UDC 681.3.06; 004.89; 623.4

V. A. Romanko
Korolov Zhytomyr Military Institute
https://orcid.org/0009-0008-5749-284X

D. V. Koval, Cand. Sc. (Tech.)
Korolov Zhytomyr Military Institute
https://orcid.org/0009-0009-5133-9542

O. V. Levchenko, Dr. Sc. (Milit.), Prof.
Yevhenii Bereznyak Military Academy
https://orcid.org/0000-0001-6254-591X

APPLICATION OF A RESIDUAL NEURAL KALMAN FILTER IN THE NAVIGATION MODULE OF AN UNMANNED AERIAL VEHICLE

The paper considers a practical implementation of an external navigation module for an unmanned aerial vehicle based on a residual neural Kalman filter. The experimental platform is a compact single-board computing module of the Raspberry Pi-like class that interacts with a flight controller, a visual channel, and a satellite navigation module. The main focus is not on flight tests but on a reproducible bench architecture, hardware-software integration, and a practical sensor configuration combining inertial, satellite, barometric, and visual channels.

It is shown that, at the current stage, it is sufficient to use the available flight-controller software stack, a reproducible bench contour, and a separate independent contour for further software development. The operability of the visual and barometric channels, communication with the flight controller, and diagnostic presence of the magnetometer are confirmed, whereas the satellite channel is confirmed only at the level of bench visibility without requiring a stable navigation fix. The selected platform is suitable for the role of an external computational contour on which sensor-data processing and further development of the navigation module can be implemented.

The obtained results form a reproducible bench basis for transition to the next research stage associated with the first flight prototype. At the same time, flight, a standard working communication channel between the external module and the autopilot, and migration to another autopilot software stack are deliberately kept outside the scope of this paper.

Keywords*: residual neural Kalman filter; external navigation module; unmanned aerial vehicle; single-board computing module; visual channel; satellite navigation; barometric channel.*

Problem statement. Increasing the navigation robustness of unmanned aerial vehicles under satellite-channel degradation is one of the key tasks of modern onboard systems. During operation, satellite measurements may lose reliability due to electronic countermeasures, multipath propagation, short-term shielding, or longer failures. Under such conditions, a navigation contour that relies only on the standard means of the flight controller does not always provide the required robustness of state estimation [1, 2].

This paper presents not an isolated result but the third link in a consecutive research cycle devoted to the development of the residual neural Kalman filter (RNKF), from the formalization of the idea to practical implementation. The basic concept of adaptive RNKF application was recorded in the Ukrainian patent application a202506585 [3]. The first paper by the authors [4] provided initial model confirmation of the approach on stand 1.1: in that work, RNKF was considered as a residual neural add-on to the classical Kalman filter, and an approximate reduction in the root mean square error of coordinate and velocity estimation by 15-40% compared with the classical Kalman filter was shown. The second paper of the cycle [5] transferred the study to a simplified three-dimensional model contour of stands 2.1 and 2.2, where the RNKF architecture was developed and its operation was analyzed under navigation-channel degradation scenarios.

Thus, whereas the first and second papers mainly answered the question of the fundamental operability and expected effect of the method in a model environment, the present paper focuses on another question: whether this approach can be transferred to a reproducible bench hardware-software architecture of an external navigation module. Therefore, the study concentrates on the transition from the model stage to stands 3.1 and 3.2, while the next stage of the cycle should be stand 4.1 as the first flight prototype.

The cycle of works forms a consistent chain of evidence: from patent formalization of the idea to the initial model effect of stand 1.1, then to extended three-dimensional modeling on stands 2.1 and 2.2, then to reproducible hardware-software bench implementation on stands 3.1 and 3.2, and later to flight verification on stand 4.1.

This paper considers one practical variant of applying the patented RNKF: when the quality of the satellite channel deteriorates, the filter should reduce trust in satellite measurements and strengthen the role of the visual and barometric channels in forming the navigation estimate. The present work does not prove a full field implementation of this mechanism; it proves the construction of a bench architecture on which such a mode can be correctly implemented and verified at the next stage.

Orange Pi Zero is used as the experimental platform. It is considered as a representative of compact Raspberry Pi-like modules for external onboard data processing. This choice is methodologically justified because the purpose is not to compare specific commercial models but to verify the fundamental suitability of a lightweight external computing module for implementing RNKF in a practical contour.

Analysis of recent research and publications. The theoretical foundations of the Kalman filter, its recursive prediction-correction scheme, and the subsequent development of the continuous variant were laid in the classical works of R. Kalman and R. Bucy [6, 7]. These results became the basis for modern inertial-satellite, visual-inertial, and combined navigation systems.

Among Ukrainian works relevant to this paper, the study by Ye. B. Artamonov, A. K. Zhutlynska, T. I. Zalozny, A. V. Radchenko, and K. M. Radchenko should be noted first; it considers the integration of GPS and IMU data in a noisy environment [1]. For inertial navigation systems of unmanned aerial vehicles, I. V. Zimchuk and T. M. Shapar performed parametric synthesis of filtering algorithms and separately studied algorithms for filtering accelerometer measurements in strapdown inertial navigation systems [8, 9]. Under distortion or intentional spoofing of satellite measurements, the results of M. Turianytsia and B. Chetverikov on applying the Kalman filter to refine GNSS survey data with account for spoofing are also of practical value [2].

For the visual channel and neural-network support in the domestic research context, works by authors from Korolov Zhytomyr Military Institute and the related scientific environment are important. In particular, S. V. Kovbasiuk, R. M. Osadchuk, M. P. Romanchuk, and L. M. Naumchak considered an algorithm for forming an a priori data set of a neural network for processing digital aerial images [10]. The work by I. A. Pilkevych, A. M. Tokar, O. V. Frandzhi, and R. I. Loboda is devoted to a training and simulation system for unmanned aerial vehicle operators and records the applied context of domestic unmanned aerial system deployment, although it does not solve the problem of onboard multisensor state estimation [11].

Recent international works mainly focus on multisensor GNSS / IMU / CAM / BARO architectures, visual-inertial localization in environments with degradation or loss of the satellite channel, and hybridization of classical filters with neural-network modules. S. A. Negru, P. Geragersian, I. Petrunin, and W. Guo proposed a hybrid federated architecture integrating GNSS, IMU, a monocular camera, and a barometer to increase the resilience of UAV navigation [12]. A. Tonini, M. Castelli, J. S. Bates, N. Lin, and M. Painho studied visual-inertial localization of aerial vehicles in the absence or unavailability of the satellite channel [13], and E. Gallo and A. Barrientos studied visual-inertial navigation for fixed-wing unmanned aerial vehicles based on a virtual vision sensor [14]. For hybrid filters with trainable components, the work of Y. Aburasain, M. Bilal, and K. Kim is also indicative; it investigates the integration of a neural network with the Kalman filter to improve prediction accuracy in dynamic systems [15].

Therefore, the analysis of recent research shows that separate aspects of inertial-satellite integration, visual-inertial navigation, barometric support, and neural correction of classical filters have been sufficiently studied. At the same time, the practical transition from the patent-algorithmic RNKF idea to a reproducible bench architecture of an external navigation module remains insufficiently covered, especially where the flight controller, a lightweight external computing module, a visual channel, and a barometric channel are combined under satellite-measurement degradation.

