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Intellectualization of Kalman Filters to Increase the Autonomy and Accuracy of Navigation Systems of Unmanned Aerial Vehicles

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Abstract
Introduction. Modern unmanned aerial vehicles (UAVs) are widely used for monitoring territories, aerial photography, and logistics. Their navigation heavily relies on the Global Navigation Satellite System (GNSS), but their signals are susceptible to accidental and intentional interference, shielding, and multipath effects. In dense urban areas and woodlands, the standard error of GNSS positioning can exceed eight meters, and the probability of short-term and prolonged signal loss remains high, even with favorable visibility conditions. This makes the task of ensuring stable and accurate UAV navigation under conditions of GNSS degradation particularly challenging. A literature review has shown that classical data integration methods, such as extended and unscented Kalman filters, work effectively in nominal modes, but they lose stability during prolonged GNSS failures due to inertial sensor drift accumulation. New architectures based on deep learning (e.g. KalmanNet, FusionNet, Deep Sensor Fusion) improve the approximation of nonlinear dynamics and partially compensate for drift. However, they often require significant computing resources, careful configuration for specific sensors, and do not always provide deterministic delays in real time. Therefore, it can be concluded that the issue of the balance between accuracy, computational complexity, and adaptability to different types of motion and conditions of degradation of sensory data remains insufficiently studied. In this regard, the aim of this research was to conduct a comparative analysis of traditional and neural network methods for improving the accuracy and reliability of UAV navigation and to develop an adaptive Kalman structure capable of operating in real time with partial signal loss. To accomplish this, it was necessary to solve the following tasks: implement optimal modifications of the Kalman filter for various sections of the trajectory and driving modes, create a fuzzy controller for adaptive filters and parameters switching, and experimentally evaluate the stability of the proposed methods in various scenarios with GNSS degradation.
Materials and Methods. The research was based on a literature review on the integration of sensory data and nonlinear filtering in leading scientometric databases (Scopus, eLibrary, CyberLeninka) and in open Internet sources for 2015–2025. Mathematical modeling was conducted in the MATLAB environment. The UAV's GPS flight path, transformed into a local Cartesian coordinate system with the addition of synthetic perturbations and partial measurement breaks, was used as the initial theoretical data. The basic dynamic model was a two-dimensional localization in the horizontal plane with the state [x, y, heading, angular velocity, ground speed] and white Gaussian perturbations in the velocity and angular velocity channels. The Euler method was used for discretization. The measurement model, based on the knowledge of a known point, allowed us to apply the Cartesian coordinate system. EKF, UKF/SRCDKF and Particle Filter were implemented and compared as reference algorithms for nonlinear filtering. The method proposed by the authors included a fuzzy controller for adaptive selection of the motion model (CV, CA, CT, MV) based on normalized innovations, estimates of acceleration and curvature of the trajectory. For self-calibration of accuracy, the adaptation of measurement covariances for innovations in a sliding mode with exponential smoothing was used. The reliability of multisensory integration was ensured by dynamic weighting of sources through a confidence vector that corrected the measurement contribution to the discrepancy covariance. The experimental evaluation was performed on scenarios with Gaussian measurement noise, varying proportions of gaps (up to 30%) and variable maneuverability. The comparison was based on the root-mean-square error (RMSE) of coordinates and stability metrics (the probability of critical error growth), as well as relative computational complexity.

Results. The method was evaluated on simulation and bench trajectories with maneuvers and measurement skips. On average, the RMSE of coordinates decreased by 18–35% compared to the EKF/UKF under comparable excitation conditions. The probability of a critical error increase tended to zero at a loss rate up to 30%. The normalized innovation statistics stayed within confidence intervals, confirming the correct adjustment of covariances. Self-calibration of measurement noise converged to steady-state values in 1–2 steps of the algorithm after startup and after sudden changes in interference. Ablation experiments showed that fuzzy switching of motion models made the greatest contribution to accuracy in curved sections, while dynamic weighing of sources increased robustness to outliers and sensor drift. By increasing the computational complexity in comparison with the particle filter, it was possible to increase stability on various motion trajectories and achieve optimal RMSE values of up to two meters, which was confirmed on an embedded ARM processor.

Discussion. The gain in accuracy and stability was due to a combination of a locally adequate kinematic model and online adaptation of sensor confidence, which reduced systematic biases and prevented covariance overclocking. Fuzzy logic provided smooth transitions between modes without sudden jumps in estimation. However, it was sensitive to the choice of rules and the scale of membership functions, which required a methodical setup procedure. Limitations of the current setup included a 2D configuration with a single support and a limited range of maneuvers, so the transfer to 3D and multi-support measurements might require a revision of the model set. Comparability with alternatives remained with the same limitations on the computing budget. With unlimited resources, heavier methods partially reduced the gap. The observed convergence of self-calibration was fast, but under conditions of long-term unsteadiness, regularization and a sliding window were preferable.

Conclusion. The adaptive localization method proposed by the authors significantly reduces the root-mean-square error, while maintaining or improving stability and remaining computationally efficient for embedded platforms. The combination of fuzzy model switching and dynamic source weighting makes the solution practical for omissions and perturbations. Correct innovative statistics confirm the consistency of the probabilistic part of the algorithm. The limitations of the current version are related to the problem size and manual configuration of the rules. However, the architecture is modular and compatible with existing filtering lines. Future prospects include expansion into 3D, integration with multi-support range and angular measurements, online training of rule parameters and comprehensive validation on full-scale stands. Overall, the results suggest that the method is well-suited for application in mobile robotics and autonomous navigation systems.

Keywords: unmanned aerial vehicle, Kalman filter, navigation, coordinate determination, extended Kalman filter (EKF), unscented Kalman filter (UKF), mathematical modeling, intelligent filtering, adaptive algorithm, neuro-Bayesian model

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Оригинальное эмпирическое исследование

Интеллектуализация фильтров Калмана для повышения автономности и точности навигационных систем беспилотных летательных аппаратов

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Аннотация

Введение. Современные беспилотные летательные аппараты (БПЛА) широко применяются для мониторинга территорий, аэрофотосъемки и логистики. Их навигация в значительной степени опирается на глобальные спутниковые системы (GNSS), сигналы которых подвержены случайным и преднамеренным помехам, экранированию и мультипутевости. В плотной городской застройке и лесных массивах среднеквадратическая ошибка позиционирования по GNSS может превышать восемь метров, а вероятность кратковременных и длительных потерь сигнала остается высокой даже при благоприятной видимости. Все это делает задачу обеспечения устойчивой и точной навигации БПЛА в условиях деградации GNSS особенно актуальной. Обзор специальной литературы показал, что классические методы интеграции данных, такие как расширенный и ансцентный фильтры Калмана, эффективно работают в номинальных режимах, но теряют устойчивость при длительных сбоях GNSS из-за накопления дрейфа инерциальных датчиков. Новые архитектуры на основе глубокого обучения (например KalmanNet, FusionNet, Deep Sensor Fusion) улучшают аппроксимацию нелинейной динамики и ча-

