Advances in Science and Technology Research Journal

Advances in Science and Technology Research Journal, 2027, 21(1), 273–286
https://doi.org/10.12913/22998624/231701
ISSN 2299-8624, License CC-BY 4.0

Received: 2026.07.15
Accepted: 2026.11.15
Published: 2026.12.01

UWB-based velocity estimation with Kalman filtering for follow-me UGV applications

Łukasz Rykała[1*], Karol Cieślik[1], Mirosław Przybysz[1], Marcin Dejewski[1]

[1] Faculty of Mechanical Engineering, Military University of Technology, 00-908 Warsaw, Poland
* Corresponding author's e-mail: lukasz.rykala@wat.edu.pl

ABSTRACT

This paper presents the findings of an experimental study on velocity estimation for unmanned ground vehicles (UGVs) operating in a follow-me scenario using Ultra Wideband technology. In the context of follow-me applications, unmanned ground vehicles (UGVs) are required to continuously track and follow a moving guide. The proposed approach utilizes two way ranging (TWR) distance measurements from ultra wideband (UWB) modules to derive velocity estimates of the tracked object. The Kalman filter was utilized to estimate velocity, with particular attention devoted to the system's capacity to function in conditions characterized by the absence of measurement signals. The development and validation of all signal processing algorithms was conducted within the MATLAB software environment. To this end, experimental tests were conducted in an outdoor setting, employing dedicated TREK1000 hardware. The results of these tests were then compared against reference measurements obtained via GNSS with RTK, in order to assess the estimation accuracy. The article assesses the findings in terms of their relevance to a follow-me system. The results showed that the Kalman filter can be used to estimate the motion parameters of objects under conditions of full or partial observation availability. Moreover, the occurrence of position signal dropouts reduces the quality of velocity estimates.

Keywords: ultra wideband, velocity estimation, unmanned ground vehicle, follow-me, Kalman filter, GNSS.

INTRODUCTION

The prevailing trend in the development of unmanned ground vehicles (UGVs) is toward enhancing their operational autonomy [1]. Autonomy is the goal, but in some cases, it is important to be able to indicate the UGV route using human movement or, for example, another machine acting as a so-called guide [2]. This operating mode, which exhibits partial autonomy, is called "follow-me" mode and is an increasingly common additional feature in UGVs. The main principle of this mode is that the vehicle automatically or autonomously follows the guide while maintaining a safe distance in a changing environment [3]. Achieving this objective requires accurate relative localization of the guide and precise estimation of its speed [4]. Particular attention should be paid to this last factor, as estimating speed is crucial for controlling the movement of the UGV and ensuring the safety of the moving guide [5].

In the context of UGV applications, the vehicle's speed is generally estimated through the use of sensors mounted on the UGV itself. These sensors may include encoders, inertial measurement units (IMUs)[6], or GNSS receivers [7]. The measurement of the guide's speed is accomplished through the use of laser scanners (LiDAR) [8], vision systems (RGB/RGB-D cameras) [9, 10], and wireless methods, including Wi-Fi, Bluetooth [11], and ultra wideband (UWB) [12]. In follow-me applications, most often a marker, which can be a transmitter [4] or a graphic symbol [8], is attached to the guide. It allows the guide to be uniquely identified among other objects in the machine's surroundings.

Due to the presence of disturbances and the varying sampling frequencies of the different

sensors used, sensor fusion methods are employed to estimate the velocity of the moving object. The most commonly used methods are various variants of the Kalman filter, including both linear (KF) [13] and nonlinear variants, such as the extended Kalman filter (EKF) [14, 15] or the unscented Kalman filter (UKF) [16]. These methods are based on a defined model of the object's motion and enable accurate estimation of the object's state, such as its position, velocity, acceleration, and orientation. The choice of the specific variant depends on the nature of the nonlinearity of the system and measurement model: the linear KF is an optimal estimator for linear systems with Gaussian noise [17]. When the system model or measurement function is nonlinear, the KF may not converge to the solution. In such cases, EKF is used, which locally linearizes nonlinearities using a Taylor series expansion, or UKF, which uses an unscented transformation to represent the nonlinear propagation of uncertainty [18].