Formulation of the research task. The aim of the work is to prove the practical feasibility of an external navigation module based on RNKF in a bench architecture using Orange Pi Zero, the SpeedyBee F405 V3 flight controller, the HBVCAM F2316HD / OV2710 camera, and the Beitian BE-252Q satellite module.

To achieve this aim, the following tasks must be solved:

build a bench architecture of the external navigation module in which the flight controller, external computing module, visual channel, satellite channel, and barometric channel form a minimally sufficient practical contour;

align the canonical multisensor IMU / GNSS / MAG / CAM architecture with the actually available configuration of inertial, satellite, barometric, and visual channels;

perform hardware-software integration of the stand nodes, determine the minimally sufficient equipment configuration, and record acceptance criteria for the bench contour;

experimentally confirm the operability of the built contour and show that it is a suitable basis for further implementation of trust redistribution from the degraded satellite channel to the visual and barometric channels.

The scientific novelty of the study lies in transferring RNKF from the patent-model and three-dimensional model contour to a reproducible bench architecture of an external navigation module, as well as in aligning the canonical sensor scheme of the research cycle with the actual hardware configuration of this paper. The practical significance consists in forming a reproducible hardware-software basis suitable for the next transition from the bench level to the flight stage.

Architecture of the external navigation module. In the proposed architecture, the SpeedyBee F405 V3 flight controller performs low-level stabilization and acts as a source of integrated sensors. The Orange Pi Zero external module serves as an additional computational contour on which RNKF, visual-data preprocessing, and measurement-trust estimation logic can be implemented. The HBVCAM F2316HD / OV2710 camera forms the visual channel, and the Beitian BE-252Q module provides satellite navigation binding through the flight controller.

Within this research cycle, RNKF has passed a consecutive path from patent description and mathematical idea to initial modeling, then to extended three-dimensional modeling, and then to the bench verification level. The evolution of stands and stages of the work cycle is summarized in Table 1.

Table 1

Evolution of stands and stages of the work cycle

Stand code	Working name	Purpose	Place in the cycle
Stand 1.1	Initial RNKF model stand	Simulation modeling of a neural Kalman filter as a residual add-on to the classical estimator, with the first quantitative estimates of accuracy and robustness	First quantitative evidence of the first paper and methodological premise of RNKF
Stand 2.1	Basic three-dimensional stand	Simplified three-dimensional modeling of nominal mode, intensive maneuvers, satellite-channel degradation, and combined channel degradation	Main model evidence of the second paper
Stand 2.2	Multilayer perceptron stand	Formation and verification of the training sample for the Multilayer Perceptron variant of RNKF	Auxiliary stand of the second paper
Stand 3.1	Canonical bench contour	Reproducible bench contour with diagnostic procedures and artifact package	Main source of evidence in this paper
Stand 3.2	Independent clean contour	Separated contour for checking an independent execution structure	Additional source of evidence in this paper
Stand 4.1	First flight prototype	Transition to limited flight tests and a new standard interaction channel	Next stage of the cycle

In this interpretation, stand 1.1 records the first technical result of the cycle: in the first paper [4], it showed an approximate reduction in the root mean square error of coordinate and velocity estimation by 15-40% compared with the classical Kalman filter, as well as increased robustness to outliers in satellite measurements and growth of inertial-sensor noise. Stands 2.1 and 2.2 deepen this result in a three-dimensional model contour, whereas stands 3.1 and 3.2, considered in this paper, transfer the cycle into a reproducible hardware-software plane.

For the integrity of the cycle, it is useful to distinguish three classes of stands. Stands 1.1, 2.1, and 2.2 belong to the model class, where the main proof is a quantitative assessment of the algorithmic effect. Stands 3.1 and 3.2 belong to the hardware-bench class, where the main proof is reproducibility of the real contour, availability of channels, and correctness of node integration. Stand 4.1 should constitute the flight class, where the main proof will already be operability under real motion and flight constraints.

In the present study, this issue is solved by clearly separating two levels of sensor-system description. In the canonical description of the series, RNKF is considered as an architecture with an Inertial Measurement Unit (IMU), a Global Navigation Satellite System (GNSS), a Magnetometer (MAG), and a Camera (CAM). In contrast, the current work focuses on a practical experimental configuration with inertial, satellite, barometric, and visual channels, corresponding to the actually assembled stand. Under this approach, the magnetometer is not conceptually excluded but is not treated as a central analysis channel, whereas the barometric channel is considered as the standard source of altitude information at the first stage [4, 5]. The practical sensor configuration and the roles of individual channels are shown in Table 2.

Table 2

Practical sensor configuration of the external navigation module

Channel	**Data source**	**Practical role in this paper**	**Status**
Inertial Measurement Unit (IMU)	SpeedyBee F405 V3 flight controller	Basic inertial channel	Required
Global Navigation Satellite System (GNSS)	Beitian BE-252Q through the flight controller	Satellite navigation binding at bench level	Required
Flight-controller barometer	Integrated flight-controller barometer	Standard altitude channel of the first stage	Required
Camera (CAM)	HBVCAM F2316HD / OV2710 connected to Orange Pi Zero	Visual channel of the external module	Required
Magnetometer (MAG)	Magnetometer in the flight-controller contour	Diagnostic or background channel	Not central

The functional distribution in the system is as follows: the flight controller provides standard stabilization contours and access to IMU, GNSS, and the barometric channel; the external module receives the visual stream, interacts with the controller, and forms an external navigation estimate; the camera provides the visual channel for feature extraction and motion estimation; the barometer is used as a practical altitude channel; and the magnetometer remains a background or diagnostic channel. The structural scheme of this configuration is shown in Fig. 1.

