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# Development of a Data Fusion method using Extended Kalman Filter for Collaborative Robots

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The article considers the development of a Data Fusion method using the Extended Kalman Filter (EKF) to enhance the efficiency of collaborative robots operating in Industry 5.0 production scenarios, where the key task is to ensure adaptability, safety, and accuracy of human–machine interaction. The object of the study is the process of processing signals from heterogeneous sensors - the OV5647 camera, the HC-SR04 ultrasonic sensor, the MPU6050 inertial module, and odometry - which together form a multisensor information system of a mobile manipulator robot. The subject of the research includes models, methods, and algorithmic support for data integration aimed at creating a consistent and unified representation of the robot's state and its surrounding environment. The goal is to develop a robust and adaptive information fusion method that compensates for measurement errors, reduces noise impact, and improves the consistency of sensor readings under dynamically changing environmental conditions. Within the study, an implementation of the EKF is proposed, in which the system state is predicted using a physical motion model, and subsequent updates are performed for each sensor considering their frequency and signal delays. The mathematical formulation of the method includes nonlinear process and measurement models, covariance matrices, Jacobian derivatives, and innovation estimation, which together ensure the filter's stability even in the presence of stochastic disturbances and measurement noise. Numerical simulations have shown that the "raw" sensor data are characterized by different mean values and dispersions (for example, HC-SR04 – 100 cm with ±20 cm deviation, camera – 50 cm with ±5 cm deviation), whereas the fused data demonstrate a smoothed trajectory with an average of about 68–70 cm and reduced variance to 8–10 cm. This indicates effective noise suppression and improved localization accuracy. The developed algorithm also provides robustness against temporary sensor signal loss, enables real-time state estimation, and supports asynchronous processing of multi-frequency data streams. The use of the Mahalanobis distance metric for measurement association improves the accuracy of relevant data selection, minimizes the influence of false observations, and enhances the safety of human–robot interaction. The results confirm that applying the Extended Kalman Filter in the Data Fusion process significantly improves distance estimation quality, navigation accuracy, motion smoothness, and control reliability under conditions of incomplete information. The conclusions emphasize that the proposed method is universal, scalable, and suitable for integration into adaptive control systems of next-generation collaborative robots operating in complex and uncertain environments within the framework of the Industry 5.0 concept.
***Ключові слова***: Data Fusion, Extended Kalman Filter, collaborative robots, sensor integration, Industry 5.0, mobile platform, adaptive control, navigation, sensors.

## Introducton

In the current context of the development of intelligent production systems within the Industry 5.0 concept, there is a growing need to create collaborative robots capable of effectively interacting with humans and adapting to dynamic working environments [1-3]. One of the key areas for ensuring such adaptability is the development of methods for integrating data from heterogeneous sensor systems, which allow for a more accurate and coordinated understanding of the state of the robot and its environment. In this context, the concept of data fusion is considered a critical information processing tool, since individual sensors, such as lidars, cameras, ultrasonic sensors, IMUs, or odometry, have limitations related to measurement errors,

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sensitivity to noise, and operating conditions [4-6]. Combining their data into a single model compensates for the weaknesses of each sensor and ensures increased accuracy and reliability of decision-making. The use of Extended Kalman Filter in the Data Fusion process on mobile robotic manipulation platforms opens up opportunities for effective trajectory tracking, improved navigation, and ensuring stability in dynamically changing environments [7, 8]. This is especially important for collaborative robots, which must take into account the presence of humans, minimize the risk of collisions, and ensure safe interaction in real time [9-11]. Thus, the relevance of the research lies in creating a method that combines the flexibility of Data Fusion with the mathematical stability of the Extended Kalman Filter, providing a new level of intelligence and autonomy for collaborative robots in the context of Industry 5.0.

Problem statement. The research problem is that collaborative robots operating in the dynamic production environment of Industry 5.0 are faced with the need to process large amounts of heterogeneous sensor data, which individually contain noise, errors, and limitations. The lack of an effective method for integrating this data makes it difficult to accurately determine the state of the robot and its environment, which reduces the safety, reliability, and adaptability of the system.

The goal of this work is to develop a robust and adaptive method of information integration that compensates for the errors and limitations of individual sensors, ensuring the accuracy and reliability of the collaborative robot system.

