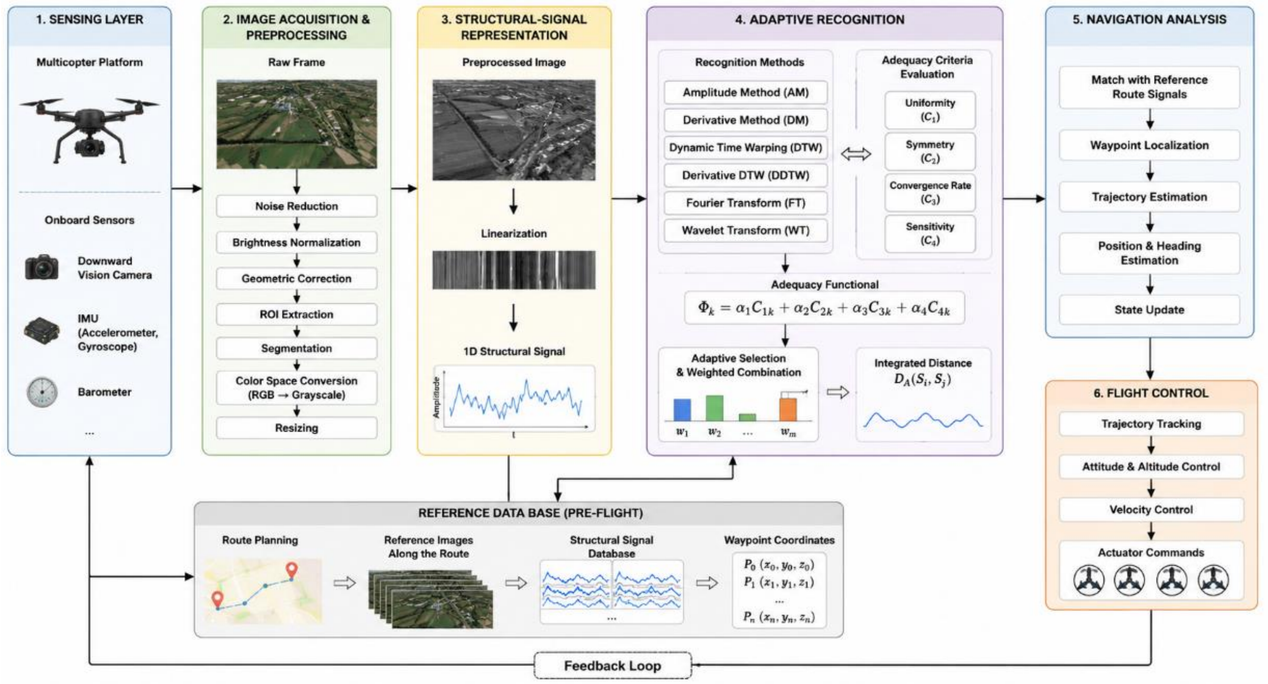

Fig. 1. Conceptual Architecture of the Proposed Terrain-Referenced Onboard Vision System for Autonomous Multicopter Navigation

The proposed approach is based on transforming Earth surface images into structural one-dimensional signal representations that preserve essential features of the observed landscape necessary for navigation-oriented recognition. The resulting signal representations are used to compare current images with reference route images and localize the multicopter's control points.

The key feature of the proposed system is the use of a set of criteria for assessing the adequacy of recognition methods, designed for the adaptive selection and weighted combination of the most stable procedures for recognizing images of the Earth's surface.

The proposed system creates a closed-loop interaction between landscape recognition procedures, navigation analysis, and multicopter motion control, enabling autonomous navigation and flight path restoration in conditions of complete or partial loss of GNSS signal.

3.2. Structural-signal representation of terrain images

One of the key features of the proposed approach is the use of a structural-signal representation of images of the Earth's surface, designed to transform spatial information of the landscape into a form suitable for computationally efficient navigation-oriented recognition.

Let $I(x, y)$ denote a digital image of the Earth's surface obtained by a multicopter's onboard video camera. The first stage of processing involves image preprocessing, including:

- noise suppression;

- brightness normalization;
- geometric correction;
- highlighting the image's informative region.

