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METHOD OF INTEGRATED ANALYSIS OF VISUAL-INERTIAL DATA OF A MOBILE ROBOTIC SYSTEM

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Abstract—This article presents a method for adaptive integrated processing of visual and inertial data in mobile robotic systems under conditions of sensor noise and temporal inconsistency. The method combines state prediction, sensor observation modelling, uncertainty estimation, and adaptive weighting of heterogeneous measurements according to their current reliability. Unlike fixed-weight fusion, the proposed approach dynamically redistributes the contribution of visual and inertial data during state estimation. Simulation results demonstrate reduced positioning error and improved stability under sensor degradation and temporal delays. The method can be applied in autonomous navigation and positioning systems operating under uncertain conditions.

Keywords—Mobile robotic system, visual-inertial data, integrated data processing, multisensor data fusion, autonomous navigation, state estimation, trajectory planning, information processing model.

I. INTRODUCTION

Modern mobile robotic systems operating in dynamic and uncertain environments require highly accurate and stable navigation mechanisms capable of processing heterogeneous sensory information in real time. The rapid development of autonomous robotic platforms has significantly increased the importance of multisensor data processing technologies, particularly in tasks related to spatial positioning, trajectory estimation, environment mapping, and adaptive motion control.

In such systems, visual and inertial sensors are among the primary sources of information used for estimating the current state of the robotic platform.

However, the separate use of visual or inertial data does not provide sufficient robustness under conditions of sensor noise, temporary signal loss, changing illumination conditions, dynamic obstacles, and temporal inconsistencies of information flows. Visual data processing systems are sensitive to image degradation, motion blur, and environmental variability, whereas inertial navigation systems are characterised by gradual accumulation of positioning errors over time. As a result, autonomous robotic systems require integrated approaches capable of combining heterogeneous sensor data into a unified information representation.

The problem of integrated visual-inertial data analysis is particularly relevant for mobile robotic

systems operating in complex environments where the reliability and stability of navigation directly affect the efficiency of autonomous movement and decision-making processes.

The integration of multisource sensor information allows compensating local errors of individual measurement channels, improving the accuracy of state estimation, and increasing the stability of trajectory formation.

Existing approaches to multisensor data fusion mainly focus either on low-level sensor integration or on isolated trajectory estimation techniques. At the same time, many existing methods do not sufficiently consider the influence of temporal delays, uncertainty propagation, inconsistency of information flows, and adaptive correction of spatial position estimates under dynamically changing operating conditions. Therefore, the development of methods for integrated analysis of visual-inertial data remains an important scientific and practical problem.

The aim of this work is to develop a method for integrated analysis of visual-inertial data of a mobile robotic system, which provides coordinated processing of heterogeneous information flows and improves the accuracy and stability of spatial state estimation under uncertainty conditions.

To achieve this goal, the structure of visual and inertial information flows in mobile robotic systems is analysed, an integrated multisensor data processing structure is developed, and the processes

of state estimation and uncertainty modelling are formalised. In addition, a mathematical framework for coordinated processing of heterogeneous sensor information is proposed, followed by simulation modelling and comparative evaluation of the developed approach.

The scientific novelty of the proposed method lies in the development of an integrated approach for coordinated processing of visual and inertial information flows that takes into account temporal inconsistencies, sensor uncertainty, and adaptive trajectory correction within a unified state estimation framework.

The practical significance of the obtained results consists in the possibility of applying the proposed method in autonomous navigation, spatial positioning, and adaptive control systems of mobile robotic platforms operating under conditions of uncertainty, sensor disturbances, and dynamically changing environments.

II. LITERATURE ANALYSIS

The rapid development of mobile robotic systems and autonomous navigation technologies has significantly increased the importance of integrated processing of heterogeneous sensory information. Modern robotic platforms require reliable methods for analysing visual, inertial, and telemetry data under conditions of uncertainty, dynamic environmental changes, and temporal inconsistencies of information flows. Therefore, the problem of multisensor data fusion remains an important research area in information systems and robotic navigation technologies.

Theoretical and methodological foundations of information processing and decision support systems are presented in [1], where considerable attention is devoted to mathematical support for complex information systems operating under uncertainty conditions. The approaches described in this work provide a basis for the formalisation of multisource information processing and state estimation tasks in autonomous robotic platforms.

The application of bio-inspired and population-based optimisation methods in information systems is considered in [2], [5], and [6]. These approaches demonstrate the possibility of solving complex optimisation problems characterised by nonlinear dependencies and multidimensional parameter spaces. Their application in autonomous systems confirms the relevance of adaptive computational procedures for processing heterogeneous information under dynamically changing operating conditions.

In article [3], a methodological approach for assessing the condition of complex organisational and technical systems is proposed. The presented methods focus on analysing the behaviour of systems under uncertainty and can be applied for evaluating the stability and reliability of autonomous robotic platforms functioning in dynamically changing environments.

The scientific-method apparatus for improving information processing efficiency using artificial intelligence methods is presented in [4].