## 1. Development of mathematical support Data Fusion method

Data Fusion in the context of developing a method for merging sensor data to determine the environment of a mobile robotic manipulation platform within the framework of Industry 5.0 concepts is the process of integrating, combining, and reconciling information from heterogeneous sensors (lidars, cameras, ultrasonic sensors, IMUs, odometers, etc.) to form a unified, more accurate, and reliable picture of the robot's status and its working environment [12-14]. This approach allows compensating for the limitations of each individual sensor, reducing the impact of noise and measurement errors, and increasing the system's resistance to dynamic changes in the workspace. Within Industry 5.0, the emphasis is on close interaction between humans and robots, which requires a high level of safety, adaptability, and accuracy in determining the environment [15]. The use of Data Fusion enables the platform to respond quickly to the appearance of moving objects, predict their trajectories, and adjust its own behavior to avoid collisions. The rationale for choosing this approach is based on the fact that combined data increases the reliability of localization and navigation, which is especially important in complex, saturated, and unpredictable production environments where several robots and humans work simultaneously [16-18]. Thus, Data Fusion is a key technology for creating “smart” sensor systems capable of adapting to changes and maintaining effective cooperation in the conditions of new-generation industrial automation [19-21].

The idea of implementing the Data Fusion method using the Extended Kalman Filter (EKF): the entire state vector is processed centrally. We perform a forecast using a physical (process) model, and then apply updates for each sensor in turn or in combination, taking into account their frequency and delay [22-24].

Below is a complete mathematical representation of the EKF filter in the form of a nonlinear system model, along with a detailed description of all parameters, their purpose, and practical aspects of configuration. In addition, alternatives to the Unscented Kalman Filter (UKF) [24] and Particle Filter (PF) [25] and their key

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parameters are briefly presented. All formulas are given in a discrete time unified form with a step index.

1. Nonlinear system model.

– predictive process model:

$$\boldsymbol{s_k} = \boldsymbol{f}(\boldsymbol{s_{k-1}}, \boldsymbol{u_{k-1}}) + \boldsymbol{w_{k-1}}, \boldsymbol{w_{k-1}} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{Q_{k-1}}) \tag{1}$$

– measurement model:

$$\boldsymbol{z_k} = \boldsymbol{h}(\boldsymbol{s_k}) + \boldsymbol{v_k}, \boldsymbol{v_k} \sim \boldsymbol{N}(\boldsymbol{0}, \boldsymbol{R_k}) \tag{2}$$

Where: $s_k \in \mathbb{R}^n$ – state vector in step $k$ (platform, manipulator, objects); $\boldsymbol{u}_{k-1}$ – vector of control inputs (commands to actuators) at step $k-1$; $f(\cdot)$ – nonlinear function of the process (kinematics/dynamics), predicts state transition; $\boldsymbol{w}_{k-1}$ – process noise (process uncertainty model); $Q_{k-1}$ – covariance matrix of process noise (dimension $n \times n$); $\boldsymbol{z}_k \in \mathbb{R}^m$ – measurement vector (all sensors, or their concatenation); $h(\cdot)$ – nonlinear observation function (projection, odometry, ultrasound, etc.); $v_k$ – measurement noise $R_k$ – its covariation $(m \times m)$.

2. Step-by-step presentation of EKF

- initialization model, describes the initial conditions for the operation of the EKF filtering algorithm and specifies the starting point for the system state estimation and the level of confidence in this estimation.

$$\hat{\boldsymbol{s}}_{\boldsymbol{0|0}} = \boldsymbol{E}[\boldsymbol{s_0}], \boldsymbol{P_{0|0}} = \boldsymbol{Cov}(\boldsymbol{s_0}) \tag{3}$$

Where: $s_0$ – the actual but unknown initial state of the system (e.g., position, velocity, orientation of the robot); $E[s_0]$ – the mathematical expectation of this state, i.e., the best available initial estimate based on prior information or previous measurements; $Cov(s_0)$ – the initial covariance matrix of the state error reflects the uncertainty or confidence level of the initial estimate $\hat{s}_{0|0}$. The diagonal elements of this matrix are the variances of individual state components (e.g., error in $X$, $Y$, velocity, angle; description given in Table 3.1), and the off-diagonal elements are the correlations between the errors of different variables. The logic is as follows: the larger the values in $P_{0|0}$, the less confident the system is in its initial state, and the more it will rely on new sensor data.

As a result, these two parameters are the foundation for the filter to start working, where $\hat{s}_{0|0}$ sets the "reference point" for the estimate, and $P_{0|0}$ - is the degree of confidence in it, which will affect the speed and accuracy of the convergence of the state estimate during further work.