However, the implementation of GNSS technology is not always feasible due to the necessity of direct line of sight to the satellites [19]. Additionally, the technology is susceptible to jamming and spoofing, which further restricts its application in specific environments and scenarios, such as areas affected by military operations [20]. In contrast, UWB technology facilitates the localization of objects in environments where numerous obstacles and interferences affect the system's performance, such as building interiors, corridors, urban environments, and forested areas [5]. Preliminary experimental studies have demonstrated the feasibility of attaining accuracies within the range of a few centimeters, contingent upon the optimal configuration of the measurement infrastructure and the advantageous placement of the receiver in the case of UWB systems [21, 21]. Additionally, UWB technology has the capacity to facilitate real-time object positioning, thereby providing measurements at a frequency sufficient to track the movement of people, vehicles, or robots [23, 24]. Due to the small size of the modules, the technology can also be used in multi-object localization systems [25].

The primary limitations of UWB technology are sensitivity to NLOS conditions [26], multipath propagation [27], the impact of anchor placement geometry on system accuracy [28], and temporary measurement dropouts [5]. Obstruction of the signal propagation path by infrastructure elements, metal objects, or human subjects can result in distance measurement errors and, consequently, a deterioration in localization accuracy [4]. Interruptions in measurement availability and delays pose significant challenges, particularly in the localization of UGVs in complex indoor environments [29]. These effects are particularly important in follow-me UGV applications, where reliable velocity estimation is needed despite the availability of position measurements. Artificial intelligence methods are also used, including feedforward networks to correct the distance measurement of UWB modules [30] and deep learning methods as localization methods in UWB systems [31].

As a result of the review of available literature, no articles describing the use of linear Kalman filters in UWB follow-me systems with realistic signal disturbances were found. Moreover, no articles were found regarding the estimation of the speed of the moving guide in the case of UWB systems.

The aim of this article is to assess the viability of estimating the velocity of a moving guide by employing UWB technology solely in an outdoor environment. The article is based on experimental data collected with a UWB system and an RTK-GNSS reference and focuses on the possibility of velocity estimation with the use of a loosely coupled Kalman filter under realistic signal disturbance conditions. The research presented in the following article extends previous work by focusing on the topic of velocity estimation using Ultra Wideband technology and loosely coupled Kalman filter in realistic, individually designed follow-me system operation scenarios. The article is organized into 5 parts: Introduction, Materials and Methods, Results, Discussion, and Conclusions.

MATERIALS AND METHODS

UWB is a wireless technology that measures distances between a specific number of receivers and transmitters, based on which the location of moving objects can be determined [5]. An important advantage of this technology is its ability to operate in areas where satellite signals are unavailable, making it a complement to robot localization capabilities in cases of partial or complete unavailability of GNSS technology. UWB represents an example of relative positioning technology, making it particularly useful for follow-me applications [4].

The determination of an object's velocity from location measurements is possible by differentiating the location coordinate courses with respect to time. However, this approach is inefficient due to the need to differentiate highly noisy signals and requires the use of appropriately selected signal filtering methods. The most common approach employed for this purpose is the Kalman filter, which functions as an optimal state estimator for a dynamic system [32].

The estimation of velocity through the utilization of positioning systems and the Kalman filter can be executed in a variety of methodologies. The first of these is the implementation of a so-called loosely coupled Kalman filter, which constitutes a specific architecture for a sensor fusion algorithm. In this algorithm, a specific sensor or several sensors (e.g., a localization system) first calculate their own output signals (e.g., the object's location coordinates x(t), y(t) of the object), while the Kalman filter fuses them as the final step in the fusion process. In this method, the linear KF is most commonly used.