After preprocessing, the RGB color space is converted to a grayscale image:

$$I(x, y) \to C(x, y),$$

where $C(x, y)$ is a grayscale image of the Earth's surface.

Using a grayscale representation reduces the computational complexity of image processing and highlights structural features of the landscape that are essential for subsequent recognition.

Further, the image is segmented and the working area is scaled to create a unified representation of the Earth's surface:

$$C(x, y) \to C_s(x, y).$$

After segmentation and scaling, the image linearization procedure is performed, as a result of which the two-dimensional image is transformed into a structural one-dimensional signal:

$$S(t) = \Im\{C_s(x, y)\}, \quad (1)$$

where $\Im$ is the image linearization operator; $S(t)$ is the structural signal of the landscape.

The linearization procedure generates a sequence of brightness values that reflects the spatial structure of the observed area of the Earth's surface. The resulting signal preserves essential landscape features necessary for subsequent recognition and localization of route control points.

Structural signal representations of images of the Earth's surface are used to form families of signals: $\Omega = \{S_1, S_2, \ldots, S_n\}$, corresponding to different sections of the multicopter's trajectory.

The resulting signal representations are then used for: (i) spectral analysis; (ii) wavelet decomposition; (iii) dynamic signal matching; and (iv) calculating distance metrics between current and reference images of the Earth's surface.

The schematic for generating the structural-signal representation of Earth's surface images is shown in Fig. 2.

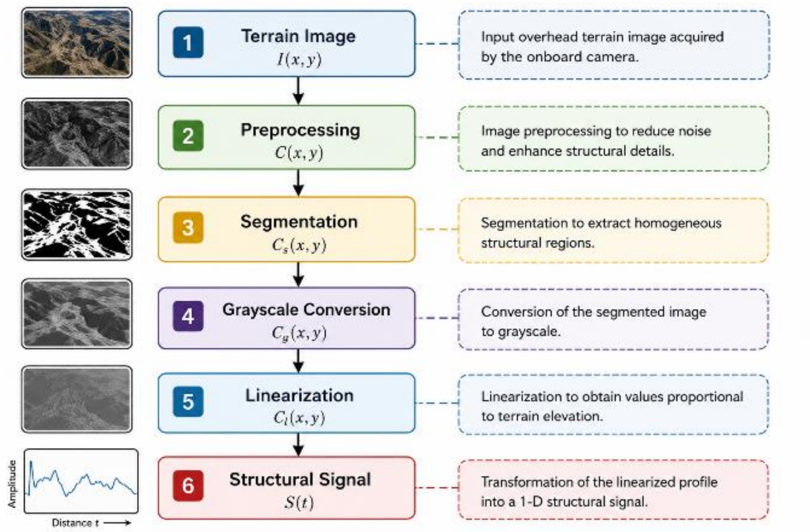

Fig 2. Structural-Signal Transformation of Terrain Images for Navigation-Oriented Recognition

3.3. Artificial terrain signal families

To analyze the stability of recognition methods and assess their adequacy, the proposed work uses artificial families of signals formed on the basis of controlled spatial transformations of images of the Earth's surface.

Let $S_0(t)$ denote the structural signal corresponding to the original image of the Earth's surface. Then the artificial family of signals is defined as:

$$\Omega_h = \{S_0(t), S_1(t), \ldots, S_n(t)\}, \quad (2)$$

where the signals $S_i(t)$ are formed by sequentially spatially shifting the original image relative to the base position with a fixed step h.

The proposed approach uses artificial signal families to model changes in Earth surface images that occur during multicopter motion. Such changes can be caused by:

- shifts in the multicopter's position;
- changes in the viewing angle;
- image scaling;
- local spatial distortions;
- changes in image formation conditions.

The formation of artificial signal families allows for controlled studies of the behavior of recognition methods when changing the parameters of Earth's surface images.