- the prediction model (Prediction/Time update) in EKF sets the mathematical mechanism by which the current assessment of the system's state is transferred to the moment in time before the next measurement and serves as an a priori assessment for the correction step.

$$\begin{gathered} \hat{\boldsymbol{s}}_{\boldsymbol{k|k-1}} = \boldsymbol{f}(\hat{\boldsymbol{s}}_{\boldsymbol{k-1|k-1}}, u_{\boldsymbol{k-1}}) \\ \boldsymbol{F_{k-1}} = \left.\frac{\partial \boldsymbol{f}}{\partial \boldsymbol{s}}\right|_{s=\hat{s}_{k-1|k-1}, u=u_{k-1}} \\ \boldsymbol{P_{k|k-1}} = \boldsymbol{F_{k-1}} \boldsymbol{P_{k-1|k-1}} \boldsymbol{F_{k-1}^T} + \boldsymbol{Q_{k-1}} \end{gathered} \tag{4}$$

The equation $\hat{\boldsymbol{s}}_{\boldsymbol{k|k-1}} = \boldsymbol{f}(\hat{\boldsymbol{s}}_{\boldsymbol{k-1|k-1}}, \boldsymbol{u_{k-1}})$ means: the predicted (a priori) estimate of the state at the moment $k$ is obtained by substituting the latest post-factum estimate

$\hat{s}_{k-1|k-1}$ and control commands $u(k-1)$ into the process (kinematically or dynamically justified) model $f$. Here $f$ is a nonlinear function describing the actual state transition over time $\Delta t$: for a platform, this can be kinematic integration $x_{k-1} = x_k + v_k \cos\theta_k \Delta t$, etc.; for a manipulator, it can be the integration of angles and their velocities (or the integration of dynamic equations for given moments $\tau$), and for moving objects, it can be a model with a constant speed or a more complex stochastic model. The notation $\hat{}$ emphasizes that an estimate (rather than the true value) is used, and $u_{k-1}$ contains commands to motors, measured revolutions, or applied moments - that is, what was actually given to the equipment.

The Jacobian matrix $F_{k-1} = \left.\frac{\partial f}{\partial s}\right|_{s=\hat{s}_{k-1|k-1}, u=u_{k-1}}$ is a linearization of the process function around the current estimate and characterizes the sensitivity of the state transition to small changes in each component of the state vector; its size is $n \times n$, where $n$ is the size of the state vector. $F$ practically transfers the covariance of the error due to the nonlinearity of the model: if we change one state variable slightly, $F$ shows how this will affect all components of the forecast. The $F$ calculation can be analytical (through explicit derivatives of kinematic/dynamic formulas) or numerical (finite differences, automatic differentiation) - the analytical option gives more accurate derivatives and smaller linearization errors, but is often more complex for many manipulator parameters.

The covariance equation $P_{k|k-1} = F_{k-1} P_{k-1|k-1} F_{k-1}^T + Q_{k-1}$ describes how the uncertainty of the estimate (matrix $P$) evolves during the transition: the first term linearly “transfers” the existing uncertainty through linearized dynamics, while the matrix $Q_{k-1}$ adds uncertainty associated with process noise (unaccounted forces, model inaccuracies, turbulence of moving objects, wheel slip, random changes in human behavior). The $Q$ size and structure (block-diagonal is proposed: $Q = diag(Q_{base}, Q_{man}, Q_{objs}, Q_{bias})$ ) are determined by hardware characteristics, experimental identification, or adaptive estimates; larger element $Q$ values mean that the filter trusts the predictive model less and the measurements more.

In practical implementation, additional details are important: the process model $f$ must take into account the integration step $\Delta t$ and can use various numerical schemes (direct Euler, RK4) to improve accuracy at large $\Delta t$. If sensor biases (e.g., IMU drifts) are included in the state vector, their evolutionary equation (random walk) is also included in $f$, and the corresponding elements $Q$ increase the uncertainty of this block. The calculation $F$ should be performed in the same discrete scheme that we use for $f$, and in case of significant nonlinearities, it is recommended to either reduce $\Delta t$ or replace EKF with UKF/Particle Filter to improve the approximation.

In the context of this study, the role of the prediction block is critically important: it provides a high-frequency a priori assessment of the state between slower camera/top-camera measurements, enables rapid trajectory correction and collision avoidance in real time, and forms the initial a posteriori uncertainty for the sensor fusion step. The right $Q$ choice and adequate $F$ linearization ensure, on the one hand, the stability and convergence of the filter and, on the other hand, the sensitivity of the system to the appearance of new objects or changes in load (which is important for safe collaboration within Industry 5.0).