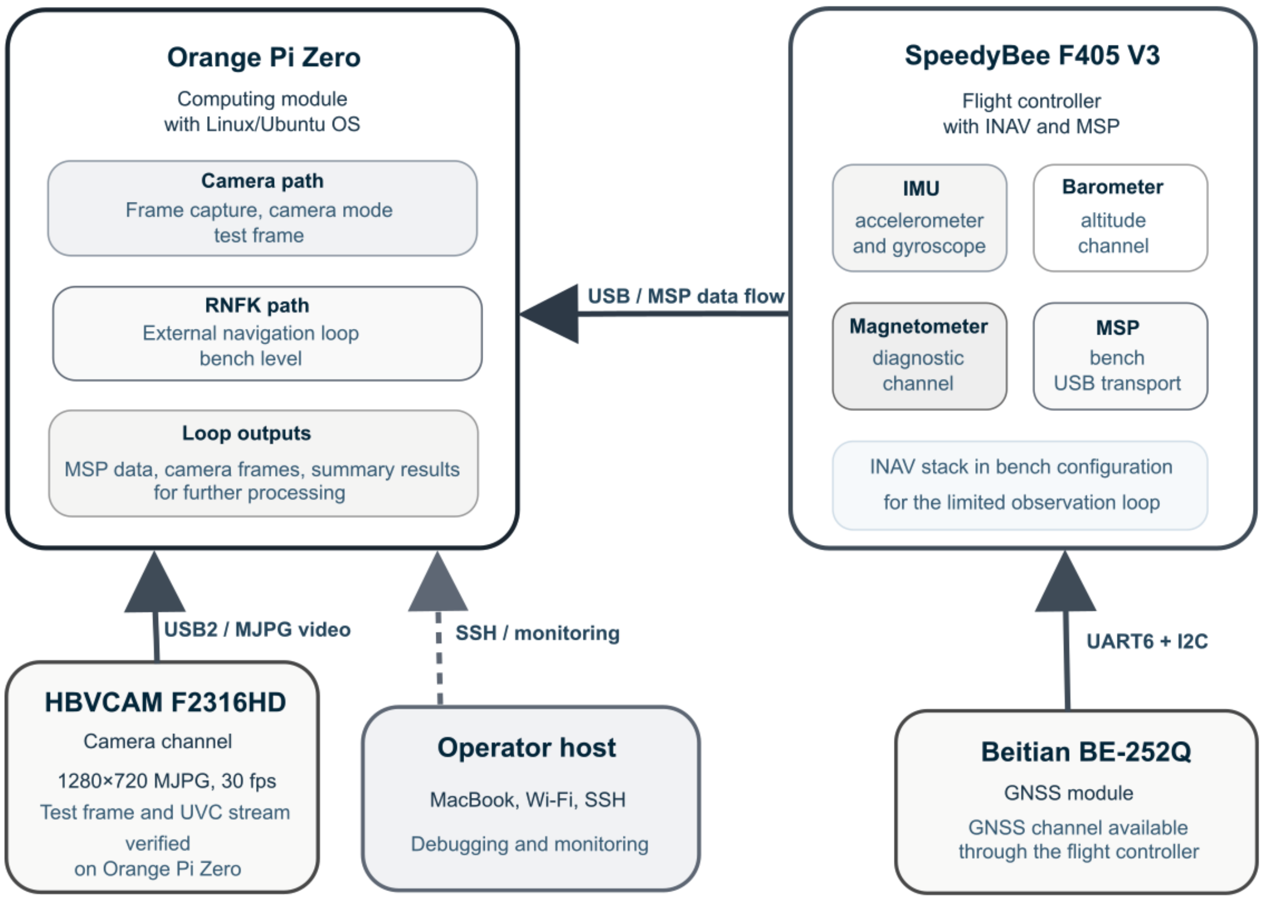

Fig. 1. Structural scheme of the external UAV navigation module in the experimental configuration

The theoretical basis of the proposed approach is the combination of the Kalman filter with residual neural correction and a mechanism of adaptive redistribution of trust in sensor channels. Within this study, it is reasonable to limit the method description to those elements directly related to the architectural role of the external module. Let the state vector include coordinates, velocities, and orientation parameters of the platform, while the measurement vector is formed from IMU, GNSS, barometric, and CAM channels. The classical estimation part is based on dynamic prediction and correction by available measurements, whereas the neural residual part forms a correction to the base estimate using innovations and sensor-set quality features [4, 6, 7, 15].

In the most general form, the discrete dynamics model of the external navigation contour can be written as

$$\mathrm{x_k} = \mathrm{F_k}\,\mathrm{x_{k-1}} + \mathrm{B_k u_k} + \mathrm{w_k}, \tag{1}$$

where x_k is the state vector at step k; F_k is the state-transition matrix; B_k is the control matrix; u_k is the vector of control or service inputs; w_k is the process noise.

The measurement model for the multisensor contour is

$$\mathrm{z_k} = \mathrm{H_k x_k} + \mathrm{v_k}, \tag{2}$$

where z_k is the measurement vector; H_k is the observation matrix; v_k is the measurement noise.

It should be noted that z_k is formed from inertial, satellite, barometric, and visual channels, while the practical configuration of the stand determines which components of this vector are actually available at each step.

Basic recursive estimation in the classical Kalman filter is performed through prediction and correction:

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1} + B_k u_k, \tag{3}$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k, \tag{4}$$

$$K_k = P_{k|k-1} H_k^T \left(H_k P_{k|k-1} H_k^T + R_k \right)^{-1}, \tag{5}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \left(z_k - H_k \hat{x}_{k|k-1} \right), \tag{6}$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1}, \tag{7}$$

where $\hat{x}_{k|k-1}$ is the predicted state before measurement update; $\hat{x}_{k|k}$ is the corrected state estimate; $P_{k|k-1}$ is the covariance matrix of the prediction error; $P_{k|k}$ is the covariance matrix after correction; Q_k is the covariance matrix of process noise; R_k is the covariance matrix of measurement noise; K_k is the Kalman gain matrix; I is the identity matrix.

In the RNKF logic, the classical estimate is supplemented by a residual neural correction:

$$\hat{x}_{k|k}^{\mathrm{RNFK}} = \hat{x}_{k|k} + \Delta x_k^{\mathrm{NN}}, \tag{8}$$

$$\Delta x_k^{\mathrm{NN}} = f_\theta(r_k, q_k), \tag{9}$$

$$r_k = z_k - H_k \hat{x}_{k|k-1}, \tag{10}$$

where $\hat{x}_{k|k}^{\mathrm{RNFK}}$ is the corrected RNKF state estimate; Δx_k^{NN} is the neural residual correction; $f_\theta(\cdot)$ is the neural-network module with parameters θ; r_k is the innovation vector; q_k denotes quality and availability features of the sensor channels.

The quantities r_k and q_k allow RNKF to reduce trust in a degraded satellite channel and strengthen the contribution of visual and barometric channels to the final navigation estimate.

The principal role of the external module is that it enables additional processing of visual-channel information, estimation of measurement quality, and restructuring of trust in channels when the quality of satellite data deteriorates, without direct intervention in the low-level stabilization contour. In the logic of the patented RNKF, this means reducing the weight of the degraded satellite channel and increasing the role of visual and barometric channels in forming the state estimate. For this paper, it is important that the bench architecture already contains the minimally sufficient set of channels on which such a mode can be implemented in subsequent works.

Hardware-software implementation and bench verification methodology. In the current work, Orange Pi Zero is used as an available experimental platform for testing the external navigation contour. The obtained results relate not only to this specific board but also to a broader class of compact Raspberry Pi-like platforms suitable for constructing external onboard computing modules.

The minimally sufficient set of the current work should be separated from the service environment. The required configuration includes the external navigation module nodes and standard sensor sources, while service access and separate power supply are needed for bench verification, artifact collection, and reproducibility support. This hardware configuration is summarized in Table 3.

To ensure reproducibility on the Orange Pi Zero single-board module, a Linux / Ubuntu-based software environment was used, namely Armbian Linux v25.5.1 for Orange Pi Zero with kernel 6.12.23-current-sunxi. In this paper, this characteristic fixes the software basis of the external module and supplements the hardware scheme of the stand without replacing it.