For each signal in the family, distances relative to the reference signal are calculated:

$$D_k(S_0, S_i),$$

where D_k is the distance metric for the k-th recognition method; S_0 is the reference signal; S_i is the current signal of the family.

Analysis of the behavior of the distance sequence $\{D_k(S_0, S_1), D_k(S_0, S_2), \ldots, D_k(S_0, S_n)\}$ allows us to evaluate the stability and sensitivity of recognition methods to spatial transformations of Earth's surface images.

3.4. Adequacy criteria framework for recognition methods

The key feature of the proposed approach is the use of a set of criteria for assessing the adequacy of recognition methods, designed for the adaptive selection of the most stable procedures for recognizing images of the Earth's surface.

Unlike traditional approaches, which treat recognition methods as fixed image processing algorithms, the proposed system views the recognition procedure as an adaptive process dependent on:

- the structure of the observed landscape;
- spatial transformations of the image;
- preprocessing parameters;
- the conditions under which the Earth's surface is imaged.

To evaluate the adequacy of recognition methods, a system of criteria is used: $C = \{C_1, C_2, C_3, C_4\}$, including: uniformity criterion (C_1); symmetry criterion (C_2); convergence rate criterion (C_3); sensitivity criterion (C_4).

The uniformity criterion characterizes the stability of changes in recognition distances with successive changes in the parameters of the signal family images. The symmetry criterion reflects the consistency of the method's behavior with respect to symmetric spatial transformations of the Earth's surface images. The convergence rate criterion determines the method's ability to identify images close to the reference state. The sensitivity criterion characterizes the method's response to changes in the signal family parameters and spatial transformations of the images.

The formulas for calculating the adequacy criteria C_1–C_4 are presented in detail in our previous study (Rzayev et al., 2024c) and are therefore omitted here for brevity. The use of this previously developed and validated set of criteria provides a unified framework for evaluating the performance of recognition methods across different families of terrain images.

For an integral assessment of the adequacy of each recognition method, the following functional is employed:

$$\Phi_k = \alpha_1 C_{1k} + \alpha_2 C_{2k} + \alpha_3 C_{3k} + \alpha_4 C_{4k}, \quad (3)$$

where Φ_k is the integral adequacy score of the k-th recognition method; α_i is the weight of the i-th adequacy criterion[1], satisfying $\sum_{i=1}^{4} \alpha_i = 1$ and $\alpha_i \geq 0$; and C_{ik} denotes the normalized value of the i-th adequacy criterion for the k-th recognition method. The adequacy criteria C_1–C_4 were introduced and formally defined in our previous studies (Rzayev et al., 2024a; Rzayev et al., 2024b).

The set of recognition methods under consideration will be denoted by

$$M=\{M_{AM}, M_{DM}, M_{DTW}, M_{DDTW}, M_{FT}, M_{WT}\},$$

where the elements of the set correspond to the amplitude method (AM), the derivative method (DM), the DTW and DDTW methods, as well as the recognition methods based on the Fourier transform (FT) and wavelet decomposition (WT).

For a given family of signals Ω_h, the most adequate recognition method is determined by the expression

$$M^*(\Omega_h) = \arg\min_{M_k \in M} \Phi_k(\Omega_h), \quad (4)$$

where M is the set of recognition methods under consideration; M_k is a separate recognition method; M^* is the method with the best adequacy indicators for the considered family of signals.

Lower values of the adequacy functional correspond to better agreement between the recognition method and the considered family of terrain signals.

Thus, a set of criteria for assessing adequacy forms the basis of the mechanism for adaptive selection of recognition methods and ensures the possibility of using the most stable procedures for analyzing images of the Earth's surface, depending on the characteristics of the observed landscape and the conditions for image formation.

3.5. Adaptive recognition and decision-making mechanism

After the formation of a structural-signal representation of the Earth's surface images and an assessment of the adequacy of the recognition

[1] In the experiments, equal weights were used (α_i=0.25, i=1, …, 4), assuming equal importance of all adequacy criteria.

methods, adaptive recognition of the current image is carried out and a decision is made on the spatial position of the multicopter relative to the route control points.