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- correction/measurement update model. We calculate the predicted measurement and Jacobian:

$$\hat{\boldsymbol{z}}_{\boldsymbol{k}} = \boldsymbol{h}(\hat{\boldsymbol{s}}_{\boldsymbol{k|k-1}})$$
$$\boldsymbol{H}_{\boldsymbol{k}} = \left.\frac{\partial \boldsymbol{h}}{\partial \boldsymbol{s}}\right|_{s=\hat{s}_{k|k-1}} \tag{5}$$

Innovation (residual) and its covariance:

$$\boldsymbol{y}_{\boldsymbol{k}} = \boldsymbol{z}_{\boldsymbol{k}} - \hat{\boldsymbol{z}}_{\boldsymbol{k}} \tag{6}$$

(for angular components $\boldsymbol{y}_k$ perform angle $y(-\pi, \pi)$ normalization)

$$\boldsymbol{S}_{\boldsymbol{k}} = \boldsymbol{H}_{\boldsymbol{k}} \boldsymbol{P}_{\boldsymbol{k|k-1}} \boldsymbol{H}_{\boldsymbol{k}}^{\mathbf{T}} + \boldsymbol{R}_{\boldsymbol{k}} \tag{7}$$

Kalman coefficient (gain):

$$\boldsymbol{K}_{\boldsymbol{k}} = \boldsymbol{P}_{\boldsymbol{k|k-1}} \boldsymbol{H}_{\boldsymbol{k}}^{\mathbf{T}} \boldsymbol{S}_{\boldsymbol{k}}^{-\mathbf{1}} \tag{8}$$

Update of state and covariance:

$$\hat{\boldsymbol{s}}_{\boldsymbol{k|k}} = \hat{\boldsymbol{s}}_{\boldsymbol{k|k-1}} + \boldsymbol{K}_{\boldsymbol{k}} \boldsymbol{y}_{\boldsymbol{k}}$$
$$\boldsymbol{P}_{\boldsymbol{k|k}} = (\boldsymbol{I} - \boldsymbol{K}_{\boldsymbol{k}}) \boldsymbol{P}_{\boldsymbol{k|k-1}} (\boldsymbol{I} - \boldsymbol{K}_{\boldsymbol{k}} \boldsymbol{H}_{\boldsymbol{k}})^{\mathbf{T}} + \boldsymbol{K}_{\boldsymbol{k}} \boldsymbol{R}_{\boldsymbol{k}} \boldsymbol{K}_{\boldsymbol{k}}^{\mathbf{T}} \tag{9}$$

Where: $\boldsymbol{y}_k$ – innovation, i.e., the difference between the measurement and the prediction; $\boldsymbol{S}_{\boldsymbol{k}}$ – innovation covariance – a measure of the uncertainty of the innovation; $\boldsymbol{K}_{\boldsymbol{k}}$ – Kalman matrix ($\boldsymbol{n} \times \boldsymbol{m}$), determines how much to trust the measurement relative to the prediction; $\boldsymbol{P}_{\boldsymbol{k|k}}$ – guarantees numerical stability.

The interpretation of the key matrices and parameters of the EKF representation is given in Table 1.

Table 1

Interpretation of key matrices and parameters of EKF representation

| Symbol | Name | Description |
|---|---|---|
| $Q_k$ | Covariance of process noise | Size $n \times n$. Block-diagonal structure: $\boldsymbol{Q} = \boldsymbol{diag}(\boldsymbol{Q}_{\boldsymbol{base}}, \boldsymbol{Q}_{\boldsymbol{man}}, \boldsymbol{Q}_{\boldsymbol{objs}}, \boldsymbol{Q}_{\boldsymbol{bias}})$ |
| | | Reflects uncertainty in the process model (incomplete model, unaccounted forces, slippage). |
| | | Roles: large $Q$ → filter responds faster to measurements; small $Q$ → more confidence in the model. |
| $R_k$ | Covariance of measurement noise | Size $n \times m$. Block-diagonal or with inter-element cross-correlations, if the sensors are correlated. |
| | | Determined experimentally or from sensor technical specifications (datasheets) |
| | | Roles: lzrge $R$ → the filter trusts the sensor data less; small $R$ → measurement corrects the condition more strongly. |
| $F_{k-1}$ та $H_k$ | Jacobians | Calculated analytically or numerically (finite differences) |
| | | Important for adequate conversion of dispersions due to nonlinearities. |
| | | Errors in calculating Jacobians lead to incorrect estimates$P$ |

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Continue of table 1

| Symbol | Name | Description |
|---|---|---|
| $P_{k\|k}$ | covariance matrix of estimates | Reflects uncertainty in each component of the state and the correlations between them |
| | | Used for gating (Mahalanobis distance) in data association and for risk-oriented planning |

We will briefly describe the features of using alternative Unscented Kalman Filter (UKF) and Particle Filter (PF) filters instead of the above-mentioned Extended Kalman Filter (EKF) in the development of the Data Fusion method. The features of using UKF and PF filters are shown in Table 2.