The second approach involves the implementation of a tightly coupled Kalman filter [33], which subsequently functions as a central filter that integrates measurements from all sensors. This approach involves the simultaneous processing of all signals within a single Kalman filter structure, as opposed to the sequential processing of each input signal individually. For this method, nonlinear variants of the Kalman filter, such as the EKF or UKF, are most commonly used [34].

It is important to note that a variety of methodologies exist for velocity estimation from location measurements, in addition to the Kalman filter. However, these techniques are predominantly employed in offline applications [35]. The Kalman filter is a mathematical model that has been employed in both offline and online applications.

A significant proportion of the research on UWB-based positioning systems is predicated on simulation studies, which most often consider the impact of a limited number of external factors on distance measurements, such as distance measurement noise [36]. Such studies generally concentrate on the selection of signal processing methods, including the positioning algorithms themselves. However, in practice, numerous additional factors inherent to real-world UWB positioning systems must be considered. In addition to the aforementioned interferences, the influence of LOS/NLOS conditions and frequent signal interruptions must be considered. Persistent interruptions can completely prevent the determination of an object's location.

The research results described in this article are based solely on experimental data and are a continuation of the research described in the following articles: [4] and [30]. The article was based on a series of motion paths of a moving guide relative to a stationary UGV. These paths were obtained using Ultra Wideband localization system (Figure 1) and a Global Navigation Satellite System (GNSS) receiver with access to real-time kinematic (RTK) corrections as a reference.

The localization system based on UWB technology shown in Figure 1, has been adapted to perform the research described in this article. A median filter with a window size of five was used

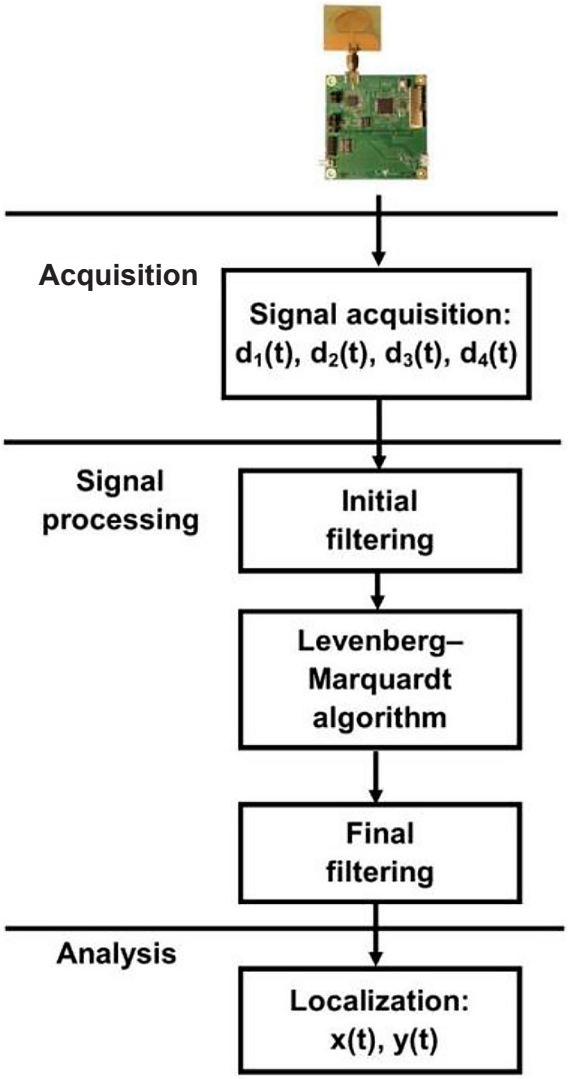


Figure 1. Schematic of the data processing in a UWB localization system

for initial signal filtering. As the localization algorithm, an algorithm based on optimization methods was chosen, i.e., Levenberg-Marquardt. In turn, for the final filtering, a moving average filter with a window size of five was selected.