The proposed approaches to data processing and adaptive analysis form the basis for developing integrated methods of visual-inertial information fusion in mobile robotic systems.

The problem of synchronisation of distributed sensor systems is investigated in [7], where a wireless sensor synchronisation method is proposed for monitoring short-term events. Temporal synchronisation of information flows is one of the key factors affecting the efficiency of integrated processing of visual and inertial data, particularly in real-time navigation systems.

The application of edge computing technologies for processing distributed information flows in Internet of Things environments is considered in [8].

The proposed approaches to distributed data processing and adaptive interaction between computational nodes are relevant for mobile robotic systems operating with limited computational resources and real-time requirements.

Works [9] – [18], a method for managing a group of unmanned aerial vehicles using a population algorithm is developed.

At the same time, analysis of the existing studies shows that many approaches mainly focus on isolated optimisation, synchronisation, or information processing tasks without sufficient consideration of coordinated integration of visual and inertial information flows within a unified state estimation framework.

In addition, the influence of temporal inconsistencies, uncertainty propagation, and adaptive correction of trajectory estimation remains insufficiently investigated.

III. PROBLEM STATEMENT

Modern mobile robotic systems operating in dynamic and uncertain environments require accurate and stable methods for estimating spatial position, trajectory parameters, and the current state of the platform.

Autonomous navigation systems rely on heterogeneous sensor information obtained from

visual and inertial measurement modules, which differ in data structure, update frequency, reliability, and sensitivity to external disturbances.

Under real operating conditions, the processing of such information is complicated by measurement noise, temporal delays, partial loss of sensor data, and inconsistencies between information flows.

The use of visual information allows obtaining detailed spatial characteristics of the environment and performing trajectory estimation based on image analysis. However, visual navigation systems are highly sensitive to changes in illumination conditions, motion blur, dynamic obstacles, and image degradation.

At the same time, inertial measurement systems provide continuous estimation of motion parameters independently of external visibility conditions, but they are characterised by gradual accumulation of positioning errors during long-term operation.

As a result, the separate use of visual or inertial information does not provide the required level of robustness and positioning accuracy for mobile robotic systems functioning under uncertainty conditions.

This necessitates the development of integrated methods capable of coordinated processing of heterogeneous sensory information within a unified state estimation framework.

The problem considered in this work consists in developing a method for integrated analysis of visual-inertial data of a mobile robotic system that ensures coordinated fusion of heterogeneous information flows, reduces the influence of sensor uncertainty and temporal inconsistencies, and improves the accuracy and stability of spatial state estimation during autonomous navigation.

To solve the stated problem, it is necessary to develop an integrated structure for multisensor data processing, formalise the processes of information fusion and uncertainty estimation, and construct a mathematical framework for coordinated processing of visual and inertial information under conditions of noise, temporal delays, and dynamic environmental changes.

The proposed approach should provide stable trajectory estimation, adaptive correction of positioning errors, and increased robustness of the mobile robotic system to disturbances affecting individual sensor channels.

Let M denote the set of visual and inertial measurement channels. At discrete time instant k , each sensor provides an observation $z_k^{(m)}$, its timestamp $t_k^{(m)}$, and measurement uncertainty matrix $R_k^{(m)}$, $m \in M$. The state of the mobile robotic system

is described by x_k , while its predicted value x_k^- is obtained from the previous state and the motion model.

The problem is to determine the estimate x_k^- that minimises the inconsistency between the predicted state and heterogeneous sensor observations, taking into account their current reliability:

$$\hat{x}_k = \arg \min_{x_k} \left[(x_k - x_k^-)^T (P_k^-)^{-1} (x_k - x_k^-) + \sum_{m \in M} \alpha_k^{(m)} (z_k^{(m)} - h^{(m)}(x_k))^T * (R_k^{(m)})^{-1} (z_k^{(m)} - h^{(m)}(x_k)) \right].$$

The weighting coefficients satisfy:

$$\alpha_k^{(m)} \geq 0, \quad \sum_{m \in M} \alpha_k^{(m)} = 1, \quad |t_k - t_k^{(m)}| \leq \Delta t_{\max}.$$

Therefore, the research task consists in developing a procedure for determining the adaptive coefficients $\alpha_k^{(m)}$ and performing state correction depending on temporal inconsistency, measurement uncertainty, and consistency of each sensor observation with the predicted system state.

IV. ELEMENTS OF THE METHODOLOGICAL FRAMEWORK

In autonomous navigation tasks of mobile robotic systems, special importance is attached to ensuring coordinated processing of multisensor data generated by heterogeneous measurement modules. The use of only one source of information does not provide the required level of reliability for determining the spatial position of the system under conditions of dynamic environmental changes, disturbances, partial data loss, and temporal inconsistency of information flows.

In this regard, the problem of integrated processing of visual and inertial data with the formation of a unified information observation space becomes relevant.

The functioning of a mobile robotic system is based on a continuous process of acquisition, transmission, synchronisation, and analysis of data obtained from sensor modules.