Table 3

Minimally sufficient hardware configuration of the stand at the current research stage

Node	**Role in the system**	**Interface / connection**	**Status in this study**
Orange Pi Zero single-board computing module	External computing module	Central node of the stand	Required
SpeedyBee F405 V3 flight controller	Source of integrated sensors and exchange channel with the external module	Universal Serial Bus (USB) host connector on Orange Pi Zero connected to the USB-C connector of the flight controller	Required
HBVCAM F2316HD / OV2710 camera	Visual channel	USB 2.0 port	Required
Beitian BE-252Q satellite module	Satellite channel	Interface to the flight controller	Required
Flight-controller barometer	Standard altitude channel	Integrated into the flight controller	Required
Flight-controller magnetometer	Background diagnostic channel	Integrated or standard external contour of the flight controller	Not central
Battery pack	Bench power supply for Orange Pi Zero	USB-A to mini-USB power cable	Only for bench power
Operator computer	Service access and material collection	Wireless network and remote access	Service

In stand 3.1, the camera is connected to the USB 2.0 port of the Orange Pi Zero board, and the flight controller is connected to Orange Pi Zero through a USB / MSP channel, where MSP denotes the MultiWii Serial Protocol. The Beitian BE-252Q satellite module is connected to the SpeedyBee F405 V3 via the sixth Universal Asynchronous Receiver-Transmitter (UART) port and the Inter-Integrated Circuit (I2C) two-wire serial bus. This configuration is specifically a bench configuration and must not be mixed with the future flight architecture. The connection scheme of stand 3.1 is shown in Fig. 2.

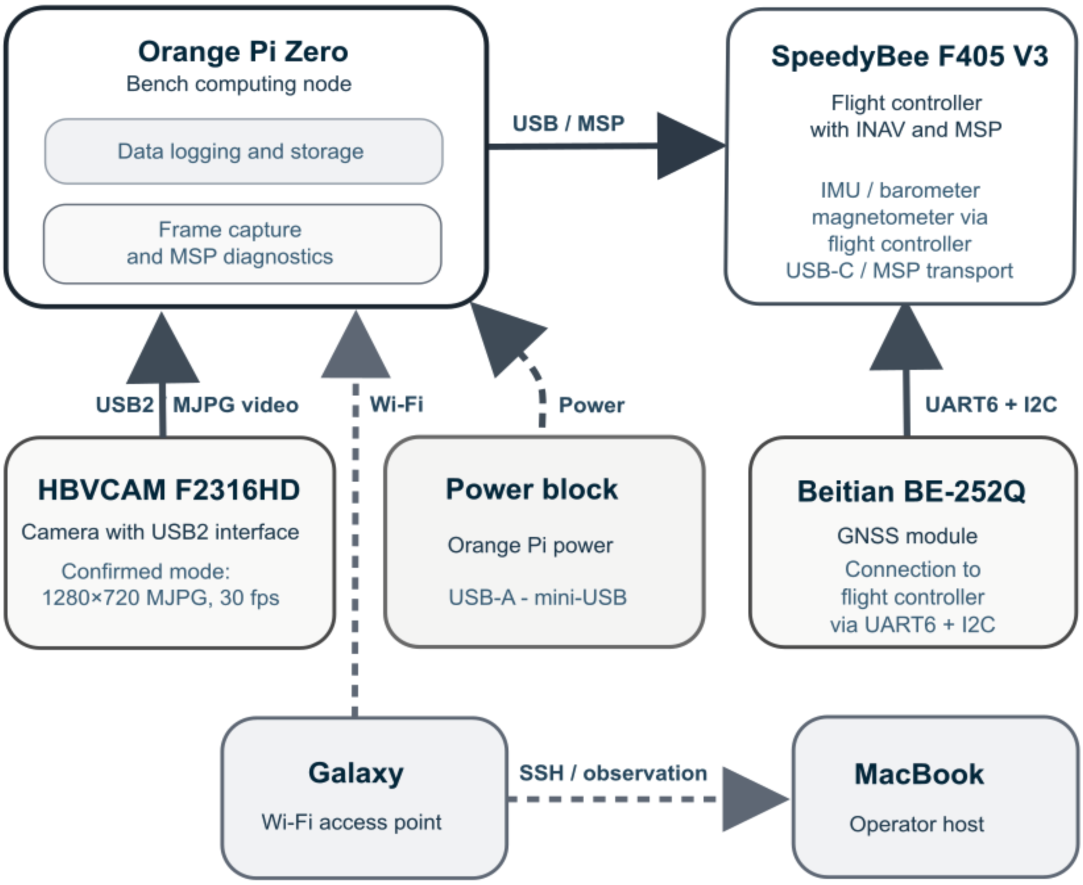

Fig. 2. Connection scheme of stand 3.1
for hardware-software verification of the external navigation module

The practical component of the study is based on two stands. Stand 3.1 is the canonical bench contour, where the main diagnostic checks, artifact package, and basic evidence of operability of the entire hardware configuration are concentrated. Stand 3.2 is an independent clean contour that separates the further execution structure from the primary bench environment. This pair of stands forms the canonical source of practical results in the current work, but stand 3.1 is the main source of figures and quantitative notes. The separation of stand roles is shown in Fig. 3, and their place in the work cycle is given in Table 1.

For interaction between Orange Pi Zero and the flight controller in the current bench configuration, the USB / MSP channel is used. This choice is sufficient for the present study, since its aim is not to build a standard working communication channel but to confirm the operability of the external navigation contour. The transition to UART as the main interaction channel is deliberately postponed to the next stage associated with the first flight prototype.