The Levenberg–Marquardt (LM) algorithm is an optimization technique which is particularly effective for solving non-linear least squares problems, which are common in UWB positioning [36]. The problem can be formulated as follows: a system of four non-linear dependencies $H_i(x)$ (i = 1, 2, 3, 4) is given:

$$F_1(x) = \sqrt{(x_T - x_1)^2 + (y_T - y_1)^2} - d_1 \quad (1)$$

$$F_2(x) = \sqrt{(x_T - x_2)^2 + (y_T - y_2)^2} - d_2 \quad (2)$$

$$F_3(x) = \sqrt{(x_T - x_3)^2 + (y_T - y_3)^2} - d_3 \quad (3)$$

$$F_4(x) = \sqrt{(x_T - x_4)^2 + (y_T - y_4)^2} - d_4 \quad (4)$$

where: d_i – the measured distance between i-th receiver A_i (i = 1, 2, 3, 4) and the transmitter, $x_T(t)$, $y_T(t)$ projections of the guide position on the x, y axes of the coordinate system, $x_i(t)$, $y_i(t)$ (i = 1, 2, 3, 4) projections of the i-th receiver positions on the x, y axes of the coordinate system.

The algorithm starts from a starting point: $x_0 = [x_o, y_o]^T$. Its purpose is to solve a set of equations $F_i(x) = 0$ (i = 1, 2, 3, 4) by minimizing the cost function g(x) defined as follows:

$$\min_x g(x) = F_1(x)^2 + F_2(x)^2 + F_3(x)^2 + F_4(x)^2 \quad (5)$$

The algorithm calculates iteratively the Jacobian matrix $J(x_k)$, which is used to determine the direction and magnitude of the parameter updates d_k, guided by a damping factor μ_k that controls the process according to the following relationship:

$$(J(x_k)^T J(x_k) + \mu_k I)s_k = -J(x_k)^T F(x_k) \quad (6)$$

where: $J(x_k)$ – Jacobian matrix of $F(x_k)$, at iteration k, s_k – search direction vector, μ_k – scalar damping parameter [36].

The estimation of the guide's velocity was achieved through the implementation of a Kalman filter, as illustrated in Figure 2.

The research itself utilized the TREK 1000 UWB system, which consists of five UWB modules, four of which are receivers (anchors) and one of which is a transmitter (tag). The system utilizes the bidirectional TWR distance measurement technique, with a data sampling frequency of 10 Hz. The research concept involves the stationary placement of four anchors (A1–A4) on the UGV (Figure 3) and the assignment of the transmitter to a moving person acting as a guide in a follow-me system.

The guide moves in a straight line away from the robot in a specific direction, thereby increasing the distance between the receivers and transmitters in the UWB system. The determination of the guide's reference position was facilitated by the utilization of a GNSS receiver, which was mounted on a pole positioned in alignment with the tag (Figure 4).

The study focused on issues related to interruptions in measurement signals. The guide's motion was studied in both one-way and round-trip scenarios, with the round-trip scenario involving a return to the initial point. These scenarios were conducted at various angles relative to the robot (as a source of deliberate disruption). The guide's body in this case acts as an intentional obstruction to the Ultra Wideband signal path. This obstruction results in signal interruptions on a frequent basis. In the non-return variant, efforts were made to minimize interruptions in order to test the performance