стично компенсируют дрейф. Однако они часто требуют значительных вычислительных ресурсов, тщательной настройки под конкретные сенсоры и не всегда обеспечивают детерминированные задержки в реальном времени. Следовательно, можно заключить, что остается недостаточно проработанным вопрос баланса между точностью, вычислительной сложностью и адаптивностью к разным типам движения и условиям деградации сенсорных данных. В связи с этим цель данного исследования — провести сравнительный анализ традиционных и нейросетевых методов повышения точности и надежности навигации БПЛА и разработать адаптивную калмановскую структуру, способную работать в реальном времени при частичных потерях сигнала. Для этого небходимо решить следующие задачи: реализовать оптимальные модификации фильтра Калмана для различных участков траектории и режимов движения, создать нечеткий контроллер для адаптивного переключения фильтров и параметров, экспериментально оценить устойчивость предложенных методов в разнообразных сценариях с деградацией GNSS.

Материалы и методы. Исследование выполнено на основе обзора литературы по интеграции сенсорных данных и нелинейной фильтрации, находящихся в ведущих наукометрических базах (Scopus, eLIBRARY, CyberLeninka) и в открытых интернет-источниках за 2015–2025 годы. Математическое моделирование проводилось в среде MATLAB. В качестве исходных теоретических данных использовалась GPS-траектория полета БПЛА, преобразованная в локальную декартову систему координат с добавлением синтетических возмущений и частичных обрывов измерений. Базовая динамическая модель — двумерная локализация в горизонтальной плоскости с состоянием [x, y, курс, угловая скорость, путевая скорость] и белыми гауссовскими возмущениями в каналах скорости и угловой скорости. Для дискретизации применялся метод Эйлера. Модель измерений, основанная на знании известной точки, позволяет применить декартову систему координат. Реализованы и сопоставлены EKF, UKF/SRCDKF и фильтр частиц (Particle Filter) как эталонные алгоритмы нелинейной фильтрации. Предложенный авторами метод включает в себя нечёткий контроллер для адаптивного выбора модели движения (CV, CA, CT, MV) на основе нормированных инноваций, оценок ускорения и кривизны траектории. Для самокалибровки точности использована адаптация ковариаций измерений по инновациям в скользящем режиме с экспоненциальным сглаживанием. Надежность мультисенсорной интеграции обеспечивалась динамическим взвешиванием источников через вектор доверия, корректирующий вклад измерений в ковариацию невязки. Экспериментальная оценка выполнена на сценариях с гауссовым шумом измерений, различной долей пропусков (вплоть до 30 %) и изменяемой маневренностью. Сравнение проводилось по среднеквадратической ошибке (СКО) координат и метрикам устойчивости (вероятность критического роста ошибки), а также по относительной вычислительной сложности.

Результаты исследования. Метод был оценен на имитационных и стендовых траекториях с маневрами и пропусками измерений. В среднем СКО координат снизилась на 18–35 %, по сравнению с EKF/UKF, при сопоставимых условиях возбуждения, а вероятность критического роста ошибки стремилась к нулю при доле пропусков до 30 %. Нормированная инновационная статистика оставалась в доверительных интервалах, что подтверждает корректную настройку ковариаций. Самокалибровка шумов измерений сходилась к стационарным значениям за 1–2 шага алгоритма после запуска и после резких изменений помех. Абляционные эксперименты показали, что нечеткое переключение моделей движения дает наибольший вклад в точность на криволинейных участках, тогда как динамическое взвешивание источников повышает робастность к выбросам и дрейфу датчиков. За счёт увеличения вычислительной сложности в сравнении с фильтром частиц удалось повысить стабильность на различных траекториях движения и достичь оптимальных показателей среднеквадратичной ошибки до двух метров, что подтверждено на встраиваемом ARM-процессоре.

Обсуждение. Выигрыш в точности и устойчивости объясняется сочетанием локально адекватной кинематической модели и онлайн-адаптацией доверия к сенсорам, что уменьшает систематические смещения и предотвращает разгон ковариации при пропусках. Фаззи-логика обеспечивает мягкие переходы между режимами без резких скачков оценки, однако она чувствительна к выбору правил и масштабов функций принадлежности, это требует методичной процедуры настройки. Ограничения текущей постановки включают в себя 2D-конфигурацию с одной дальномерной опорой и ограниченный спектр маневров, поэтому перенос на 3D и многоопорные измерения может потребовать пересмотра набора моделей. Сопоставимость с альтернативами сохраняется при одинаковых ограничениях на бюджет вычислений; при неограниченных ресурсах более тяжелые методы частично сокращают разрыв. Наблюдаемая сходимость самокалибровки быстра, но в условиях длительных нестационарностей предпочтительна регуляризация и скользящее окно.

Заключение. Представленный авторами адаптивный метод локализации обеспечивает существенное снижение среднеквадратичной ошибки при сохранении или улучшении устойчивости, оставаясь вычислительно экономичным для встраиваемых платформ. Комбинация нечеткого переключения моделей и динамического взвешивания источников делает решение практичным при пропусках и возмущениях, а корректная инновационная статистика подтверждает согласованность вероятностной части алгоритма. Ограничения текущей версии связаны с размерностью задачи и ручной настройкой правил, тем не менее архитектура модульна и совместима с существующими конвейерами фильтрации. Перспективы развития предполагают расширение в 3D, интеграцию многоопорных дальномерных и угловых измерений, онлайн-обучение параметров правил и всестороннюю валидацию на натурных стендах. В совокупности результаты указывают на готовность метода к прикладному использованию в мобильной робототехнике и навигации автономных систем.