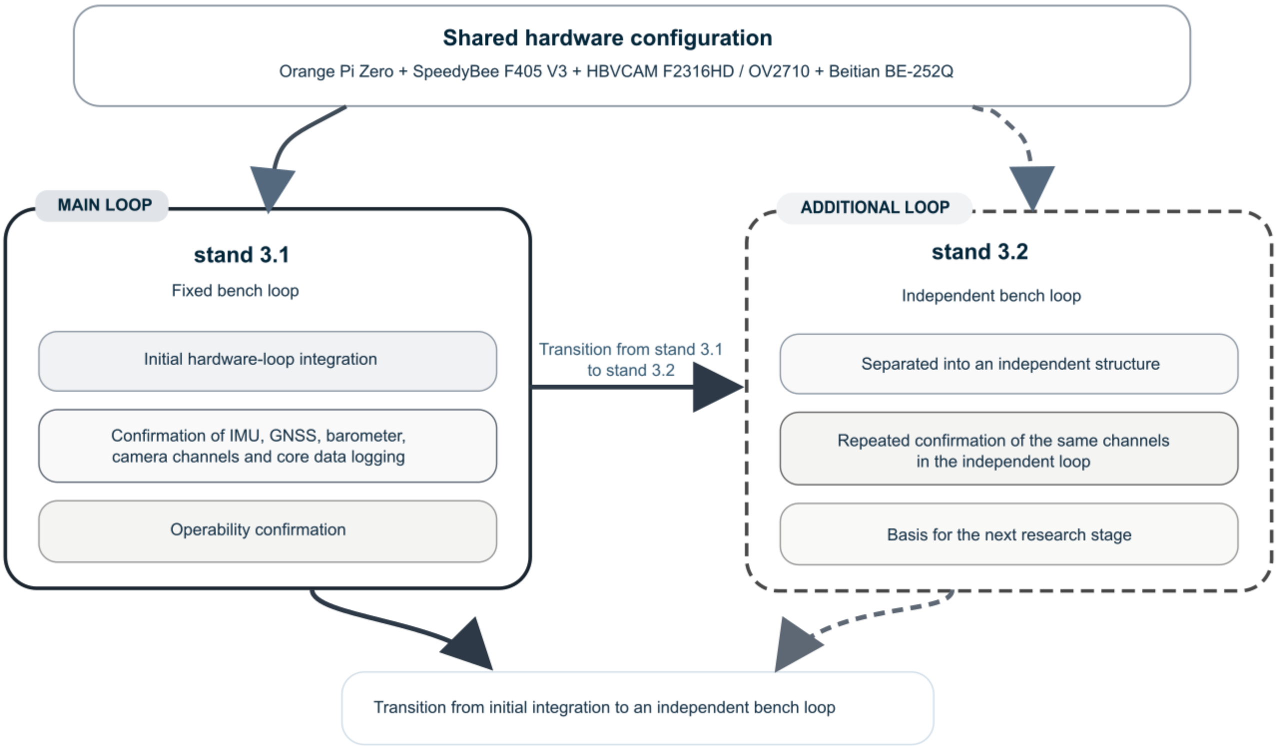

Fig. 3. Separation of stands 3.1 and 3.2 in the structure of practical implementation

The editorial boundary between this paper and the next flight-oriented work must be explicitly fixed: the current work proves a completed bench contour but not a standard flight interaction channel and not flight. This boundary is visualized in Fig. 4, and the parameters of the two stages are compared in Table 4.

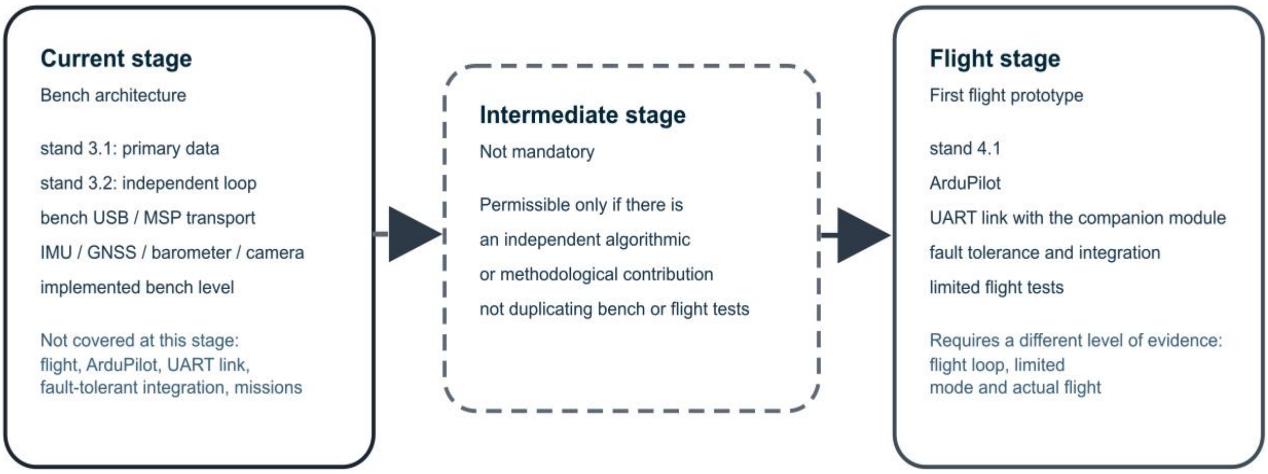

Fig. 4. Prospects for further research: from bench architecture to the first flight prototype

Table 4

Boundary between this study and the prospective publication

Parameter	**This paper**	**Next paper**
Canonical stands	stand 3.1, stand 3.2	stand 4.1
Flight-controller stack	INAV autopilot stack, i.e., navigation-oriented flight-controller software, is sufficient	ArduPilot or another separately justified flight stack
Channel between Orange Pi Zero and flight controller	bench USB / MSP is acceptable	UART is the main channel
Level of evidence	completed bench contour, device diagnostics, reproducible artifacts	flight execution contour, fault tolerance, limited flight tests
Mandatory flight	no	yes

The actual camera check showed that the base operating mode for Orange Pi Zero is 1280 x 720 in Motion JPEG (MJPG) format at 30 frames per second. Modes at 60 frames per second were not confirmed either on MacBook or on Orange Pi Zero; therefore, they should not be included as a mandatory architectural requirement.

The bench verification methodology includes checking the camera (CAM), communication with the flight controller through USB / MSP, the Inertial Measurement Unit (IMU), the satellite channel (GPS), the barometric channel (BARO), and the magnetometer (MAG). The canonical bench contour of stand 3.1 is considered completed if the top-level doctor command returns pass status and artifacts of all key checks, a test frame, FC / MSP overview data, and compact figures are stored locally. The independent stand 3.2 is considered prepared if its doctor command also returns pass status, confirming that the execution structure does not depend on the canonical bench contour. Acceptance criteria are given in Table 5.

Table 5

Acceptance criteria for the stand at the current research stage

Check	**Expected result**	**Source of evidence**
CAM	The camera is detected and provides a valid stream	camera_check.json, camera_test.jpg
UART / USB / MSP	The flight controller is detected through USB / MSP	uart_check.json, bench_doctor.json
IMU	IMU is read through the flight controller	imu_check.json
GPS	GNSS is visible in the MSP contour	gps_check.json
BARO	The barometric channel is read through the flight controller and MSP	baro_check.json
MAG	The magnetometer has a valid raw / status signal	mag_check.json
Stand 3.1 doctor	The canonical stand returns pass status	bench_doctor.json
Stand 3.2 doctor	The independent clean contour returns pass status	stand_doctor.json

Bench verification results and discussion. The practical result of the study is the construction and reproducible confirmation of the bench architecture of an external UAV navigation module based on Orange Pi Zero in interaction with the SpeedyBee F405 V3 flight controller, the HBVCAM F2316HD / OV2710 camera, and the Beitian BE-252Q satellite module. Unlike a purely model-based formulation, this work shows that the specified hardware components can be integrated into a single hardware-software contour with reproducible verification procedures and diagnostic-artifact preservation.

For stand 3.1, the operability of the bench contour was confirmed: the camera channel, communication with the flight controller through USB / MSP, and basic diagnostic visibility of the inertial measurement unit, satellite navigation, barometric altitude channel, and magnetometer through the flight controller are available. The canonical run of stand 3.1 formed a locally stored artifact package: bench_doctor.json, channel statuses in JavaScript Object Notation (JSON), a test frame, FC / MSP overview data in JSON and Comma-Separated Values (CSV) formats, and three compact vector figures in Scalable Vector Graphics (SVG) format for the results section.

For stand 3.2, the possibility of moving the further execution contour to an independent structure without mixing it with the primary bench environment was confirmed; however, a separate secondary artifact package for it is not yet a mandatory condition for completing this research stage. Thus, the work proves not a complete flight prototype but a completed and reproducible bench level of practical implementation of an external navigation module with inertial, satellite, barometric, and visual channels.