Such data include video streams, inertial measurements, spatial positioning parameters, motion characteristics, and service telemetry information.

At the same time, different data arrival frequencies, transmission delays, limited computational resources, and the influence of external factors lead to the emergence of uncertainty during estimation of the current system state.

To ensure stable operation of autonomous navigation systems, it is advisable to use an integrated information technology that combines data from different sensors within a unified process of mobile platform state estimation. Such an approach makes it possible to improve trajectory estimation accuracy, reduce the influence of local errors of individual measurement modules, and

provide adaptive correction of motion parameters in real time. The structure of integrated processing of sensor information flows of the mobile robotic system is shown in Fig. 1.

The presented scheme illustrates the process of formation and coordination of data obtained from visual and inertial sensors with subsequent trajectory generation and environment map construction.

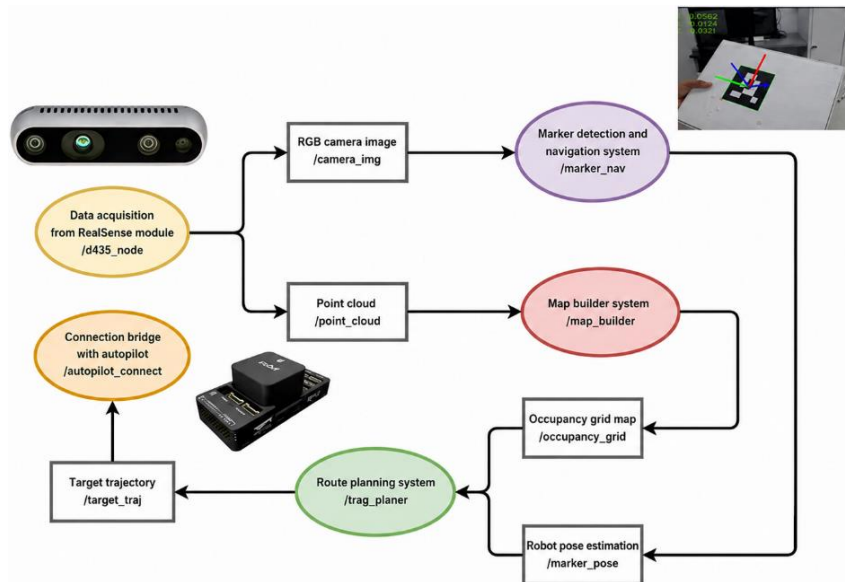


Fig. 1. A generalised scheme for the integrated processing of visual and inertial data

The presented structure includes a visual data formation module, an inertial measurement unit, a motion parameter estimation subsystem, an environment mapping module, and a control signal generation system.

The main feature of the proposed scheme is the organisation of a unified information processing loop within which heterogeneous data flows are coordinated and adaptive refinement of the system spatial position parameters is performed.

During system operation, data from sensor modules are transmitted to the integrated processing subsystem, where synchronisation, filtering, and formation of a coordinated information representation of the environment are carried out.

Based on the obtained results, trajectory estimation of the mobile platform and generation of control signals for stabilisation of the navigation process are performed. In addition, the integrated processing subsystem ensures continuous updating of spatial information during the movement of the robotic platform.

This makes it possible to improve the consistency of navigation data and reduce the influence of temporary instability of individual sensor channels.

The proposed approach also supports adaptive interaction between computational and sensor modules depending on changes in operating conditions and the current state of the environment. Such adaptability increases the robustness of the navigation process under conditions of uncertainty and dynamic external disturbances.

The architecture of information interaction between the components of the mobile robotic system is shown in Fig. 2.

The presented structure reflects the interconnection between computational modules, sensor devices, the automated control system, and the external environment.

The presented architecture provides functional distribution between the levels of data acquisition, information processing, and control signal generation.

The lower level ensures data acquisition from measurement and executive devices, the middle level implements sensor information processing and supports automated control algorithms, while the upper level performs coordination of navigation processes, trajectory planning, and information exchange with external computational systems.

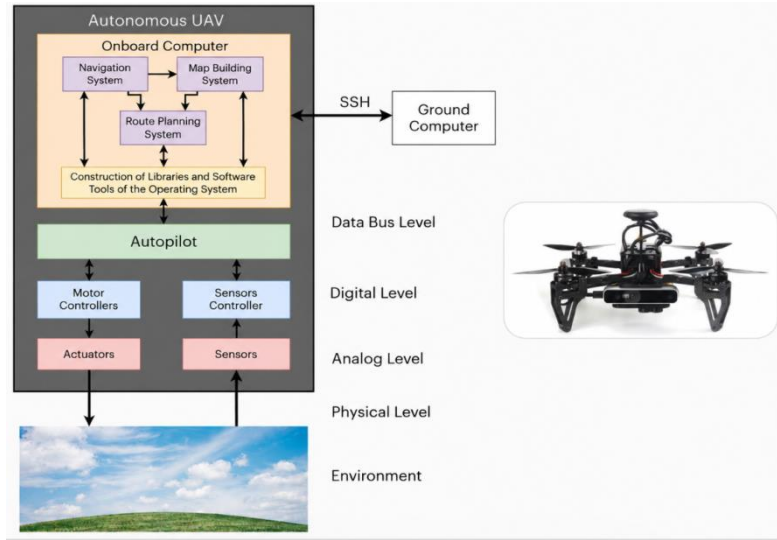


Fig. 2. Architecture of information exchange between components

The use of the proposed architecture makes it possible to ensure system scalability, coordinated interaction of hardware and software components, and adaptive management of data flows depending on the operating conditions of the mobile robotic platform.