Table 2

Features of using UKF and PF filters

| Filter name | Descriptio | Parameters | Advantages/Disadvantages |
|---|---|---|---|
| UKF | Instead of linearization, it generates sigma points $x_i$ around $\hat{s}$, passes them through $f, h$, then restores the mean and covariance. | Quantity of sigma parameters $(\alpha, \beta, k)$, number of sigma points $2n+1$ | Advantage: more accurate with strong nonlinearities; disadvantage: higher computational costs. |
| PF | Represents the distribution of the state by a set of particles $\left\{\boldsymbol{s}_{\boldsymbol{k}}^{(\boldsymbol{i})}\right\}$ with weights $w^{(i)}$. Steps: prediction of each particle (process), calculation of weights based on measurement believability $\boldsymbol{p}(\boldsymbol{z}_{\boldsymbol{k}} \mid \boldsymbol{s}_{\boldsymbol{k}}^{(\boldsymbol{i})})$ ,normalization, resampling | Number of particles $N$, proposal distribution, resampling strategy. | Advantages: works with multimodal distributions; disadvantage - high computational cost. |

Let's consider a step-by-step method of merging data from sensors (Data Fusion) of a collaborative manipulator robot using the EKF described above.

*Input:*

– stream of sensor data with time stamps: IMU (high frequency), encoders (medium), onboard camera (medium/low), top camera (low), ultrasound (medium);

– control commands/inputs $\boldsymbol{u}_k$ (optional);

– initial state estimates $\hat{s}_0$ and $P_0$;

– calibration parameters: $K, R_c, t_c, H_{top}$, sensor covariances $R_k$, platform $(R, L)$ geometric dimensions, DH parameters, etc [26-28].

*Step 1: Initialization*.

Set $\hat{s}_0$, $P_0$, $Q$, $R_k$. Perform initialization $x, y, \theta$ using the top camera and initialize

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IMU biases from static calibration.

*Step 2: Perform the main cycle of the real-time method for each received sensor packet with a timestamp:*

2.1. If IMU (high frequency) is received, forecast:

– calculate the forecast model $\hat{\boldsymbol{s}}_{\boldsymbol{k}|\boldsymbol{k}-1} = \boldsymbol{f}(\hat{\boldsymbol{s}}_{\boldsymbol{k}-1|\boldsymbol{k}-1}, \boldsymbol{u}_{\boldsymbol{k}-1}) + \boldsymbol{w}_{\boldsymbol{k}-1}$ using IMU and odometry as input for motion integration; specifically, IMU provides $w$ and $\boldsymbol{a}$ for updating position/orientation/velocities;

– calculate $J_f$ at point $\hat{s}_{k|k}$;

– predict covariance $\boldsymbol{P}_{\boldsymbol{k}|\boldsymbol{k}-1} = \boldsymbol{J}_{\boldsymbol{f}} \boldsymbol{P}_{\boldsymbol{k}-1|\boldsymbol{k}-1} \boldsymbol{J}_{\boldsymbol{f}}^{\mathbf{T}} + \boldsymbol{Q}$ ;

– the prediction is made for each IMU frame or for each discrete time $\Delta t$.

2.2. If another sensor (odometry, camera, top, ultrasound) is received at the input, we perform an update step for the corresponding measurement:

– formulate the measurement $z_{\boldsymbol{k}}$ for the corresponding sensor;

– calculate the predicted measurement $\hat{\boldsymbol{z}} = \boldsymbol{h}(\hat{\boldsymbol{s}}_{\boldsymbol{k}|\boldsymbol{k}-1})$;

– calculate the innovation (residual) $\boldsymbol{y}_{\boldsymbol{k}} = z_{\boldsymbol{k}} - \hat{z}_{\boldsymbol{k}}$, apply angle normalization for angular components;

– calculate the Jacobian of the measurement $\boldsymbol{J}_{\boldsymbol{h}} = \left.\frac{\partial \boldsymbol{h}}{\partial \boldsymbol{s}}\right|_{\hat{\boldsymbol{s}}_{\boldsymbol{k}|\boldsymbol{k}-1}}$ ;

– calculate the innovation covariance $\boldsymbol{S}_{\boldsymbol{k}} = \boldsymbol{J}_{\boldsymbol{h}} \boldsymbol{P}_{\boldsymbol{k}|\boldsymbol{k}-1} \boldsymbol{J}_{\boldsymbol{h}}^{\mathbf{T}} + \boldsymbol{R}_{\boldsymbol{sensor}}$ ;