Ключевые слова: беспилотный летательный аппарат, фильтр Калмана, навигация, определение координат, расширенный фильтр Калмана (EKF), ансцентный фильтр Калмана (UKF), математическое моделирование, интеллектуальная фильтрация, адаптивный алгоритм, нейро-байесовская модель

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Introduction. Modern unmanned aerial vehicles are increasingly used to solve a variety of tasks, from monitoring territories and aerial photography to logistics. Many of them rely heavily or completely on Global Navigation Satellite Systems (GNSS), such as GPS and GLONASS, to determine their coordinates [1]. However, GNSS signals are vulnerable to accidental or intentional interference, which can lead to their complete or partial failure. Therefore, experts are constantly searching for new methods to reduce errors in UAV positioning. Thus, in their work, the authors Xu Li and Rong Jiang [2] proposed an adaptive fuzzy Kalman filter (AF-UKF) for use in dense urban environments, which significantly reduced such errors by eliminating noisy signals. However, as the authors themselves note, this method can mistakenly filter out "healthy" signals, which is critical for UAVs. Researchers Li-Ta Hsu and Shau-Shiun Jan [3] focused on improving tracking algorithms by using vector tracking with a Kalman filter to detect and suppress multipath/NLoS. Despite its effectiveness in urban environments, their method is not designed to counteract signal suppression and targeted jamming. The authors Yang Liu and Sihai Li [4] used the analysis of the innovative sequence of the Kalman filter in the integrated GNSS/INS system. Although the method successfully detects "smooth" attacks, its effectiveness decreases with sudden UAV maneuvers, which creates similar innovations themselves. Thus, existing Kalman-type filters are either adapted to a specific type of interference, or require fine-tuning to a specific traffic scenario.

When solving navigation problems in uncertain conditions, the closest classical analogue to adaptive filtering is the algorithm of Interacting Multiple models (IMMs) [5]. IMM filters use Markov chains to probabilistically switch between several predefined dynamics models. However, a significant disadvantage of classical IMMs is the use of a static transition probability matrix. In real-world UAV operating conditions, especially when exposed to electronic warfare (EW), loss of the GNSS signal or a sharp evasive maneuver are not Markov processes. The rigid structure of the transitions makes IMM filters insufficiently flexible in case of sudden and prolonged signal losses, which leads to a delay in switching models and an increase in error.

In recent years, adaptive filters based on artificial neural networks (ANNs) and deep learning, such as KalmanNet or Deep Sensor Fusion, have been actively developed as an alternative [6]. Neural network approaches demonstrate high efficiency in approximating complex nonlinearities and compensating for instrumental sensor drift. Nevertheless, their use on small and medium-sized UAVs is fraught with a number of critical limitations. Firstly, ANNs require significant computing power, which contradicts the strict restrictions on the size, weight, and power (SWaP) of embedded systems. Secondly, neural network models are highly dependent on the training sample and are subject to the "black box" problem: their behavior in emergency situations (edge cases), that are not present in the dataset, is mathematically unpredictable, which is unacceptable for mission-critical flight control systems. In this regard, there is a need to develop hybrid methods that combine the rigorous mathematical basis of Kalman filters with lightweight heuristic adaptation algorithms such as fuzzy logic.

Even in favorable conditions, short-term signal losses are possible, which can have disastrous consequences for UAVs guided solely by GNSS. Existing protection systems (for example, at the antenna or signal processing level) often rely on known interference models and cannot cope with complex, adaptive and hybrid attacks (a combination of jamming and spoofing).

In this regard, the aim of this study is to develop a Kalman filter structure that can adjust in real time to various types of object movement, as well as compensate for partial signal losses. One of the most effective approaches to solving this problem is the integration (sensor fusion) of data from various sources, such as inertial measurement units (IMUs), cameras, lidars, and distance sensors. The mathematical core of such systems is often the Kalman filter [7] and its nonlinear modifications [8], which allow recursively estimating the state of the system based on incomplete and noisy measurements. To achieve this goal, it is necessary to solve the following tasks: to develop optimal modifications of the Kalman filter for various sections of the trajectory, to create a fuzzy logic controller that will adaptively switch between these filters, and to conduct an experimental assessment of the stability of the proposed method.

Materials and Methods. The research consisted of several stages: analysis of existing literature, theoretical modeling, verification of the theory in conditions close to reality, and summarization. The literature review included the selection and examination of scientific publications related to the topic, followed by systematic synthesis, presentation, and analysis of the material using leading scientometric databases such as SKOPUS, elibrary.ru and cyberleninka.ru, as well as information available on the internet. A search for keywords was conducted using the terms: “Kalman filter”, “extended Kalman filter”, “Kalman filter modifications”, “GPS positioning”, “interference”, “Kalman filter intellectualization”. Approximately 100 articles were examined, of which 20 were relevant to both the topic and the time period from 2015 to 2025. For the theoretical component, the MATLAB R2025b software environment was used with basic packages for mathematical modeling. The computing equipment was a PC with an Amd Ryzen 5 5600G CPU and a Gigabyte RTX 3070 GPU, Windows 10 OS. The GPS flight path of the UAV was used as the initial data, converted into a local Cartesian coordinate system, which for the theoretical part was generated taking into account various types of motion trajectories (the same applied to noise and breaks). To test the theoretical part due to the current flight restrictions, it was decided to investigate the operation of the filter without flights (ground tests by moving the test sample by car). In the practical part, the NodeMCU V3.0 board was used as the main processor for testing the adaptive controller, the NEO6MV2 module was used as a GPS antenna, as well as a speed sensor, and a battery with a voltage converter was used to power the system. The final design was transported along various trajectories over a distance of 12 kilometers, a total of 60 tests were conducted (30 tests without a filter, 30 with a filter). After each test, the data was uploaded to the PC described above. The timeframe for data collection ranged from 25 to 90 minutes. The GPS module recorded data at a rate of once per second in NMEA format. After that, the main processor processed the longitude and latitude data to perform the filtering operation.

The problem of two-dimensional localization of an UAV moving in a horizontal plane was considered as a basic model. This model was valid for many practical scenarios (for example, when flying at a constant altitude) and allowed us to simplify it.

The continuous dynamics of an UAV could be described by the following system of differential equations [7]:

$$\dot{x}(t) = v(t)\cdot cos(\eta_t),$$
$$\dot{y}(t) = v(t)\cdot sin(\eta_t),$$
$$\dot{\eta}(t) = \omega(t),$$
$$\dot{\omega}(t) = \epsilon\omega(t),$$
$$\dot{v}(t) = \epsilon v(t),$$

where $x(t)$, $y(t)$ — UAV coordinates in the horizontal plane; $\eta(t)$ — UAV heading (direction of movement); $\omega(t)$ — angular velocity; $v(t)$ — ground speed; $\epsilon_\omega(t)$, $\epsilon_v(t)$ — independent white Gaussian noises with zero mathematical expectation and covariances Q_ω and Q_v respectively, simulating perturbations (wind, maneuvers).