To formalise the process of integrated processing of visual-inertial data, it is necessary to move from the structural description of the system to the mathematical representation of its information flows, states, and data coordination mechanisms.

The schemes presented in Figs 1 and 2 illustrate the general logic of interaction between sensor, computational, and control components; however, for further analysis, these processes should be described as a sequence of formalised stages.

Step 1. Formation of a multicomponent information flow. At the first stage, sensor data are represented as a set of heterogeneous information flows received from visual, inertial, and control modules:

$$D(t) = \{V(t), I(t), P(t), U(t)\}, \quad t \in [0, T],$$

where $D(t)$ is the multicomponent information flow at time t ; $V(t)$ is the visual data flow; $I(t)$ is the inertial measurement flow; $P(t)$, is the positioning data flow; $U(t)$ is the control information flow; t is the current time instant; and T is the duration of the considered observation interval.

Step 2. Description of the mobile system state vector. The current state of the system is represented as a multidimensional vector combining spatial coordinates, velocity, orientation, and derived motion parameters:

$$x_k = [r_k^T \quad v_k^T \quad \Theta_k^T \quad w_k^T \quad b_k^T]^T,$$

where v_k^T is the linear velocity vector; Θ_k^T is the orientation vector; w_k^T is the angular velocity vector; b_k^T is the vector of sensor bias parameters.

Step 3. System state prediction model. The dynamics of state variation are described using a nonlinear transition model that takes into account the previous state, control input, and external disturbances:

$$x_{k+1} = f(x_k, u_k, \Delta t_k) + G_k w_k,$$

where $f(\cdot)$ is the nonlinear state transition function describing the system dynamics; u_k is the control input vector; Δt_k is the time interval; G_k is the process noise influence matrix; w_k is the process noise vector.

Step 4. Sensor observation model. Measurements obtained from different sensor modules are represented as the result of observing the current system state with consideration of measurement noise:

$$z_k^{(m)} = h^{(m)}(x_k) + v_k^{(m)}, \quad m = 1, \dots, M.$$

Step 5. Coordination of heterogeneous sensor information flows.

We determine the time inconsistency of each source:

$$\Delta t_k^{(m)} = |t_k - t_k^{(m)}|.$$

We determine the discrepancy between the sensor measurements and the predicted state:

$$r_k^{(m)} = z_k^{(m)} - h^{(m)}(x_k^-).$$

We define the normalised measure of observation inconsistency:

$$d_k^{(m)} = (r_k^{(m)})^T (S_k^{(m)})^{-1} r_k^{(m)},$$

$$S_k^{(m)} = H_k^{(m)} P_k^- (H_k^{(m)})^T + R_k^{(m)}.$$

where $d_k^{(m)}$ is the normalised inconsistency measure of the m -th sensor observation; $S_k^{(m)}$ is the innovation covariance matrix; $H_k^{(m)}$ is the Jacobian matrix; $R_k^{(m)}$ is the prior covariance matrix of the predicted state estimation error.

We introduce a rule for discarding clearly unreliable measurements:

$$\gamma_k^{(m)} = \begin{cases} 1, & d_k^{(m)} \leq d_{\max} \wedge \Delta t_k^{(m)} \leq \Delta t_{\max}, \\ 0, & \text{otherwise.} \end{cases}$$

where $\gamma_k^{(m)}$ is the binary validity indicator of the m -th sensor measurement; $d_{\max}$ is the maximum allowable value of the normalised inconsistency measure;

We are formulating a specific assessment of current reliability:

$$q_k^{(m)} = \gamma_k^{(m)} \frac{\exp[-\lambda_i \Delta t_k^{(m)} - \lambda_d d_k^{(m)}]}{\varepsilon + \text{tr}(R_k^{(m)})}.$$

Normalisation:

$$\alpha_k^{(m)} = \frac{q_k^{(m)}}{\sum_{j=1}^M q_k^{(j)}},$$

where $\alpha_k^{(m)}$ is the normalised weighting coefficient of the m -th sensor channel at the k -th step.

Step 6. Uncertainty estimation of the integrated state.

To consider the influence of noise, errors, and temporal inconsistencies, a covariance representation of state estimation uncertainty is introduced:

$$P_k^* = \left(\sum_{m=1}^M \alpha_k^{(m)} (P_k^{(m)})^{-1} \right)^{-1}.$$

Step 7. Formation of the coordinated state estimation criterion.