– gating/filtering of anomalies, calculate the Mahalanobis distance $\boldsymbol{d}^{\mathbf{2}} = \boldsymbol{y}_{\boldsymbol{k}}^{\mathbf{T}} \boldsymbol{S}_{\boldsymbol{k}}^{-\mathbf{1}} \boldsymbol{y}_{\boldsymbol{k}}$ if $\boldsymbol{d}^{\mathbf{2}} > \zeta$ it is recommended to reject the measurement (outlier) [29]. Nearest-Neighbor based on Mahalanobis is a method of associating measurements with predicted objects, which is used in Data Fusion to select the most likely match between a new sensor observation and an already tracked target. In the context of a mobile robotic manipulation platform, the method allows you to unambiguously determine which sensor signal belongs to which target, even in an environment with multiple moving objects and noisy measurements, which is critical for the stable operation of the data fusion system;

– Kalman coefficient $\boldsymbol{K}_{\boldsymbol{k}} = \boldsymbol{P}_{\boldsymbol{k}|\boldsymbol{k}-1} \boldsymbol{J}_{\boldsymbol{h}}^{\mathbf{T}} \boldsymbol{S}_{\boldsymbol{k}}^{-\mathbf{1}}$ ;

– we update the state and covariance $\hat{\boldsymbol{s}}_{\boldsymbol{k}|\boldsymbol{k}} = \hat{\boldsymbol{s}}_{\boldsymbol{k}|\boldsymbol{k}-1} + \boldsymbol{K}_{\boldsymbol{k}} \boldsymbol{y}_{\boldsymbol{k}}$ and $\boldsymbol{P}_{\boldsymbol{k}|\boldsymbol{k}} = (\boldsymbol{I} - \boldsymbol{K}_{\boldsymbol{k}} \boldsymbol{J}_{\boldsymbol{h}}) \boldsymbol{P}_{\boldsymbol{k}|\boldsymbol{k}-1}$ ;

– optionally, it is recommended to apply symmetrization $\boldsymbol{P} \leftarrow \frac{(\boldsymbol{P} + \boldsymbol{P}^{\mathbf{T}})}{\mathbf{2}}$

2.3. After each update, output the current estimate $\hat{\boldsymbol{s}}_{\boldsymbol{k}|\boldsymbol{k}}$ .

*Step 3. Asynchrony and multi-frequency:*

– IMU predicts the state at a high frequency; other sensors trigger corrections when they arrive. That is, predict at IMU rate, update at sensor rate [30];

– if the sensor has latency, you can either compensate with time stamps (roll back/reintegrate) or add state augmentation (store state history)

*Step 4. Data association (for cameras/multiple landmarks):*

– For each visual measurement, you need to associate observations with landmarks/objects in the state. Use Nearest-Neighbor based on Mahalanobis distance

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[31] or JCBB [32] for multiple compatibility. Inconsistent measurements create new objects (birth).

*Step 5. Estimation Error (EE) evaluation and results output:*

– After updating, calculate the EE position $\boldsymbol{T_G^{EE}(\hat{s}_{k|k})}$ and the covariance of the EE position through linearization $\boldsymbol{P_{EE} = J_{EE} P_{k|k} J_{EE}^{\mathrm{T}}}$.

– Generate output data for the planner $x, y, \theta$: covariance, list of tracked objects $\boldsymbol{(x^{(j)}, y^{(i)}, \mathrm{cov})}$.

*Output:* At each step $k$:

– $\hat{s}_{k|k}$ - state estimation.

– $P_{k|k}$ - covariance;

– additionally, EE position $\boldsymbol{T_G^{EE}}$ and its covariance, list of tracked objects with estimates and covariances.

$\Omega_o$ – object recognized as areas with a geometric shape of a cylinder;

$\Omega_t$ – object recognized as areas with a geometric shape of a cone.

The robot collected new data and underwent additional training to recognize a new type of object (for example, a parallelepiped ($\Omega_{rh}$)) or new rules of behavior when interacting with this object. Then the changes in training $\Delta\mathbb{M}(t)$ will look like this:

$$\Delta\mathbb{M}(t) = \Omega_{rh} + \text{ new rules of conduct} \quad (10)$$

Where: $\Omega_{rh}$ – the object is recognized as an area with a rectangular parallelepiped geometric shape.

Then the updated state of the trained model at time $t$, for this example, will look like this:

$$\mathbb{M}(t) = \Omega_s, \Omega_o, \Omega_t + \Omega_{rh} + \text{ new rules of conduct} \quad (11)$$

Thus, the robot manipulator constantly adapts its model based on new knowledge, allowing it to better cope with new situations or objects in the working area. This can be implemented as part of machine learning algorithms that allow the robot to “learn” while working, or through software updates based on feedback from sensors and control systems.