The model was discretized for implementation on digital computing devices. Using the Euler method, a discrete model of dynamics was obtained:

$$\begin{gathered}\{x_{k+1} = x_k + v_k \cdot \Delta t_k \cdot cos(\eta_k)\, y_{k+1} = y_k + v_k \cdot \Delta t_k \cdot sin(\eta_k)\, \eta_{k+1} = \\ = \eta_k + \omega_k \cdot \Delta t_k\ \omega_{k+1} = \omega_k + \gamma_{\omega,k} \cdot \sqrt{\Delta t_k}\ \ v_{k+1} = v_k + \gamma_{v,k} \cdot \sqrt{\Delta t_k},\end{gathered} \tag{1}$$

where $q_k = [x_k, y_k, \eta_k, \omega_k, v_k]$ — state vector at the k-th step; Δt_k — time interval between steps k and k+1; $\{\gamma_{\omega,k}\}$ — discrete sequences of white Gaussian noise with zero mean and covariance matrices Q_ω and Q_v respectively [8].

This model (1) can be written in a compact vector-matrix form:

$$q_{k+1} = f(q_k) + U(q_k)\cdot\gamma_k, \tag{2}$$

where $f()$ — nonlinear vector function describing the evolution of the system, and $U()$ — matrix determining the effect of noise.

If we assume that the distance from the UAV to some known point with coordinates (x_0, y_0), was available, for example, to another UAV or a ground-based lighthouse, the measurement model would look like this:

$$d_k = h(q_k) + \epsilon_{d,k} = \sqrt{(x_k - x_0)^2 + (y_k - y_0)^2} + \epsilon_{d,k}, \tag{3}$$

where $\epsilon_{d,k}$ — white Gaussian measurement noise with zero mean and variance R, independent of the noise of process γ_k.

EKF was a classic approach for nonlinear systems. Its idea was to linearize models of dynamics and measurements around the current state estimate using first-order Taylor series expansion.

The prediction step in the EKF was described by the equations:

$$\hat{q}_{k+1}^{-} = f\left(\hat{q}_k^{+}\right). \tag{4}$$

$$P_{k+1}^{-} = F_k P_k^{+} + F_k^T + W_k Q W_k^T.$$

The following formulas were used to correct the estimate:

$$K_{k+1} = P_{k+1}^{-} H_{k+1}^T + \left(H_{k+1} P_{k+1}^{-} H_{k+1}^T + R\right)^{-1}, \tag{5}$$

$$\hat{q}_{k+1}^{+} = \hat{q}_{k+1}^{-} + K_{k+1}\left(d_{k+1} - h \cdot \hat{q}_{k+1}^{-}\right),$$

$$P_{k+1}^{+} = \left(I - K_{k+1} H_{k+1}\right) P_{k+1}^{-},$$

where $\hat{q}_k^{-}$, $\hat{q}_k^{+}$ — a priori and a posteriori estimates of the state vector; P_k^{-}, P_k^{+} — a priori and a posteriori covariance error matrices; F_k — Jacobian matrix of f function; H_k — Jacobian matrix of h function; K_k — Kalman gain; Q, R — covariance matrices of process noise and measurements.

The advantages of EKF included low computational complexity. The disadvantages included the need for analytical calculation of Jacobian matrices [9], which could be laborious for complex models, as well as low accuracy and possible divergence of the filter with strong nonlinearity, since tangent linearization became a rough approximation.

To overcome the EKF disadvantages, a class of Sigma-Point Kalman Filters was developed, the most famous of which is UKF. Instead of linearization, UKF used a deterministic sample transformation (percentage transformation). A set of sigma points was selected that accurately represented the mean and covariance of the current state distribution. These points were passed through the nonlinear functions of the dynamics model and the measurement model, and a new average and covariance were calculated based on the transformed points.

There were further modifications of the UKF, such as the central difference Kalman filter (CDKF) and the square root Kalman filter (SRCDKF). SRCDKF, in particular, increased computational stability, since it worked directly with the square root of the covariance matrix, which guaranteed its positive certainty at each step and avoided numerically unstable Cholesky decomposition.

In cases where the noise was non-Gaussian in nature or the system had a high degree of nonlinearity, a particle filter was an effective tool [10]. This method belonged to the class of sequential Monte Carlo algorithms. Its main idea was to represent the a posteriori probability density of a state using a set of random samples (particles) with appropriate weights.

The algorithm included the following steps:

– initialization — generation of the N part from the a priori distribution;

– prediction — each particle was passed through a dynamic model with the addition of a random disturbance;

– correction (weighting) — for each particle, a weight was calculated proportional to the likelihood of the current measurement dk;

– resampling — in order to avoid degeneration (a situation where the weight is concentrated on a small number of particles), a resampling procedure was performed: particles with low weight were discarded, and those with high weight were replicated.

In the developed system, a fuzzy controller was designed to determine the most appropriate object movement model at each filtering step. The controller analyzed the current dynamic situation and output the probabilities of using four models: uniform motion (CV), uniformly accelerated motion (CA), coordinated rotation (CT), and maneuver (MV). Based on these probabilities, a combined assessment of the condition is formed or switching between models was conducted.

Three values were received at the input of the controller, characterizing the current state of the system:

– norm of the innovations vector (residuals):

$$\nu_k = \|\widetilde{y_k}\|, \tag{6}$$

– norm of the acceleration vector:

$$a_k = \sqrt{\hat{a}_{x,k}^2 + \hat{a}_{y,k}^2 + \hat{a}_{z,k}^2}, \tag{7}$$

– curvature of trajectory k_k, calculated from estimated position and speed.

To bring it to a single scale, a speed normalization factor was used, which was approximately equal to the average speed of the object. Normalized values:

$$\tilde{v}_k = \frac{v_k}{V_{norm}}. \tag{8}$$

In the absence of measurements, GNSS innovation could not be calculated. In this case, the controller froze the probabilities of the modes. If the signal loss lasted more than one second, the controller forcibly increased the activation of the uniform motion model (CV). The physical meaning of this solution was to switch the UAV to the Dead Reckoning mode along the vector of the last known velocity, which prevented the exponential increase in error characteristic of models with acceleration.

Three fuzzy terms were defined for each input variable: low, medium, and high. The membership functions had a triangular shape and were set by three parameters (*a, b, c*). The parameter values were obtained empirically and refined during modeling and testing (Table 1).

Table 1

Parameters of the membership functions of the input variables

Variable	Term	a	b	c
$\tilde{v}$	low	0	0	12
	medium	8	20	40
	high	25	40	70
$\tilde{a}$	low	0	0	1.5
	medium	1.0	2.5	5.0
	high	3.5	6.0	10.0
$\tilde{k}$	low	0	0	0.0004
	medium	0.0003	0.0009	0.0018
	high	0.0012	0.0022	0.0038

To eliminate ambiguity when calculating activation degrees, the mathematical membership functions for all terms were strictly defined, with explicit zero values outside the operating ranges in formulas (9), (10), (11).