At the final stage, a criterion is formed that minimises the deviation between the predicted and observed system states while taking uncertainty into account:

$$J_k = (z_k^* - H_k \hat{x}_k)^T (P_k^*)^{-1} (z_k^* - H_k \hat{x}_k) \rightarrow \min.$$

Step 8. Determination of the optimal integrated state estimate:

$$\hat{x}_k = \left[(P_k^-)^{-1} + \sum_{m=1}^M \alpha_k^{(m)} (H_k^{(m)})^T (R_k^{(m)})^{-1} H_k^{(m)} \right]^{-1} * \\ * \left[(P_k^-)^{-1} x_k^- + \sum_{m=1}^M \alpha_k^{(m)} (H_k^{(m)})^T (R_k^{(m)})^{-1} z_k^{(m)} \right].$$

Step 9. Adaptive updating of sensor reliability coefficients. Once the data $\hat{x}_k$ has been received, we determine the offset for each sensor:

$$r_k^{(m)} = z_k^{(m)} - h^{(m)}(\hat{x}_k).$$

We determine the comprehensive reliability measure:

$$q_k^{(m)} = \frac{\exp[-\lambda_1 (r_k^{(m)})^T (R_k^{(m)})^{-1} r_k^{(m)} - \lambda_2 \Delta t_k^{(m)}]}{\varepsilon + \text{tr}(R_k^{(m)})},$$

where ε is a small positive constant preventing division by zero; and $\text{tr}(R_k^{(m)})$ is the trace of the measurement noise covariance matrix of the m -th sensor channel.

We define the weights for the next iteration:

$$\alpha_{k+1}^{(m)} = \frac{q_k^{(m)}}{\sum_{j=1}^M q_k^{(j)}}.$$

To verify the operability of the proposed mathematical model, simulation modelling was performed in the Python environment.

Figure 3 (a, b) shows the dynamics of positioning error and the corresponding redistribution of visual and inertial sensor weights during the simulation process. Increased visual measurement noise and temporal delay lead to a reduction in the contribution of the visual channel, while the weight of the inertial measurements increases.

During the interval of increased inertial measurement noise, the opposite redistribution is observed. The proposed adaptive fusion method provides the lowest positioning error compared with

visual-only, inertial-only, and fixed-weight fusion approaches.

The obtained results confirm that adaptive adjustment of sensor contributions according to their current reliability, measurement uncertainty, and temporal consistency improves the accuracy and stability of spatial state estimation.

Figure 4 (a, b) shows the influence of visual measurement noise and temporal delay on the positioning RMSE. The fixed-weight fusion approach demonstrates a substantial increase in error as the degradation of the visual channel grows.

The proposed adaptive fusion method maintains lower RMSE values over the considered parameter range due to dynamic adjustment of sensor contributions. This confirms improved robustness of the proposed method to uncertainty and temporal inconsistency of multisensor information.

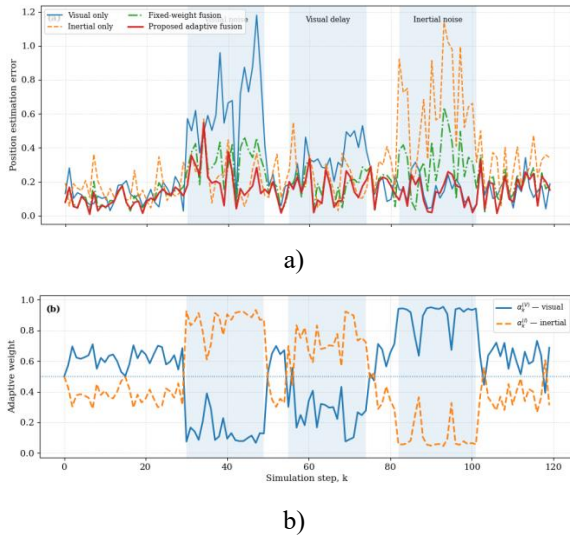
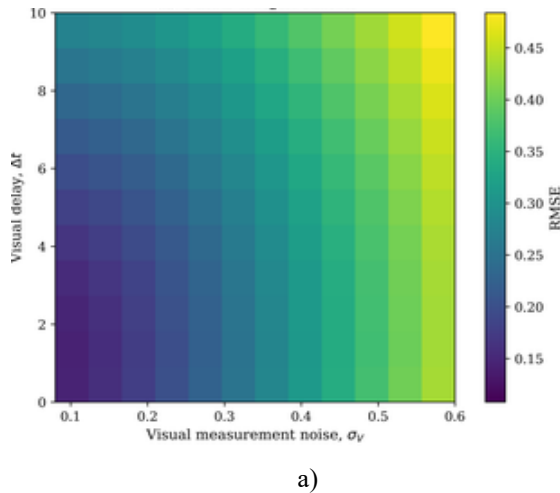
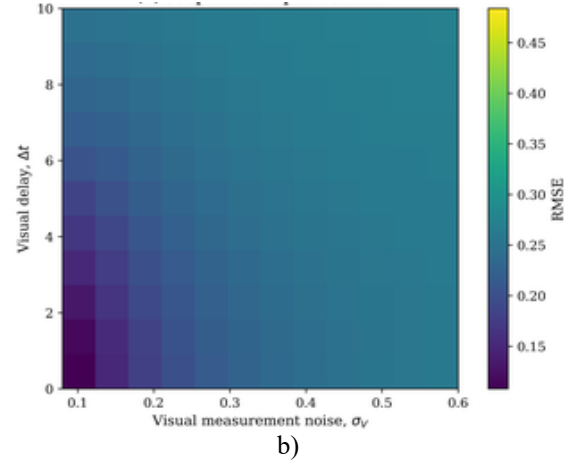