## 2. Results of numerical modeling

To perform data fusion modeling [33,34], it is proposed to use the following ‘raw’ data to simulate the operation of the sensor system of a collaborative mobile manipulator robot. The selected ranges of loc and scale parameters for modeling raw sensor data in the Data Fusion method are determined by the physical characteristics of each sensor and the operating conditions of the mobile manipulation robot [35,36]. The loc value corresponds to the expected average measurement under normal conditions, for example, 50 pixels for the OV5647 camera with an average object size in the frame or 100 cm for the HC-SR04 ultrasonic sensor at a typical distance to the obstacle. The scale parameter describes random measurement errors caused by sensor noise, lighting changes, vibrations, or the influence of a dynamic environment. For the camera, it is smaller (5) because visual measurements are relatively stable, while for ultrasound, it is larger (10) due to the greater influence of external factors. The IMU data has an average close to zero (loc=0) and very low dispersion (scale=0.05), which corresponds to the high sensitivity of the accelerometer. The upper camera has a mean value of 75 and a spread of 8, reflecting a different perspective and observation geometry. Such parameterization allows simulating a realistic picture

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of sensor measurements, which, after data fusion, should demonstrate a reduction in spread and an increase in localization accuracy.

Using the proposed parameters to obtain "raw" data for simulating data fusion based on the developed method, a simulation was performed, the results of which are shown in Figure 1.

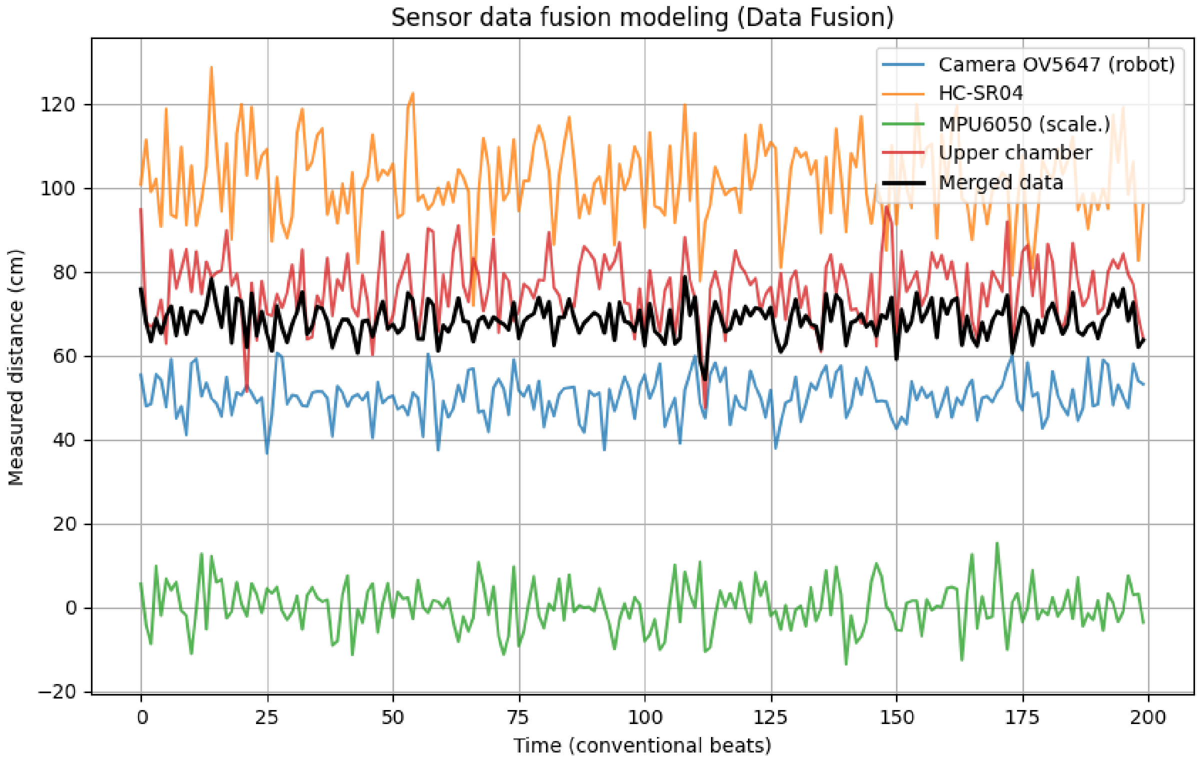


Fig. 1. Graph of data fusion simulation based on the developed method using "raw" data

The graph shows (Fig. 1) that the "raw" data from each sensor has a different average level and dispersion, reflecting the specifics of their physical measurement principles. The OV5647 camera shows stable values around 50 cm with a spread of approximately ±5 cm, the HC-SR04 ultrasonic sensor fluctuates around 100 cm with high variability up to ±20 cm, data from the MPU6050 after scaling is in the range of about 0–15 cm with minimal noise, and the upper camera gives readings averaging 75 cm with fluctuations of ±8 cm. The merged data (black line) shows a noticeably smoothed trend with an average value of about 68–70 cm and significantly less dispersion compared to most individual sensors, indicating effective noise suppression. Numerically, it can be seen that the amplitude of fluctuations has decreased from ranges of 20–40 cm in the "raw" signals to about 8–10 cm in the merged result. Logically, this can be explained by the fact that the noise components of different sensors have different natures and weak correlation, so their combination using the Data Fusion method allows random errors to be compensated. A qualitatively fused signal better reflects the actual position of the object in the working area of the mobile manipulator robot and is more resistant to short-term measurement failures of one or more sensors, which is critical for localization in dynamic conditions.