In a short overview run of 4.6 s for stand 3.1, the indicators gps_active_ratio = 1.0, gps_fix_ratio = 0.0, and satellites_max = 0 were obtained. This means that GNSS within this paper should be interpreted as bench visibility through FC / MSP rather than as evidence of a stable satellite navigation fix. At the same time, the camera test frame and JSON status data confirm CAM operability, while IMU, the barometric channel, and MAG are presented as real diagnostic channels of the canonical bench contour.

Two additional successful runs of stand 3.1 with pass status confirm the reproducibility of the canonical bench procedure at a level sufficient for this research stage. The channel-activity timing diagram is shown in Fig. 5; GNSS is interpreted here as bench visibility of the channel through MSP, not as evidence of a stable satellite navigation fix. An overview of selected real signals is presented in Fig. 6; the figure is intended as a compact illustration of real time series rather than flight validation. A compact summary diagram of the stand state and repeated successful runs is shown in Fig. 7.

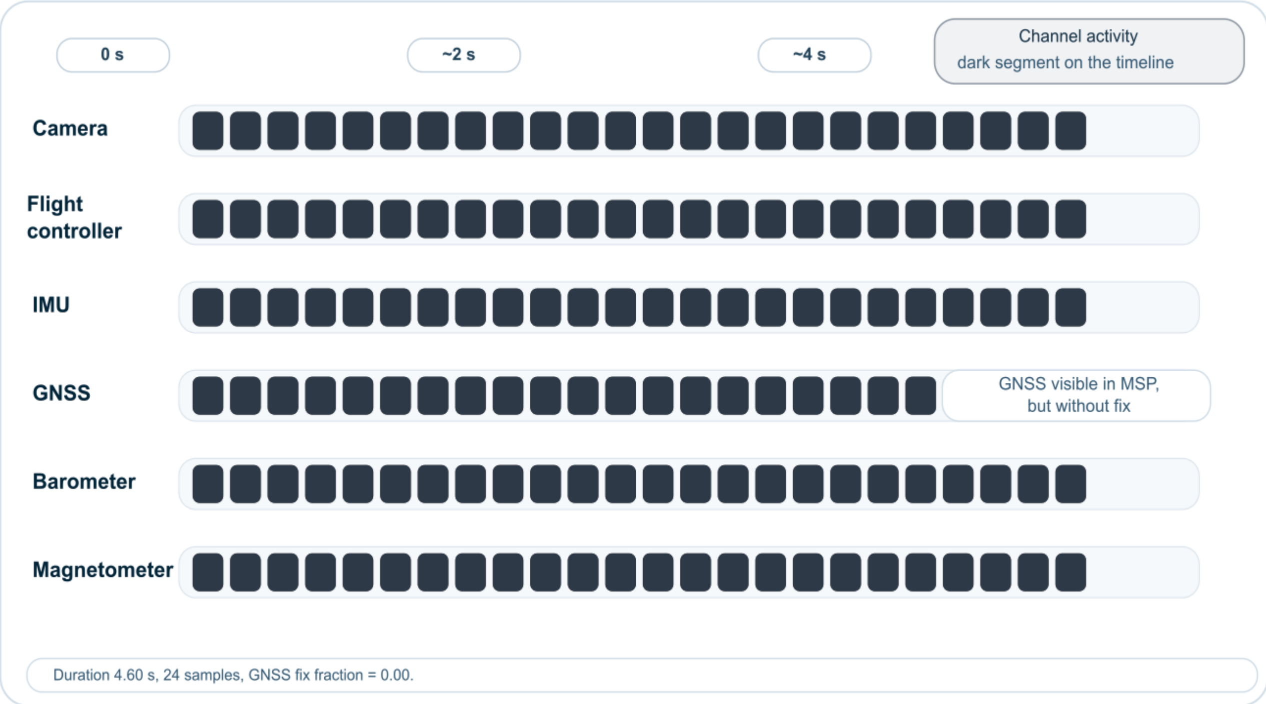

Fig. 5. Channel-activity timing diagram of stand 3.1 during the canonical run

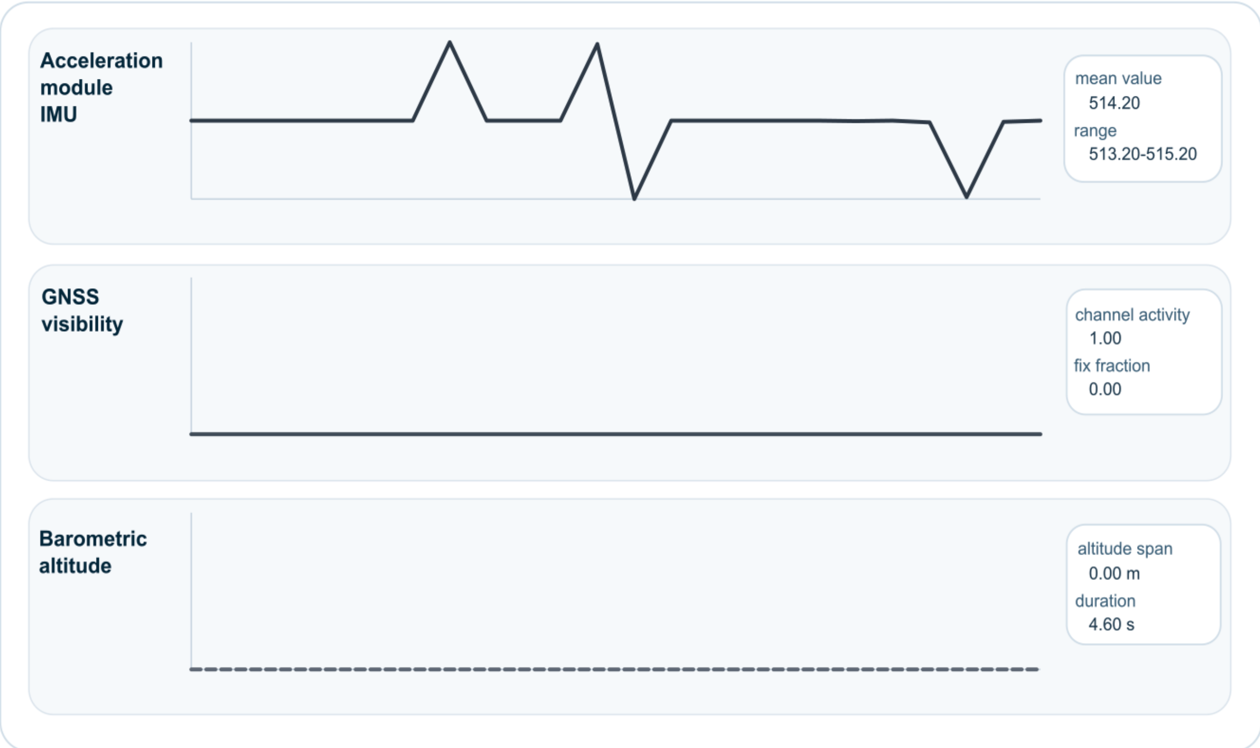

Fig. 6. Overview of selected real IMU, GNSS, and barometric-channel signals read in the canonical bench contour of stand 3.1