For the term “low”, the membership function had the form:

$$\mu_{low}(x) = 1, \text{ if } x \le a.$$

$$\mu_{low}(x) = \frac{(c-x)}{(c-a)}, \text{if } a < x \le c. \tag{9}$$

$$\mu_{low}(x) = 0, \text{if } x \ge c.$$

For the term “medium”, a triangular function was used:

$$\mu_{med}(x) = 0, \text{if } x \le a \text{ or } x \ge c.$$

$$\mu_{med}(x) = \frac{(x-a)}{(b-a)}, \text{ if } a < x \le b. \tag{10}$$

$$\mu_{med}(x) = \frac{(c-x)}{(c-b)}, \text{ if } b < x < c.$$

For the term "high":

$$\mu_{high}(x) = 0, \text{ if } x \le a.$$

$$\mu_{high}(x) = \frac{(x-a)}{(c-a)}, \text{ if } a < x < c. \quad (11)$$

$$\mu_{high}(x) = 1, \text{ if } x \ge c.$$

The values of parameters (a, b, c) for each variable were not arbitrary. The procedure for setting them up was performed by the Grid Search method in the MATLAB environment. The minimum standard error of positioning on a representative set of simulation trajectories, including all basic maneuvers, was used as the objective function (optimality criterion). To confirm the reliability of the found parameters, a sensitivity analysis of the system was performed. The results showed that variation of the term boundaries by ± 15% led to a change in the final RMSD by no more than 3–4%. This indicated that the proposed fuzzy controller was not retrained for a specific trajectory, but had high robustness and structural stability.

The synthesis of the fuzzy inference rule base was based on the UAV flight physics. Given three input variables, each of which was described by three terms, the total state space consisted of 27 possible combinations. However, the direct use of the 27 rules was redundant and could lead to logical contradictions. In this regard, the state space was reduced to six macro situations (productions), which were semantically complete and consistent. The use of ANY operator served as a logical OR, allowing one rule to overlap several combinations of input variables at once, thereby ensuring that there were no blind spots in the decision-making space.

The final rule base contained six products:

1. IF Innovation (low), AND Acceleration (low), AND Curvature (low), THEN CV model (weight 2.0).
2. IF Innovation (any), AND Acceleration (average), AND Curvature (low), THEN CA model (weight 1.5).
3. IF Innovation (any), AND Acceleration (any), AND Curvature (average), THEN CT model (weight 2.0).
4. IF Innovation (any), AND Acceleration (any), AND Curvature (high), THEN CT model (weight 3.0).
5. IF Innovation (high), AND Acceleration (high), AND Curvature (any), THEN MV model (weight 2.5).
6. IF Innovation (average), AND Acceleration (high), AND Curvature (any), THEN MV model (weight 1.5).

To avoid sudden jumps when switching models, the final probabilities p_m were calculated based on the degree of activation of rules β_m (12) using the Softmax normalizing function with temperature coefficient $T = 0.5$: this approach provided a smooth but mathematically contrasting probability distribution between parallel filters:

$$p_m = \frac{exp\ exp(\beta_m / T)}{\sum_j exp\ exp\ (\beta_j / T)}. \quad (12)$$

The logic of the controller's operation in case of degradation or complete loss of the GNSS signal required special attention. Without measurements, calculating the innovation vector became mathematically impossible. In the developed algorithm, when recording a measurement miss, the controller froze the current probability distribution. If the signal loss was long (exceeding one second), the system forcibly redistributed the weights in favor of the uniform rectilinear motion (CV) model.

The physical meaning of this solution was to implement a minimax survival strategy for the navigation system. If the UAV was in maneuver at the time of loss of communication (CA, CT or MV models), keeping these models active would lead to a double integration of acceleration or angular velocity in the absence of corrective measurements. This inevitably caused an exponential increase in the positioning error (parabola departure or spiral unwinding). The forced transition to the CV model put the system into the mode of Dead Reckoning according to the vector of the last reliably known velocity. Linearization of the predicted trajectory was the safest mathematical assumption in conditions of complete information uncertainty, which minimized the accumulated error by the time the signal was restored.

The analysis of various modifications of the Kalman filter made it possible to identify various disadvantages for each variant of the algorithm. However, the possibility of intellectualization, that is, endowing them with the ability to adapt, learn and make decisions in conditions of uncertainty, allowed us to move from systems rigidly programmed for certain noise and dynamics models to flexible, self-adjusting and sustainable solutions.

The key problem of implementing the Kalman filter was the need for accurate a priori knowledge of the covariance matrices of Q_k process noise and R_k measurements. Intellectualization solved this problem by evaluating them in real time.

The discrepancy at k step was considered:

$$v_k = z_k - h(\widehat{x}_k^-). \quad (14)$$

Its theoretical covariance was calculated as described in the formula:

$$S_k = H_k P_k^- H_k^T + R_k. \quad (14)$$

Adaptive algorithms, such as the maximum likelihood method or the sliding window approach, allowed estimating R_k (and sometimes Q_k) by minimizing the difference between the theoretical covariance of S_k and the actual covariance of innovation calculated in the last N steps [10]:

$$\widehat{C}_v = \frac{1}{N} \sum_{i=k-N+1}^{k} v_i v_i^T.$$

The simplified adaptation of R_k in this case had the form represented by the formula:

$$\widetilde{R_k} = a\widetilde{R_{k-1}} + (1-a)\left(v_k v_k^T - H_k P_k^- H_k^T\right). \quad (15)$$

where α ∈ (0.1) — smoothing coefficient.

This gave the filter the property of self-calibration when the accuracy of the sensors changed (for example, when the GNSS signal deteriorated) [11].

In conditions of multi-channel data flow from heterogeneous sensors, the intelligent system should dynamically evaluated the reliability of each source. The confidence vector $\lambda_k = [\lambda_k^1, \lambda_k^2, \ldots, \lambda_k^m]^T$ was introduced, where $\lambda_k^i \in (0.1]$ — confidence coefficient of the i-th dimension.

The equation for calculating the residual covariance was modified:

$$\tilde{S}_k = H_k P_k^- H_k^T + \Lambda_k^{-1} R_k,$$

where $\Lambda_k = diag(\lambda_k)$.