Let $S_{cur}(t)$ denote the structural signal formed from the current image of the Earth's surface, and $R=\{R_1, R_2, \ldots, R_N\}$ be the base of reference signals corresponding to the control images of the route.

Each reference signal R_i corresponds to a control point $P_i = (x_i, y_i, z_i)$, whose coordinates were saved during the flight route generation stage. Based on the adequacy assessment results obtained in Subsection 3.4, the most preferred recognition method is determined for the considered family of signals Ω_h using (4).

Moreover, to improve the robustness of recognition, the proposed system utilizes not only the selection of an individual method but also the ability to form an ensemble of recognition methods based on their adequacy assessments. In this case, an integral recognition metric is computed as a weighted combination of the distances produced by individual recognition methods:

$$D_A(S_{cur}, R_i) = \sum_{k=1}^{m} w_k D_k(S_{cur}, R_i)\,, \quad (5)$$

where $D_k(S_{cur}, R_i)$ is the distance between the current terrain signal S_{cur} and the reference signal R_i computed by the k-th recognition method; w_k is the weighting coefficient assigned to that method according to its adequacy assessment; and m is the total number of recognition methods included in the ensemble.

To ensure comparability of the results obtained by different recognition methods, normalization of recognition distances and adequacy criteria is performed before the aggregation procedure, which allows eliminating the influence of differences in measurement scales on the results of the adaptive selection of methods and the formation of an integral recognition metric.

The weights are derived from the integral adequacy scores of the recognition methods according to the following expression:

$$w_k = \frac{(\Phi_k + \varepsilon)^{-1}}{\sum_{r=1}^{m} (\Phi_r + \varepsilon)^{-1}}\,. \quad (6)$$

This approach ensures greater contribution from methods with better adequacy metrics for the signal family under consideration.

For each reference signal in the database, the integral recognition metric is calculated. The point corresponding to the minimum distance value is selected as the most probable route checkpoint:

$$P^* = \arg\min_i D_{\text{int}}(S_{cur}, R_i)\,. \quad (7)$$

The resulting checkpoint is considered an estimate of the multicopter's current spatial position relative to the pre-defined flight route.

In addition to localizing the checkpoint, the system generates a quantitative assessment of recognition reliability. This is done using the relative difference between the minimum and subsequent values of the integral recognition metric. The greater the difference between the best and alternative solutions, the greater the system's confidence in the correct localization.

Using an adaptive recognition method selection mechanism allows for consideration of the observed landscape's characteristics and the conditions under which Earth's surface is imaged. Unlike systems using a fixed recognition method, the proposed approach enables dynamic weighting between recognition methods based on their suitability for a specific observation situation.

The adaptive recognition mechanism determines the most probable route checkpoint, evaluates the reliability of the decision, and generates navigation information necessary for subsequent trajectory reconstruction and multicopter control.

Thus, the adaptive recognition mechanism not only localizes the most probable route checkpoint but also generates a quantitative assessment of the decision's reliability. Using adequacy criteria, the contribution of individual recognition methods can be dynamically adjusted depending on the observed landscape and the Earth's surface imaging conditions.

The adaptive mechanism generates navigation information, including an assessment of the multicopter's current position relative to the route checkpoints, as well as the reliability of the decision. From a systems perspective, the proposed adaptive decision-making mechanism follows the general principles of analytical decision support, where the final decision is formed by integrating multiple evaluation criteria and selecting the most appropriate alternative (Rzayev, 2016).

The general diagram of adaptive recognition and navigation decision generation is shown in Fig. 3.