Fig. 3. Dynamics of positioning error and corresponding redistribution of weights of visual and inertial sensors during the simulation process: (a) position estimation error; (b) adaptive sensor weights



a)



b)

Fig. 4. Sensitivity of positioning RMSE to visual measurement noise and temporal delay: (a) fixed-weight fusion; (b) proposed adaptive fusion

Figure 5 shows the spatial distribution of the position estimation error of the mobile robotic system along the X and Y coordinates. The points represent individual position estimation results, while the ellipses characterise the error dispersion region for each data processing approach.

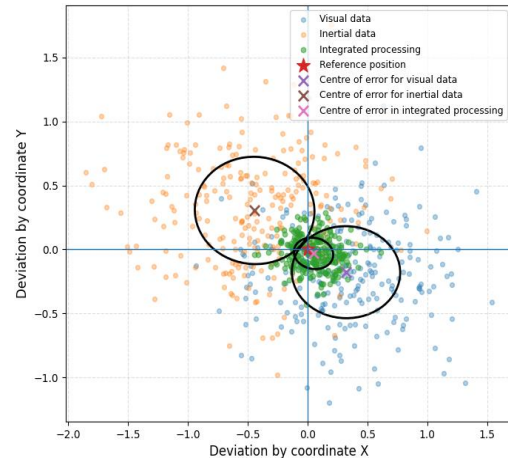


Fig. 5. Spatial distribution of error

The largest dispersion area is observed when visual and inertial data are used separately. Integrated processing forms a more compact error region located closer to the reference position, which indicates improved spatial stability of the estimation process.

The constructed graphical dependencies confirm the effectiveness of the proposed approach to integrated processing of visual-inertial data of a mobile robotic system under conditions of uncertainty, sensor measurement noise, and temporal inconsistency of information flows.

The simulation results demonstrate that separate use of visual or inertial data leads to gradual accumulation of positioning errors, increased

instability of state estimation, and significant spatial deviation of the motion trajectory.

At the same time, integrated processing of heterogeneous sensor information flows provides mutual compensation of local errors of individual information sources, which makes it possible to improve the accuracy of spatial state estimation of the mobile robotic system. Analysis of the obtained results demonstrates a reduction in average and maximum positioning errors, improved trajectory stability, and a decrease in the spatial error dispersion area compared to methods based on separate data processing.

In addition, the simulation results confirm that the proposed approach is characterised by lower sensitivity to sensor measurement noise and temporal delays in data transmission. This makes it possible to ensure more stable operation of the autonomous navigation system under conditions of dynamic environmental changes and partial degradation of individual measurement channels.

The obtained results confirm the feasibility of applying integrated processing of visual-inertial data in tasks of autonomous navigation, spatial positioning, and adaptive control of mobile robotic platforms. They also demonstrate the possibility of practical application of the proposed approach in systems operating under conditions of increased uncertainty and limited reliability of sensor information.

To quantitatively evaluate the effectiveness of the proposed approach, a comparative analysis of separate and integrated sensor data processing results was carried out (Table I).

TABLE I. COMPARATIVE ANALYSIS

Processing method	RMSE	Average error	Maximum error
Visual data	0.339	0.259	1.179
Inertial data	0.367	0.292	1.139
Integrated processing	0.246	0.208	0.636
Proposed adaptive fusion	0.174	0.149	0.547

The data presented in Table I demonstrate the advantage of adaptive visual-inertial data fusion over both separate sensor processing and conventional fixed-weight fusion.

The proposed method provides the lowest RMSE of 0.174 and the lowest average positioning error of 0.149, whereas the corresponding values for fixed-weight fusion are 0.246 and 0.208. The maximum positioning error is also reduced from 0.636 for fixed-weight fusion to 0.547 for the proposed method. These results indicate that adaptive redistribution of sensor contributions according to

measurement reliability and temporal consistency improves both the accuracy and stability of mobile robotic system state estimation.