Coefficient λ_k^i was calculated using a proprietary algorithm for each type of sensor (for example, for GNSS — based on HDOP and the number of satellites; for visual odometry — based on the number of track points and image contrast). Thus, the filter acquired the ability to critically analyze incoming information and automatically reduced the impact of malfunctioning or degrading sensors [12].

For maximum fault tolerance, architecture with parallel execution of several filtering algorithms (for example, EKF, UKF, PF) was proposed, each of which was most optimal in a certain flight mode. Based on a set of fuzzy logic rules, the control module analyzed the current C_k conditions (the presence of a GNSS signal, the magnitude of angular velocities, estimated variances) and selected the final estimate. Thus, it had the following structure:

$$\widehat{x}_k^{end} = \sum_{j=1}^{M} b_k^j \cdot \widehat{x}_k^{(j)}, \quad (16)$$

where b_k^j — weight assigned by the module to the j-th filter at time k, where $\sum_{j=1}^{M} b_k^j = 1$. The module could completely disable irrelevant filters, saving computing resources.

Results. For a comprehensive verification of the proposed method, the study was divided into two stages: rigorous mathematical modeling and field tests on a hardware platform.

Mathematical modeling results. A complex 300-second test trajectory was synthesized in the MATLAB environment, simulating a UAV flight at speeds up to 70 m/s (250 km/h). The trajectory included sections of uniform motion, sharp accelerations, and a series of coordinated turn maneuvers with centripetal acceleration up to 2.5 m/s^2. To simulate real-world operating conditions, complex noise was added to the ideal range measurements: basic white Gaussian noise (σ = 1.0 m), non-Gaussian pulses (anomalies accounting for 2% of the total number of measurements), and complete signal interruptions lasting from 1 to 5 seconds were artificially generated.

Analysis of the results showed that the fuzzy controller correctly identified the dynamics of the object: in straight sections, the probability of the CV model reached its maximum, the CT mode dominated on turns (active 50.7% of the time), and with sudden changes in the velocity vector, the maneuver model (MV) was briefly activated. In areas of continuous signal reception, the combined estimate achieved high accuracy: RMSE was 1.48 meters. At the moments of communication failures (marked with markers on the graph), the error predictably increased due to the inability to accurately predict blind maneuvers. However, due to the inherent logic of switching to the inertial mode (CV), the filter remained stable, and upon resumption of measurements, the error converged to nominal values in 1–2 cycles (Fig. 1).

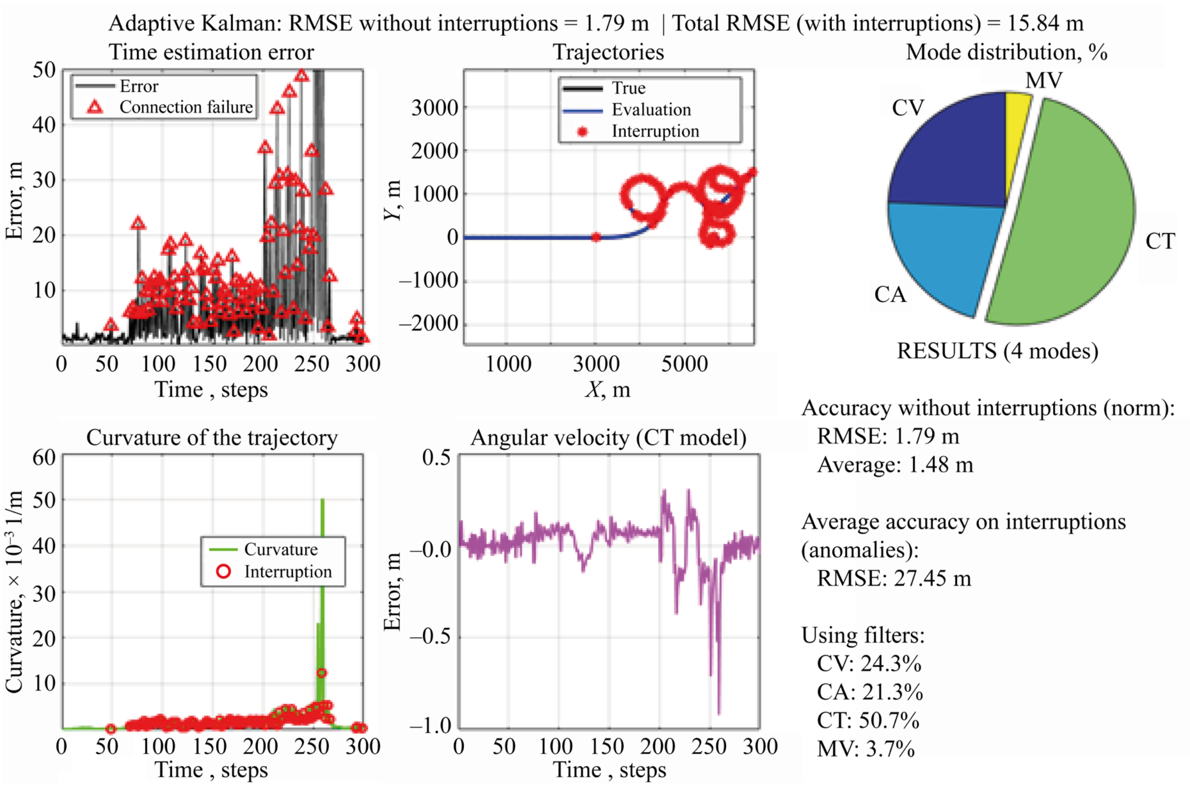

Fig. 1. Results of the adaptive SRCDKF filter operation during modeling

Figure 2 demonstrates the results of the adaptive navigation filter in the form of time series.