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## 3. Conclusions

The developed method of merging sensor data for the localization system of a collaborative mobile manipulator robot provides a significant improvement in the accuracy of position and orientation estimation compared to traditional approaches due to the combined use of information from IMU, visual, and ultrasonic sensors. The use of an extended Kalman filter with adaptive parameter correction allows for effective consideration of measurement errors, motion nonlinearities, and variable noise structures, which is especially important in dynamic environments with obstacles and human presence. The proposed method improves the system's resistance to temporary loss of signals from individual sensors and ensures smooth trajectory updates even in cases of sharp maneuvers or vibrations. An additional factor is the use of Mahalanobis metrics in the measurement association block, which increases the reliability of relevant data selection and reduces the impact of false observations. Compared to existing methods, the solution demonstrates better temporal consistency and less processing delay, allowing for a quick response to environmental changes. Optimization of the data fusion process reduces computational costs without compromising localization quality, and the modular structure of the algorithm simplifies integration into other robotic systems. Thus, the proposed approach is more reliable, scalable, and adaptive, making it an effective tool for application in the Industry 5.0 concept.

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# Розробка метода Data Fusion з використанням Extended Kalman Filter для колоборатівних роботів

У статті розглядається розробка методу Data Fusion з використанням Extended Kalman Filter (EKF) для підвищення ефективності функціонування колаборативних роботів у виробничих сценаріях Industry 5.0, де ключовим завданням є забезпечення адаптивності, безпеки та точності взаємодії між людиною і машиною. Об'єктом дослідження є процес обробки сигналів з різнорідних сенсорів – камери OV5647, ультразвукового датчика HC-SR04, інерційного модуля MPU6050 та одометрії, що формують мультисенсорну інформаційну систему мобільного маніпуляційного робота. Предметом дослідження виступають моделі, методи та алгоритмічне забезпечення інтеграції даних для формування узгодженого уявлення про стан робота і навколишнє середовище. Метою є створення стійкого та адаптивного методу злиття інформації, що дозволяє компенсувати похибки, зменшити вплив шумів і покращити узгодження вимірювань при роботі в умовах динамічної зміни параметрів середовища. У рамках дослідження запропоновано реалізацію EKF, де стан системи прогнозується за фізичною моделлю руху, а подальше оновлення виконується для кожного сенсора з урахуванням частоти та затримок сигналів. Математичний опис методу включає нелінійні моделі процесу та вимірювань, використання матриць коварацій, похідних Якобі та оцінку інновацій, що забезпечує стабільність фільтра навіть за наявності шумових та стохастичних збурень. У ході чисельного моделювання показано, що «сирі» сигнали сенсорів характеризуються різним рівнем дисперсії та середнім значенням (наприклад, для HC-SR04 – 100 см із коливаннями ±20 см, для камери – 50 см із коливаннями ±5 см), тоді як об'єднані дані після злиття демонструють згладжену траєкторію з середнім значенням близько 68–70 см і зменшенням розкиду до 8–10 см. Це

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свідчить про ефективне приглушення шумів та підвищення достовірності локалізації. Розроблений метод також забезпечує стійкість до втрати сигналу окремого сенсора, дозволяє виконувати оцінку стану в режимі реального часу та реалізує асинхронну обробку багаточастотних потоків даних. Використання метрики Махаланобіса для асоціації вимірювань підвищує точність відбору релевантних даних, знижує вплив хибних спостережень і сприяє безпечній взаємодії робота з людиною. Результати підтверджують, що застосування Extended Kalman Filter у процесі Data Fusion дозволяє значно підвищити якість оцінки відстаней, точність навігації, плавність траєкторій руху й надійність керування в умовах неповної інформації. У висновках зазначено, що розроблений метод є універсальним, масштабованим і придатним для інтеграції в системи адаптивного керування колаборативними роботами нового покоління, що функціонують у складних і невизначених середовищах у межах концепції Industry 5.0.

***Ключові слова:*** Data Fusion, Extended Kalman Filter, колаборативні роботи, сенсорна інтеграція, Industry 5.0, мобільна платформа, адаптивне керування, навігація, сенсори.

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