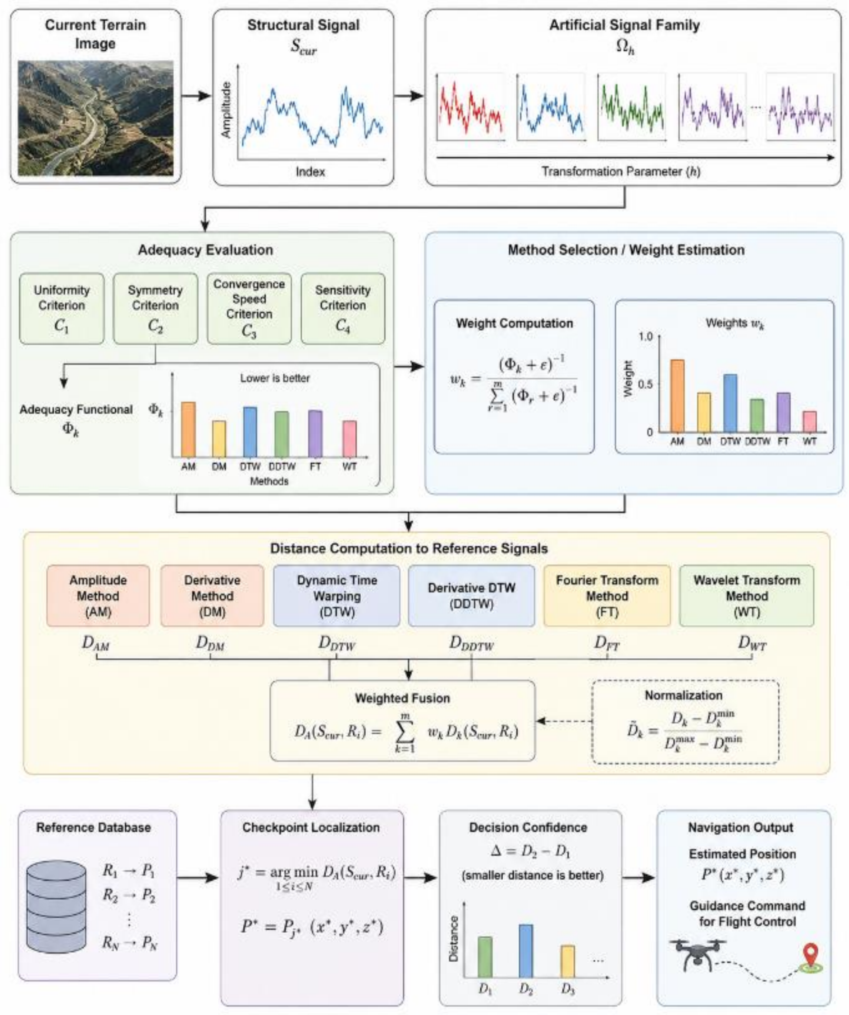

Fig. 3. Adaptive recognition and navigation decision-making workflow

3.6. Terrain-referenced navigation and flight control

The results of adaptive recognition are used to solve the main navigation problem: determining the current position of the multicopter relative to a previously formed flight route and restoring the trajectory of movement in conditions of partial or complete unavailability of signals from global navigation satellite systems.

In the proposed system, navigation is based on a sequence of route checkpoints $P=\{P_1, P_2, \ldots, P_N\}$, each of which is associated with a corresponding reference image R_i of the Earth's surface and its structural-signal representation. Checkpoints are generated during the preliminary flight phase or during the mission and are stored in the onboard navigation database.

Let $P^*=(x^*, y^*, z^*)$ denote the checkpoint localized by the adaptive recognition mechanism. The current position of the multicopter is then determined relative to the nearest checkpoint and adjacent route elements.

To improve navigation stability, sequential localization of control points is used. Unlike independent recognition of individual images, the system takes into account the relative positions of previously identified route control points and verifies the logical consistency of recognition results. This reduces the likelihood of erroneous localization in the presence of visually similar terrain.

Based on a sequence of localized control points, an estimate of the current position of the multicopter relative to the trajectory of movement $T=\{P_1, P_2, \ldots, P_N\}$ is formed.

If the GNSS signal is lost, the system searches for the nearest control point on the route and determines the direction of further movement based on the saved sequence of control images.

To implement the autonomous return mode, a reverse trajectory is used

$$T^{-1}=\{P_N, P_{N-1}, \ldots, P_1\},$$

generated by inverting the sequence of route checkpoints. Each newly recognized checkpoint is used to refine the multicopter's current position and adjust its motion parameters.