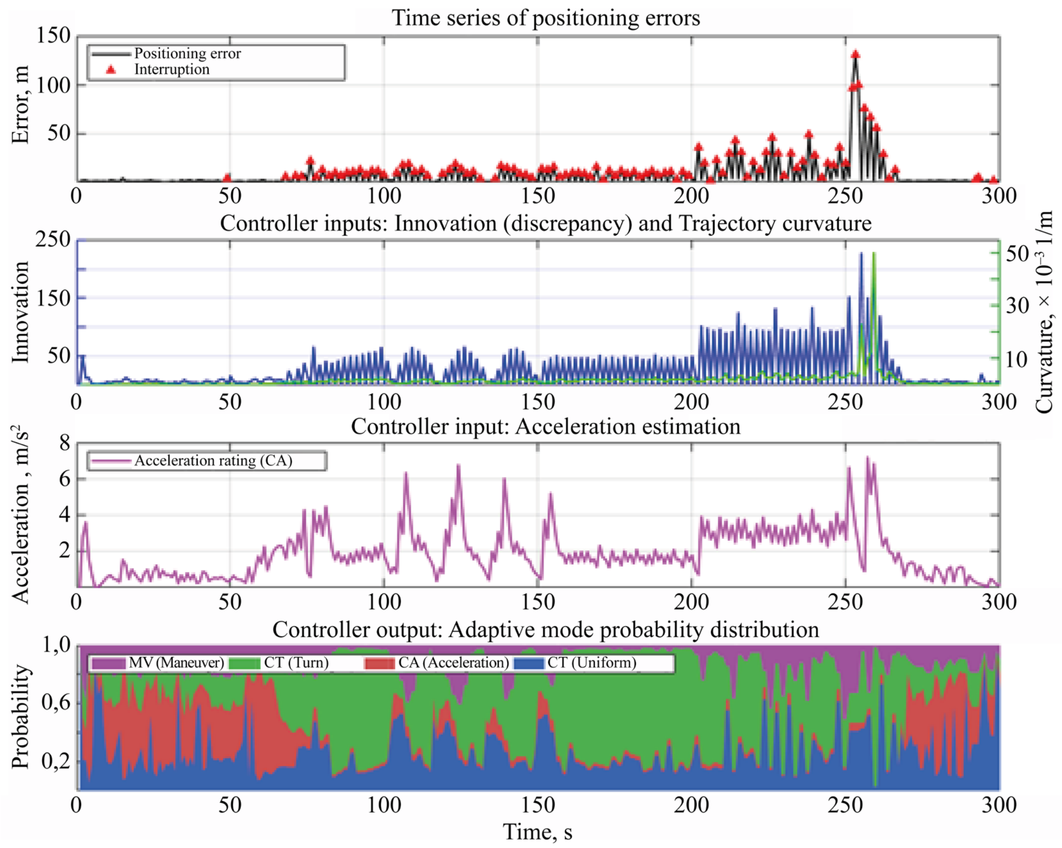

Fig. 2. Time series of positioning errors and dynamics of fuzzy logic controller parameters

The absolute positioning error was displayed on the upper panel with the marks of the moments of loss of the measuring signal (red markers). In the range from 0 to 200 s, the error varied from 0 to 30 m. At the 250–260 s time stamp, a maximum error jump reaching 130 m was recorded, which coincided with a dense series of measurement gaps. After 270 seconds, the error value returned to a level of less than 5 m.

The second and third panels showed the values of the input linguistic variables of the fuzzy controller. The innovative sequence (blue curve) showed regular fluctuations in the first half of the experiment and a sharp increase after 200 seconds, reaching a peak value of more than 200 units at 255 seconds. The trajectory curvature estimate (green curve) kept values close to zero for most of the route, with a local maximum of about $60 \cdot 10^{-3}$ m^{-1} in the range of 250–260 s. The longitudinal acceleration estimate (lower curve) varied in the range from 0 to 7.5 m/s^2 with pronounced peaks at 110, 125 and 255 s.

The bottom panel showed the output probability distribution (weights) of the four kinematic models. The initial segment (0–50 s) was dominated by the uniform rectilinear motion model (CV, blue area) with a probability from 0.6 to 1.0. In the range of 50–200 s, an increase in the proportion of models of equidistant motion (CA, red region) and coordinated rotation (CT, green region) was recorded. During the period of registration of the maximum values of curvature and innovation (250–260 s), the activation of the intensive maneuvering model (MV, purple area) and the predominance of the CT model were observed, after which the system returned to the predominant use of the CV model.

Practical tests results. A mobile test bench was developed to validate the algorithm in conditions of real hardware noise and imperfect sensors. The computing core was the NodeMCU V3.0 microcontroller (ARM architecture), to which the cost effective NEO6MV2 GPS module with a refresh rate of 1 Hz was connected. The choice of such a simple navigation module was not accidental: it had a high inherent error ($\sigma \approx 3$–5 m) and was prone to frequent loss of satellites signal in difficult conditions. This made it possible to naturally emulate the conditions of severe degradation of the navigation field, typical for the use of UAVs in areas of electronic warfare (EW) systems.

A high-precision dual-frequency RTK GNSS receiver (U-blox ZED-F9P) was used as the source of the true (reference) trajectory, providing centimeter positioning accuracy in the post-processing kinematics (PPK) mode. The bench was moved by car along a 12 km route (60 tests were conducted in total). The route specifically passed through areas of dense urban development, alleys with canopy trees and under bridges to provoke natural GPS failures. Figure 3 demonstrates one of these tests with signal loss zones.