VI. CONCLUSIONS

This paper considered the problem of integrated processing of visual-inertial data in autonomous navigation systems of mobile robotic platforms. The conducted analysis demonstrated that the use of only one source of sensor information does not provide the required level of accuracy and stability of spatial state estimation under conditions of sensor noise, temporal delays, and dynamic changes in environmental parameters. In this regard, the problem of coordinating heterogeneous information flows with the formation of a unified integrated representation of the mobile platform state becomes highly relevant.

During the research, a generalised structure for integrated multisensor data processing was developed, combining visual and inertial information flows within a unified system state estimation loop. The proposed architecture ensures coordinated interaction between sensor, computational, and control components and supports adaptive trajectory formation of the mobile robotic system in real time.

A mathematical framework for integrated data processing was developed in the study, including formalisation of the multicomponent information flow, description of the system state vector, prediction and sensor observation models, procedures for coordinating heterogeneous data flows, and uncertainty estimation mechanisms. The proposed approach makes it possible to consider the influence of measurement noise, temporal inconsistency of information flows, and local errors of individual sensor sources.

To verify the effectiveness of the proposed approach, simulation modelling of integrated visual-inertial data processing was carried out.

The obtained simulation results confirmed that integrated processing improves the accuracy of spatial state estimation of the mobile robotic system, reduces error accumulation, and increases resistance to destabilising factors compared to separate use of visual or inertial information. Analysis of graphical dependencies and comparative evaluation results demonstrated a reduction in the spatial error dispersion area and the formation of a more stable system motion trajectory.

The practical significance of the obtained results lies in the possibility of applying the proposed approach in autonomous navigation, spatial

positioning, and adaptive control systems of mobile robotic platforms operating under conditions of uncertainty, limited reliability of sensor information, and dynamic environmental changes. The proposed solutions can be used in the development of information technologies for integrated multisensor data processing in modern autonomous robotic systems.

REFERENCES

- [1] S. O. Kashkevich, (Ed.) *Decision support systems: mathematical support*. Kharkiv: 2025. TECHNOLOGY CENTER PC. <https://doi.org/10.15587/978-617-8360-13-9>.
- [2] K. A. Tamer, O. Sova, O. Shaposhnikova, V. Yashchenok, I. Stanovska, S. Shostak, O. Rudenko, S. Petruk, O. Matsyi, & S. Kashkevich, "Development of a solution search method using a combined bio-inspired algorithm," *Eastern-European Journal of Enterprise Technologies*, 1(4/127), 6–13, 2024. <https://doi.org/10.15587/1729-4061.2024.298205>.
- [3] B. A. Mohammed, I. Stanovska, S. Kashkevich, A. Lebedynskyi, Y. Vakulenko, N. Protas, O. Klyuchak, O. Lastivka, A. Semeniuk, and O. Kivshar, "Development of a methodological approach for assessing the condition of complex organizational and technical systems," *Eastern-European Journal of Enterprise Technologies*, 2(3(134)), 47–53, 2025. <https://doi.org/10.15587/1729-4061.2025.326468>.
- [4] S. Kashkevich, I. Dmytriiev, I. Shevchenko, O. Lytvynenko, L. Shabanova-Kushnarenko, and N. Apenko, "Scientific-method apparatus for improving the efficiency of information processing using artificial intelligence," *Information and control systems: modelling and optimizations: collective monograph*. Kharkiv: Technology Center PC, 2024, pp. 137–167. <https://doi.org/10.15587/978-617-8360-04-7.ch5>.
- [5] M. S. Braik, "Chameleon swarm algorithm: a bio-inspired optimizer for solving engineering design problems," *Expert Systems with Applications*, vol. 174, 114685, 2021. <https://doi.org/10.1016/j.eswa.2021.114685>
- [6] S. Yakymiak, Y. Vdovytskyi, Y. Artabaiev, L. Degtyareva, Y. Vakulenko, S. Nevhad, V. Andronov, R. Lazuta, P. Shapoval, & Y. Artamonov, "Development of the solution search method using the population algorithm of global search optimization," *Eastern-European Journal of Enterprise Technologies*, vol. 3, no. 4 (123), pp. 39–46, 2023. <https://doi.org/10.15587/1729-4061.2023.281007>.
- [7] A. Zuev, D. Karaman, and A. Olshevskiy, "Wireless sensor synchronization method for monitoring short-term events", *Advanced Information Systems*, vol. 7, no. 4, pp. 33–40, 2023. <https://doi.org/10.20998/2522-9052.2023.4.04>
- [8] N. Kuchuk, S. Kashkevich, V. Radchenko, Y. Andrusenko, H. Kuchuk, "Applying edge computing in the execution IoT operative transactions," *Suchasni informatsiyini systemy*, vol. 8, no. 4, pp. 59–79, 2024. <https://doi.org/10.20998/2522-9052.2024.4.07>.
- [9] W. Hilal, S. A. Gadsden, and J. Yawney, "Fraud: A Review of Anomaly Detection Techniques and Recent Advances," *Expert Syst. Appl.*, 193, 116429, 2022. <https://doi.org/10.1016/j.eswa.2021.116429>
- [10] X. Zhang, F. Guo, T. Chen, L. Pan, G. Beliaikov, and J. Wu, "A Brief Survey of Machine Learning and Deep Learning Techniques for E-Commerce Research," *J. Theor. Appl. Electron. Commer. Res.*, 18, 2188–2216, 2023. <https://doi.org/10.3390/jtaer18040110>
- [11] N. Baisholan, K. Baisholanova, K. Kubayev, Z. Alimzhanova, and N. Baimuldina, "Corporate Network Anomaly Detection Methodology Utilizing Machine Learning Algorithms," *Smart Sci.*, 12, 666–678, 2024. <https://doi.org/10.1080/23080477.2024.2375457>
- [12] M. Ikermane, M. Mohy-eddine, and Y. Rachidi, "Credit Card Fraud Detection: Comparing Random Forest and XGBoost Models with Explainable AI Interpretations," In *Innovative Technologies on Electrical Power Systems for Smart Cities Infrastructure. ICESST 2024*, 126–135. Abouddrar, I., Ilahi Bakhsh, F., Nayyar, A., Ouachtouk, I., Eds.; Sustainable Civil Infrastructures; Springer: Cham, Switzerland, 2025. https://doi.org/10.1007/978-3-031-86705-7_12
- [13] I. Achituve, S. Kraus, and J. Goldberger, "Interpretable Online Banking Fraud Detection Based on Hierarchical Attention Mechanism," In *Proceedings of the IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Barcelona, Spain, 4–8 May 2020, pp. 1–9.
- [14] S. O. Hnatyuk, R. Sh. Berdybayev, V. M. Sydorenko, O. K. Zhigarevych, & T. V. Smirnova, "Event correlation and cybersecurity incident management system at critical infrastructure facilities," *Cybersecurity: Education, Science, Technology*, 3(19), 176–196, 2023. <https://doi.org/10.28925/2663-4023.2023.19.176196>
- [15] V. Sydorenko, S. Gnatyuk, A. Tolbatov, A. Fesenko, Y. Yevchenko, & Y. Sotnichenko, "Experimental FMECA-based assessment of the critical information infrastructure importance in aviation," *CEUR Workshop Proceedings*, 2732, 2020, 136–156. <https://doi.org/10.55056/ceur-ws.org/Vol-2732/20200136.pdf>
- [16] M. J. A. Alkhafaji, S. Kashkevich, A. Shyshatskyi, Sova, O., Nalapko, O., Buyalo, O., Yula, O., Shaposhnikova, O., Matsyi, O., Dvorskyi, M. (2024). Development of a method for managing a group of unmanned aerial vehicles using a population algorithm.