Navigation data generated by the recognition system is fed to the multicopter's motion control circuit. Based on this data, spatial position errors are calculated:

$$\Delta x = x_r - x,$$
$$\Delta y = y_r - y,$$
$$\Delta z = z_r - z,$$

where (x, y, z) are the current coordinates of the multicopter; (x_r, y_r, z_r) are the coordinates of the target waypoint.

The resulting errors are used to generate control actions that correct the trajectory, stabilize the spatial position, and execute navigation commands.

In the proposed architecture, the processes of terrain recognition, checkpoint localization, trajectory restoration, and motion control are integrated into a single closed loop. Unlike traditional systems, which treat image recognition and navigation as independent tasks, the proposed system uses recognition results directly to generate control actions and correct the multicopter's motion in real time.

Thus, the integration of adaptive Earth surface image recognition with the navigation and control loops enables autonomous spatial orientation, route restoration, and return of the multicopter in conditions of degradation or complete unavailability of external navigation information.

4. Experimental results

To experimentally validate the proposed approach, Earth surface images obtained during multicopter flight simulations and presented in previous studies on landscape recognition and drone motion control were used. The original images were subjected to feature extraction, scaling, and subsequent linearization, resulting in the formation of corresponding structural signals used as recognition targets.

In accordance with the proposed methodology, artificial signal families were generated by sequentially spatially shifting the base Earth surface image. Signal families generated for shift values of d_1=2 and d_2=4 were used for analysis, enabling us to examine the robustness of the recognition methods under varying observation parameters. The resulting signal families were used to compare recognition methods based on the WT and FT transforms. The results of the assessment of the conformity of recognition methods with the adequacy criteria C_1, C_2 and C_3 for the family of signals with offset d_1=2 are presented in Table 1.

Table 1. Adequacy criteria values for d_1=2

Method	C_1	C_2	C_3
WT	1.2656	0.7357	0.3491
FT	0.7019	0.3120	0.5852

The results obtained demonstrate that the methods under consideration exhibit different behavior with respect to uniformity, symmetry, and convergence rate criteria, confirming the need for their comparative evaluation before use in a machine vision system. These values were obtained in an experiment comparing artificial families of Earth surface signals.

A similar experiment was performed for a family of signals with an offset d_2=4. The results are presented in Table 2.

Table 2. Adequacy criteria values for d_2=4

Method	C_1	C_2	C_3
WT	2.0951	0.23165	0.5802
FT	1.1253	0.02714	0.6673

As can be seen from Table 2, increasing the spatial bias leads to changes in the adequacy criteria for both recognition methods. This confirms the dependence of recognition performance on the structure of the analyzed images and the parameters of the artificial signal families.

To assess the robustness of the recognition methods, sensitivity criterion C_4 was calculated based on a comparison of the results obtained for different bias values.

The corresponding sensitivity coefficients are presented in Table 3.

Table 3. Sensitivity coefficients of recognition methods

Method	u_1	u_2	u_3	u_k
WT	1.6554	0.31487	1.6621	3.6324
FT	1.6032	0.08697	1.1404	2.8306

The obtained values demonstrate the superior robustness of the wavelet transform-based recognition method compared to the Fourier transform-based method.

Based on the sensitivity coefficients, weighting factors were calculated for the adaptive recognition procedure. The results are presented in Table 4.

Table 4. Adaptive weights of recognition methods

Criterion	WT	FT
C_1	0.50801	0.49199
C_2	0.78358	0.21642
C_3	0.59308	0.40692
C_4	0.56203	0.43797

From Table 4 it follows that the method based on the wavelet transform has a higher integral priority when forming an adaptive recognition procedure. It is these weights that are used to form an integral recognition metric and subsequent localization of route control points.

To illustrate the adaptive recognition process, real images of the Earth's surface were used, obtained along the route of the multicopter. The reference image of the control point and the corresponding test images of the landscape are presented in Fig. 4.