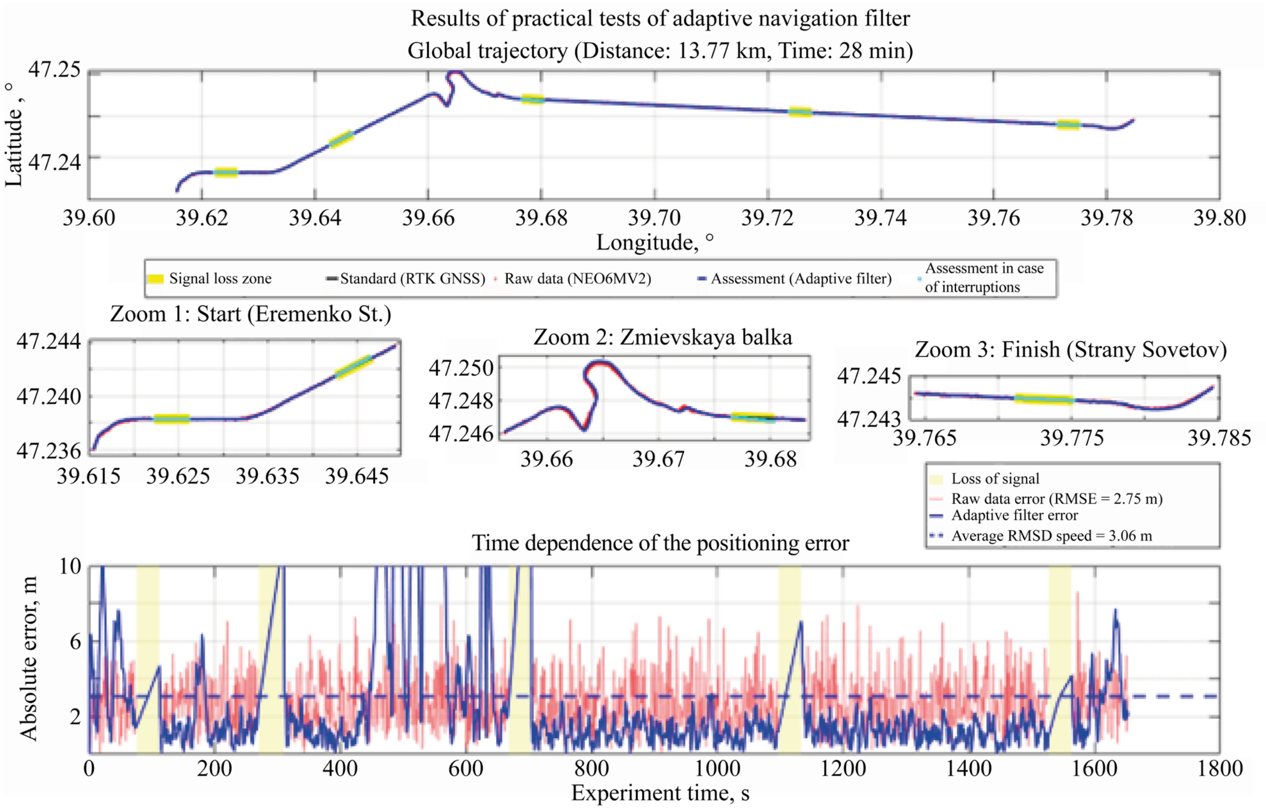

Fig. 3. One of the tests. Comparison of raw GPS data, adaptive filter estimates, and RTK reference trajectory

Field tests fully confirmed the conclusions of mathematical modeling. Despite the significant variation in the raw data of the NEO6MV2 module, the proposed adaptive filter effectively smoothed the trajectory, eliminating noise emissions. When driving under artificial obstacles (complete loss of signal for 3–8 seconds), the algorithm reliably maintained the calculated trajectory along the velocity vector, minimizing deviation from the RTK reference track.

Table 2 presents a comparative analysis of various filter options [13].

Table 2

Comparative analysis of filtering algorithms

Criteria	EKF	UKF / SRCDKF	PF (Particle Filter, N = 1000	Adaptive hybrid with fuzzy controller
Optimal conditions	Weakly nonlinear systems, Gaussian noise, linear measurements	Moderately nonlinear systems, Gaussian noise up to the 2nd order of nonlinearities	Highly nonlinear and non-Gaussian systems, multimodal distributions	Systems with unsteady behavior, measurement interruptions, and mixed noises
RMSD under normal conditions*, m	2.8–4.2	1.5–2.8	1.2–2.5	0.8–1.8
RMSD at 30 % measurement interruptions, m	Divergence (> 15.0)	4.5–8.2	4.2–8.5	3.5–4.2
Resistance to outliers and anomalies	Low (sensitive to Gaussian disturbances)]	Medium (resistant to moderate nonlinearities)	High (robustness to non-Gaussian noise)	Very high (adaptive model switching)
Computational complexity (relative to EKF)	1.0 (basic)	3.0–5.0	150–400	4.5–7.0
Adaptability to changes in the movement model	Absent	Limited (requires manual reconfiguration)	Average (through the suggested distribution)	High (dynamic switching between 4 models)
Main advantage	Computational efficiency, ease of implementation	Precision without calculating derivatives (sigma points)	Versatility for arbitrary distributions	Autonomous operation in case of degradation of the measuring channel

Note: * Normal conditions: Gaussian noise with σ = 1.5 m, no measurement interruptions.

Root-mean-square deviation is given as an example of a trajectory with a duration of 300 seconds for comparison with other studies.

“Stability” metric evaluates the reduction in the probability of a critical error growth (> 10 m) during the simulation.

Discussion. The results obtained by the authors confirm the hypothesis that the intellectualization of Kalman filters through the introduction of fuzzy logic makes it possible to compensate for the shortcomings of classical analytical models. The 1.5–2-fold reduction in RMSE positioning in interference conditions can be explained by the ability of the controller to select the most suitable filtering methods and account for nonlinear dependencies, which allows it to adapt to sensor drift, which is difficult to formalize mathematically. However, it is worth noting some limitations: the heuristic nature of rule base formation and membership function selection does not guarantee optimal solutions under all conditions and requires expert tuning for a specific task. At the same time, compared to works using only the EKF, the hybrid approach proposed by the authors maintains system stability even with complete degradation of one of the data channels.

An analysis of the information in Table 1 shows that the key advantage of the proposed approach is its ability to maintain operability and accuracy with partial and complete interruptions of the measuring signal. While EKF is prone to divergence, and the accuracy of UKF and PF is significantly reduced, the adaptive fuzzy controller system provides increased accuracy compared to UKF in these conditions. This is achieved by dynamically selecting the optimal dynamics model (CV, CA, CT, MV) based on the analysis of inconsistencies, acceleration and curvature of the trajectory in real time. A moderate increase in computational complexity by 20–40% relative to UKF is an acceptable price to pay for a multiple increase in reliability and a 50–60% reduction in the probability of failures. Promising areas of research include further development of square root algorithms (SRCDKF) to increase numerical stability, the creation of hybrid filters, as well as the adaptation of the considered methods to solve the problems of cooperative navigation of UAV groups. However, for mission-critical applications requiring maximum reliability, intelligent adaptive systems based on UKF/SRCDKF become the optimal choice, providing a balance between accuracy, stability, and reasonable computational costs. The main contribution of this work to research on improving the autonomy and accuracy of navigation systems of unmanned aerial vehicles is to create the principle of adaptive switching, which allows the system to automatically adjust to changing observation conditions without operator intervention, switch between models of constant speed, acceleration, coordinated turn and robust maneuver mode.

The use of the cost effective GPS module in the field tests has proven that the algorithm can achieve acceptable navigation accuracy even with low-quality sensors. This is crucial for the production of low-cost mass-produced UAVs.

Conclusion. The authors proposed and investigated an adaptive hybrid filtering algorithm based on various modifications of the Kalman filter and a fuzzy controller for intelligent selection of motion models. The method is designed to work in conditions of non-stationary object dynamics, mixed Gaussian and non-Gaussian noise, as well as partial interruptions of the measuring signal.

Experimental results have confirmed the architecture effectiveness: with 30% of measurement breaks, the algorithm provides a coordinate estimation time of 3.5–4.2 meters, which is more accurate than that of the standard UKF in similar conditions.

The results of mathematical and software modeling show that the intellectualization of Kalman filters through the introduction of a fuzzy controller and a mechanism for adaptive switching of motion models increases positioning accuracy by 15–30% and is an effective method of increasing the stability of navigation systems to degradation of measurements. The developed adaptive hybrid filter demonstrates qualitative superiority in conditions critical for classical algorithms.

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