Eastern-European Journal of Enterprise Technologies, 6 (9 (132)), 108–116. <https://doi.org/10.15587/1729-4061.2024.318600>

- [17] A. E. Quossini, Y. I. Daradkeh, S. M. Al Tabib, S. Gnatyuk, T. Okhrimenko and V. Kinzeryavyy, "Improved Model of Quantum Deterministic Protocol Implementation in Channel with Noise," *2019 10th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*, Metz, France, 2019, pp. 572–578, <https://doi.org/10.1109/IDAACS.2019.8924287>

- [18] O. Turovsky, Y. Khlaponin, M. Mohamed, T. Okhrimenko, I. Goncharenko, & M. Iavich, (2020). Combined System of Phase Synchronization with Increased Astatism order in Frequency Monitoring Mode. *International Workshop on Control, Optimisation and Analytical Processing of Social Networks*.

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С. О. Кашкевич, С. В. Подельський. Метод інтегрованого аналізу візуально-інерціальних даних мобільної робототехнічної системи

У статті представлено метод адаптивної інтегрованої обробки візуальних та інерціальних даних мобільних робототехнічних систем в умовах шумів сенсорних вимірювань і часової неузгодженості інформації. Метод поєднує прогнозування стану, моделювання сенсорних спостережень, оцінювання невизначеності та адаптивне зважування різномірних вимірювань відповідно до їх поточної надійності. На відміну від об'єднання даних із фіксованими ваговими коефіцієнтами, запропонований підхід забезпечує динамічний перерозподіл внеску візуальних та інерціальних даних у процесі оцінювання стану. Результати імітаційного моделювання показали зменшення похибки позиціонування та підвищення стійкості оцінювання за умов деградації сенсорних даних і часових затримок. Метод може бути використаний у системах автономної навігації та позиціонування, що функціонують в умовах невизначеності.

Ключові слова: мобільна робототехнічна система, візуально-інерціальні дані, інтегрована обробка даних, об'єднання даних з різних датчиків, автономна навігація, оцінка стану, планування траєкторії, модель обробки інформації.

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Напрямок наукової діяльності: обробка та аналіз даних в каналах зв'язку безпілотних літальних апаратів; моделювання та оптимізація функціонування інформаційних мереж; застосування штучного інтелекту для аналізу даних.

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