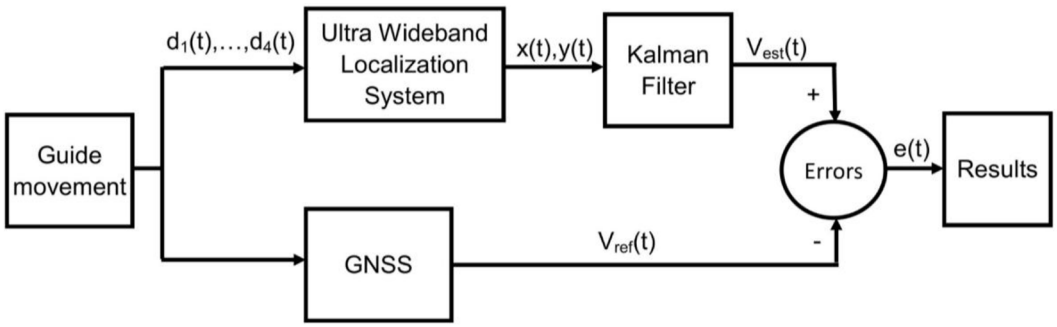


Figure 2. Schematic of the conducted research

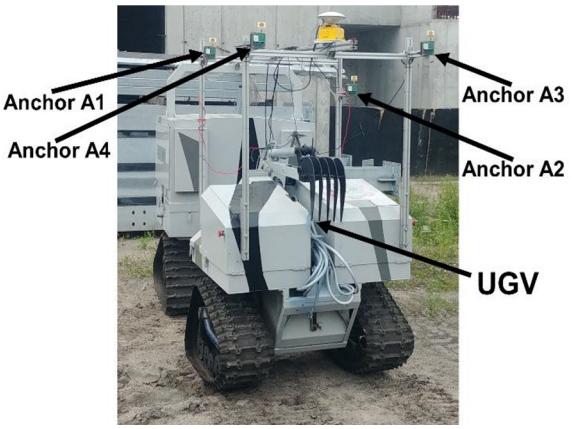


Figure 3. Arrangement of anchors A1–A4 on the UGV [35]

of the Kalman filter under conditions involving short and isolated interruptions. In the return-path variants, interruptions are more frequent and longer in duration.

In this study, a linear Kalman filter with a constant-velocity (CV) kinematic model in a two-dimensional system was used to describe the motion of the guide. The Kalman filter model equations can be described using the following relationship:

$$x_{k+1} = Ax_k + Bu_k + w_k \tag{7}$$

$$y_k = Hx_k + v_k \tag{8}$$

where: x_k – the state vector at time instant k, u_k – control input, y_k – the measurement vector, A – the state-transition matrix, B – the control-input matrix, H – the observation matrix, w_k and v_k – zero-mean process and measurement noise with covariance matrices Q and R [37].

In the case under consideration, the following state vector was adopted:

$$x_k = \begin{bmatrix} s_x(k) \\ s_y(k) \\ v_x(k) \\ v_y(k) \end{bmatrix} \tag{9}$$

where: s_x, s_y – position components in the 2D system, v_x, v_y – velocity components in the 2D system.

The operation of the Kalman filter is divided into two distinct parts: the prediction stage and the filtering stage. The prediction stage can be described as follows:

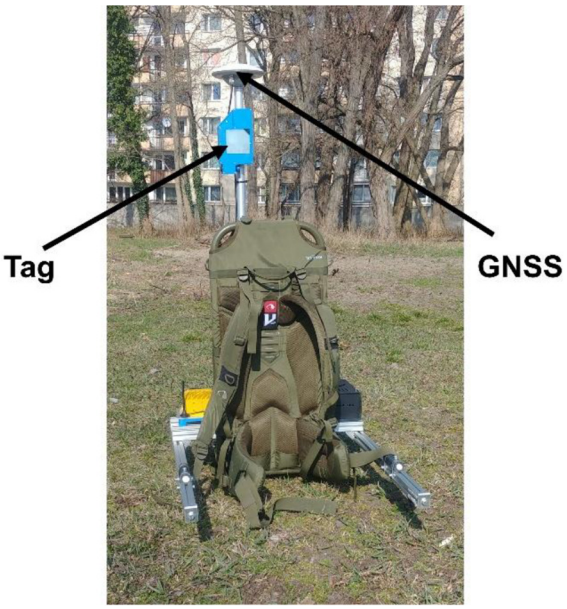


Figure 4. Location of the tag and the GNSS receiver [35]

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} \tag{10}$$

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q \tag{11}$$

$$A = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{12}$$

$$Q = \begin{bmatrix} q_p & 0 & 0 & 0 \\ 0 & q_p & 0 & 0 \\ 0 & 0 & q_v & 0 \\ 0 & 0 & 0 & q_v \end{bmatrix} \tag{13}$$

where: A – transition matrix, q_p – process noise variance associated with the position, q_v – process noise variance associated with the velocity [37].