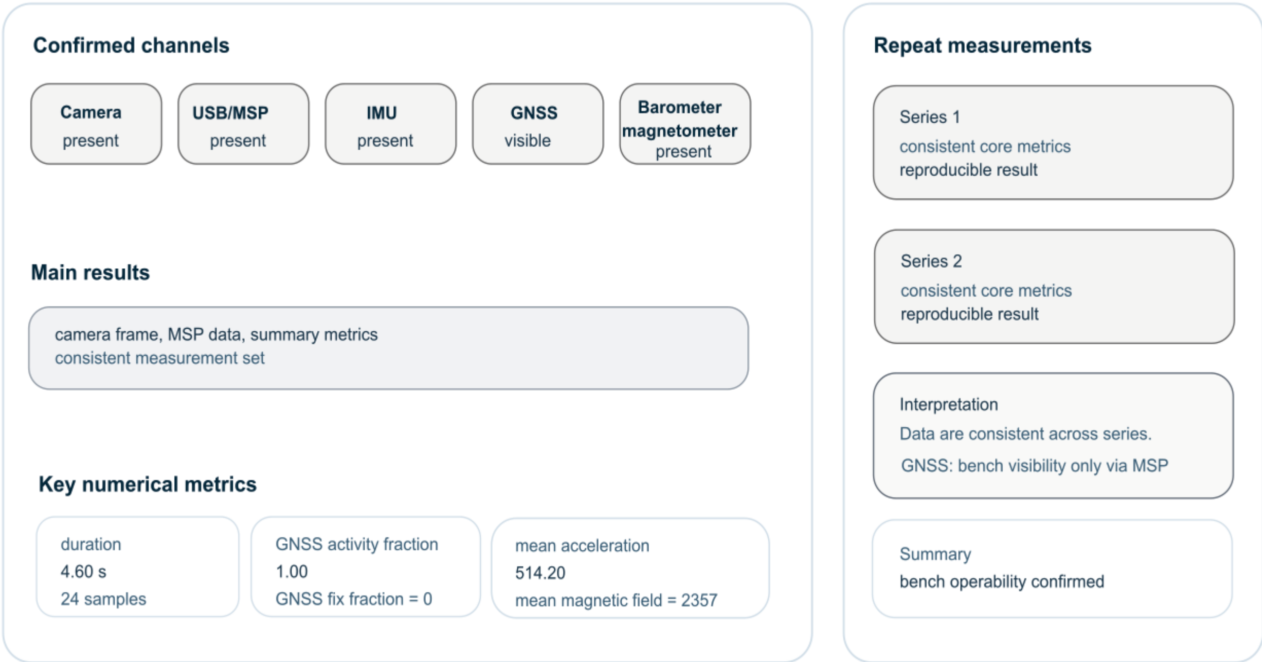

Fig. 7. Compact summary diagram of stand 3.1
status and repeated successful runs confirming reproducibility of the completed bench contour

An important result is also the alignment of the canonical RNKF multisensor architecture with the actually available experimental configuration. If the general methodological contour of the work series considers the IMU / GNSS / MAG / CAM configuration, then this paper practically tests a configuration with inertial, satellite, barometric, and visual channels, where the barometric channel is used as a standard source of altitude information and the magnetometer remains a diagnostic or background channel. This does not narrow the concept of the method but transfers it into a form suitable for real bench implementation.

If the work cycle is considered as a single chain of evidence, stand 1.1 described in the first paper [4] provided the initial quantitative estimate of the method's technical result. It showed an approximate reduction in the root mean square error of coordinate and velocity estimation by 15-40% compared with the classical Kalman filter; under intensive maneuvers, horizontal coordinate RMSE decreased from 12.4 m to 7.1 m, and velocity error decreased from 1.8 m/s to 1.1 m/s. For the GNSS outlier scenario, the maximum trajectory deviation decreased approximately from 65 m to 38 m. Within the present study, these data are not re-estimated but are used as the initial model basis for the transition to stands 3.1 and 3.2.

The results of previous three-dimensional modeling presented in the second paper [5] of the RNKF cycle additionally show the expected applied effect of its use. For the three-dimensional stand under the Satellite Channel Degradation and Combined Channel Degradation scenarios, compared with the base Extended Kalman Filter (EKF), an approximate reduction of coordinate Root Mean Square Error (RMSE) by 74.9%, a reduction of velocity RMSE by about 47.0%, a reduction of maximum deviation by 61.2%, and a reduction of filter failures by about 96.4% were obtained. For the real stand, these values should be interpreted not as a direct result but as quantitative justification for constructing an external navigation module based on RNKF.

The obtained results practically confirm the architectural and sensor suitability of the stand for further testing of navigation-support algorithms under satellite-channel degradation. This publication did not aim to prove the full field mechanism of replacing GNSS with visual and barometric channels. Instead, it formed a reproducible hardware-software base on which such a mechanism can be studied at the next stage.

The main practical conclusion of the study is that Orange Pi Zero is a methodologically suitable platform for constructing a reproducible RNKF bench architecture. At the same time, this publication does not claim flight readiness of the system; it records a completed and reproducible level of bench implementation.

Conclusions. The paper practically substantiates the bench architecture of an external UAV navigation module based on Orange Pi Zero, the SpeedyBee F405 V3 flight controller, the HBVCAM F2316HD / OV2710 camera, and the Beitian BE-252Q module.

It is shown that, for the described research stage, a bench level of verification is sufficient and methodologically correct, with the practical configuration of inertial, satellite, barometric, and visual channels being central.

The reproducibility of two interrelated stands is confirmed: stand 3.1 as the canonical bench contour for diagnostic procedures and stand 3.2 as an independent clean contour for the next execution stage.

The through logic of the work cycle is aligned: stand 1.1 records the first quantitative model result of the first paper [4], stands 2.1 and 2.2 deepen it in a three-dimensional model contour, and stands 3.1 and 3.2 transfer the method into the reproducible hardware-software plane of this research stage.

Thus, the overall structure of the work cycle already has a consistent form: from the algorithmic idea and its model confirmation to three-dimensional robustness verification, then to real bench reproducibility, and later to flight verification. This sequence makes the contributions of individual papers non-contradictory and mutually complementary.

The presence and operability of the camera channel, communication with the flight controller through USB / MSP, IMU channels, the barometric channel, and diagnostic visibility of the magnetometer through the flight controller are confirmed; for GNSS, bench visibility of the channel in the MSP contour is proved without requiring a stable satellite navigation fix.

A practical hardware-software basis is formed for further study of navigation-support mechanisms under satellite-channel degradation; however, full field testing of GNSS replacement by visual and barometric channels is planned for the future.

Therefore, within this paper, not the final flight effect of the patented RNKF is confirmed, but the correctness of one practical way of applying it: building an external navigation module in which trust can be redistributed to visual and barometric channels under satellite-channel degradation.