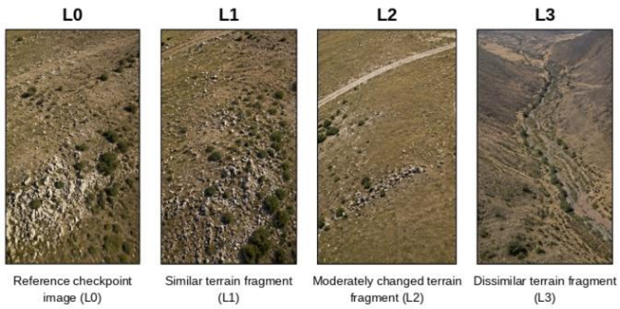

Fig. 4. Reference and test terrain images used for adaptive recognition experiments

After preprocessing, segmentation, and linearization, each Earth surface image is converted into a corresponding structural-signal representation. The resulting signals are used as objects for further recognition and method validation. Examples of structural-signal representations of the images shown in Figure 4 are shown in Fig. 5.

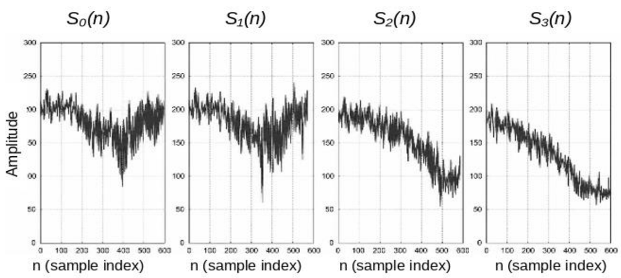

Fig. 5. Structural-signal representations of terrain images after feature extraction, segmentation and linearization

Additional verification was performed using real images of the Earth's surface obtained along the multicopter's flight path. Similarity scores were calculated for several control images relative to the reference image. The results are presented in Table 5.

Table 5. Recognition results for terrain images

Method	L_1	L_2	L_3
WT	26.286	137.53	214.24
FT	18.861	45.234	56.916
Convolution	24.236	112.05	170.81

The results demonstrate that the use of adaptive additive convolution provides robust recognition performance and allows for the advantages of individual methods to be taken into account depending on the characteristics of the analyzed landscape.

Thus, the experiments confirm the feasibility of using artificial signal families to evaluate the adequacy of recognition methods and their subsequent adaptive selection. The results demonstrate that the proposed approach provides a formalized procedure for selecting the most robust methods for recognizing Earth's surface images and can serve as a basis for developing onboard vision systems for multicopters operating in environments with limited or completely unavailable external navigation information.

The obtained results confirm that adequacy-based adaptive weighting improves the stability of terrain recognition compared with the use of a fixed recognition method. This demonstrates the practical applicability of the proposed adaptive onboard vision architecture for navigation-oriented image analysis.

5. Conclusion and future work

The work proposes an adaptive technical vision system for autonomous navigation of a multicopter using images of the Earth's surface in conditions of limited availability or complete absence of signals from global navigation satellite systems. The proposed approach is based on the structural-signal representation of landscape images, the formation of artificial signal families, and the adaptive selection of recognition methods based on a set of adequacy criteria.

A conceptual architecture of the on-board system has been developed, combining the processes of landscape recognition, localization of route control points, navigation decision-making and flight control.

The experiments carried out confirmed the possibility of using adequacy criteria to assess the stability of recognition methods and the formation of adaptive procedures for selecting the most effective algorithms depending on the characteristics of the observed landscape.

The obtained results demonstrate that the proposed approach provides a consistent methodological framework for integrating terrain recognition, adaptive decision-making, and navigation support within a unified onboard vision system.

This framework can serve as a basis for developing computationally efficient multicopter navigation systems capable of autonomous spatial orientation, trajectory restoration, and reliable operation under degraded or unavailable GNSS conditions.

Further research will focus on expanding the landscape imagery database, integrating additional recognition methods and data from various onboard sensors, and experimentally verifying the proposed system on a real multicopter platform.

Of particular interest is the development of online adaptation and self-learning mechanisms to improve the accuracy and stability of navigation in changing environmental conditions.

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