REFERENCES

1. Artamonov, Ye. B., Zhultynska, A. K., Zaloznyi, T. I., & Radchenko, A. V., et al. (2024). Vykorystannia filtra Kalmana dlia intehratsii danykh GPS ta IMU v zashumlenomu seredovyshchi [Using the Kalman Filter for Integrating GPS and IMU Data in a Noisy Environment]. *Tekhnichna inzheneriia [Technical Engineering], 2* (94), 69–80. https://doi.org/10.26642/ten-2024-2(94)-69-80 [in Ukrainian].

2. Turianytsia, M., & Chetverikov, B. (2025). Zastosuvannia filtra Kalmana dlia utochnennia danykh HNSS-znimannia z urakhuvanniam spufinhu [Application of the Kalman Filter to Refine

GNSS Survey Data Taking into Account Spoofing]. *Visnyk Lviv. Politekhniky [Lviv. Polytechnics Bulletin], 49,* 61–70. Retrived from https://ena.lpnu.ua/handle/ntb/118523 [in Ukrainian].

3. Romanko, V. A. (2025). *Sposib adaptyvnoho navedennia vysokodynamichnoho aparata z vykorystanniam rezydualnoho neironnoho filtra Kalmana: zaiavka na vynakhid Ukrainy [Method of Adaptive Guidance of a High-Dynamic Platform Using a Residual Neural Kalman Filter. Patent Application of Ukraine]* a202506585 (Declared 29.12.2025; Under Examination) [in Ukrainian].

4. Romanko, V. A., & Sribnyi, O. M. (2025). Intehratsiia neironnoho filtra Kalmana v systemu navedennia vysokodynamichnykh aparativ [Integration of a Neural Kalman Filter into Guidance of High-Dynamic Platforms]. *Problemy stvorennia, vyprobuvannia, zastosuvannia ta ekspluatatsii skladnykh informatsiinykh system: zb. nauk. prats [Problems of Construction, Testing, Application and Operation of Complex Information Systems: Scientific Journal of Korolov Zhytomyr Military Institute], 29,* 125–139. Zhytomyr: KZhMI. https://doi.org/10.46972/2076-1546.2025.29.09 [in Ukrainian].

5. Romanko, V. A., & Zhovnovatiuk, R. M. (2026). Rezydualnyi neironnyi filtr Kalmana dlia pidvyshchennia zavadostiikosti navihatsii BpLA [Residual Neural Kalman Filter for Improving UAV Navigation Robustness]. *Tekhnichna inzheneriia [Technical Engineering], 1* (97), 382–396. https://doi.org/10.26642/ten-2026-1(97)-382-396 [in Ukrainian].

6. Kalman, R. E. (1960). A New Approach to Linear Filtering and Prediction Problems. *Journal of Basic Engineering, 82,* 1, 35–45. https://doi.org/10.1115/1.3662552

7. Kalman, R. E., & Bucy, R. S. (1961). New Results in Linear Filtering and Prediction Theory. *Journal of Basic Engineering, 83,* 1, 95–108. https://doi.org/10.1115/1.3658902

8. Zimchuk, I. V., & Shapar, T. M. (2025). Parametrychnyi syntez alhorytmiv filtratsii dlia inertsialnykh navihatsiinykh system bezpilotnykh litalnykh aparativ []. *Problemy stvorennia, vyprobuvannia, zastosuvannia ta ekspluatatsii skladnykh informatsiinykh system: zb. nauk. prats [Problems of Construction, Testing, Application and Operation of Complex Information Systems: Scientific Journal of Korolov Zhytomyr Military Institute], 28* (I), 37–50. Zhytomyr: KZhMI. https://doi.org/10.46972/2076-1546.2025.28.04 [in Ukrainian].

9. Zimchuk, I. V., Shapar, T. M., & Kovba, M. V. (2024). Alhorytm filtratsii vymiriuvan akselerometrychnykh datchykiv u bezplatformenykh inertsialnykh systemakh navihatsii bezpilotnykh litalnykh aparativ [Filtering Algorithm of Accelerometrical Sensors Measurements in Platformless Inertial Navigation Systems Unmanned Aircraft]. *Problemy stvorennia, vyprobuvannia, zastosuvannia ta ekspluatatsii skladnykh informatsiinykh system: zb. nauk. prats [Problems of Construction, Testing, Application and Operation of Complex Information Systems: Scientific Journal of Korolov Zhytomyr Military Institute], 27* (I), 44–55. Zhytomyr: KZhMI. https://doi.org/10.46972/2076-1546.2024.27.04 [in Ukrainian].

10. Kovbasiuk, S. V., Osadchuk, R. M., Romanchuk, M. P., & Naumchak, L. M. (2022). Alhorytm formuvannia naboru apriornykh danykh neironnoi merezhi dlia obrobky tsyfrovykh aeroznimkiv [An Approach to Forming a Prior Dataset of Neural Network for Processing Digital Aerial Photos]. *Problemy stvorennia, vyprobuvannia, zastosuvannia ta ekspluatatsii skladnykh informatsiinykh system: zb. nauk. prats [Problems of Construction, Testing, Application and Operation of Complex Information Systems: Scientific Journal of Korolov Zhytomyr Military Institute], 23,* 77–88. Zhytomyr: KZhMI. https://doi.org/10.46972/2076-1546.2022.23.06 [in Ukrainian].

11. Pilkevych, I. A., Tokar, A. M., Franzhi, O. V., & Loboda, R. I. (2021). Navchalno-trenuvalna systema dlia pidhotovky operatoriv bezpilotnykh aviatsiinykh kompleksiv [A Training System for Preparing Operators of Aerial Vehicle Systems]. *Problemy stvorennia, vyprobuvannia, zastosuvannia ta ekspluatatsii skladnykh informatsiinykh system: zb. nauk. prats [Problems of Construction, Testing, Application and Operation of Complex Information Systems: Scientific Journal of Korolov Zhytomyr Military Institute], 20*, 83–97. Zhytomyr: KZhMI. https://doi.org/10.46972/2076-1546.2021.20.08 [in Ukrainian].

12. Negru, S. A., Geragersian, P., Petrunin, I., & Guo, W. (2024). Resilient Multi-Sensor UAV Navigation with a Hybrid Federated Fusion Architecture. *Sensors, 24,* 3. Article 981. https://doi.org/10.3390/s24030981

13. Tonini, A., Castelli, M., Bates, J. S., & Lin, N. N., et al. (2024). Visual-Inertial Method for Localizing Aerial Vehicles in GNSS-Denied Environments. *Applied Sciences, 14,* 20. Article 9493. https://doi.org/10.3390/app14209493

14. Gallo, E., & Barrientos, A. (2023). Long-Distance GNSS-Denied Visual Inertial Navigation for Autonomous Fixed-Wing Unmanned Air Vehicles: SO(3) Manifold Filter Based on Virtual Vision Sensor. *Aerospace, 10,* 8. Article 708. https://doi.org/10.3390/aerospace10080708

15. Aburasain, Y., Bilal, M., & Kim, K. (2024). Optimizing Prediction Accuracy in Dynamic Systems through Neural Network Integration with Kalman and Alpha-Beta Filters. *PLOS ONE, 19,* 10. e0311734. https://doi.org/10.1371/journal.pone.0311734