In turn, the filtering part can be described as follows:

$$\mathrm{K} = P_{k|k-1}H^T\left(HP_{k|k-1}H^T + R\right)^{-1} \tag{14}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K\left(y_k - H\hat{x}_{k|k-1}\right) \tag{15}$$

$$P_{k|k} = (I - KH)P_{k|k-1} \tag{16}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{17}$$

$$R = \begin{bmatrix} r & 0 \\ 0 & r \end{bmatrix} \tag{18}$$

where: H – the observation matrix, r – the variance of the measurement noise of the localization system [37].

The values of matrixes Q and R were selected experimentally. In turn, the velocity estimation error is defined as follows:

$$v_{vt} = v_{est} - v_{ref} \tag{19}$$

where: v_{est} – estimated speed, v_{ref} – reference speed.

RESULTS

Four characteristic cases were considered in the study. Case No.1 depicts a recorded short linear movement of the guide characterized by a single interruption in the guide's position signals. In contrast, cases No.2, 3, and 4 also depict linear motion of the guide, but this is a return motion (including a return to the starting point). Due to the human body obstructing the tags, the number of interruptions in these variants is significantly higher, and their duration is longer.

The Kalman filter demonstrates the capacity to function in the presence of signal dropouts. In the event that observations are absent in successive steps, three distinct approaches can be distinguished depending on the duration of the interruption. In the case of brief interruptions, the measurement update is omitted. In contrast, for longer interruptions, so-called soft and hard resets of the estimator are applied. The most common approach is used for short-term gaps and involves performing only the prediction step while skipping the measurement update. This results in a gradual escalation of the estimation error, while preserving the uninterrupted progression of the filtering process.

A soft reset is a method of adjusting system parameters that involves maintaining the current state values while increasing the values of the covariance matrix P. This variant of the Kalman filter has been shown to respond more quickly to increasing uncertainty. However, it should be noted that this approach may result in the estimation of incorrect velocity values.

A hard reset is a technical procedure that involves the interruption of the current sequence and the reinitialization of the estimator with a new state. This new state is derived from new input signals and rigidly defined matrices P, Q, and R. In practice, a new covariance matrix with significantly increased values is assigned. This reflects high uncertainty regarding changes in the object's motion.

Table 1 presents the characteristics of the interruptions that occurred, while Table 2 presents the statistics of speed estimation errors.

The present article employs an approach predicated on calculating the duration of subsequent measurement interruptions. The maximum duration of interruptions was determined using numerical analysis and set to T=1 s (reset threshold). In instances where the duration of interruptions fell below this threshold, the measurement update was omitted (Table 1). In the absence of this, a hard reset was performed. The results of the experiments for cases 1, 2, 3, and 4 are presented in Figures 5, 6, 7, and 8, respectively. As illustrated in Figures 5a, 6a, 7a, and 8a, the waveforms of the guide's position coordinates

Table 1. Characteristics of the interruptions

Case no.	Interrupt pattern	Number of interrupts	Interrupt duration, s
1	Single short interruption	1	0.5
2	Multiple interruptions	5	1.50
3	Multiple interruptions	5	4.10
4	Frequent/long interruptions	8	5.50

Table 2. Statistics of velocity estimation errors

Case no.	Min, m/s	Mean, m/s	MAE, m/s	RMSE, m/s	Max, m/s
1	-0.37	0.09	0.15	0.21	0.94
2	-0.79	0.18	0.28	0.57	3.82
3	-0.89	0.18	0.31	0.59	3.73
4	-1.21	0.34	0.48	1.03	5.70

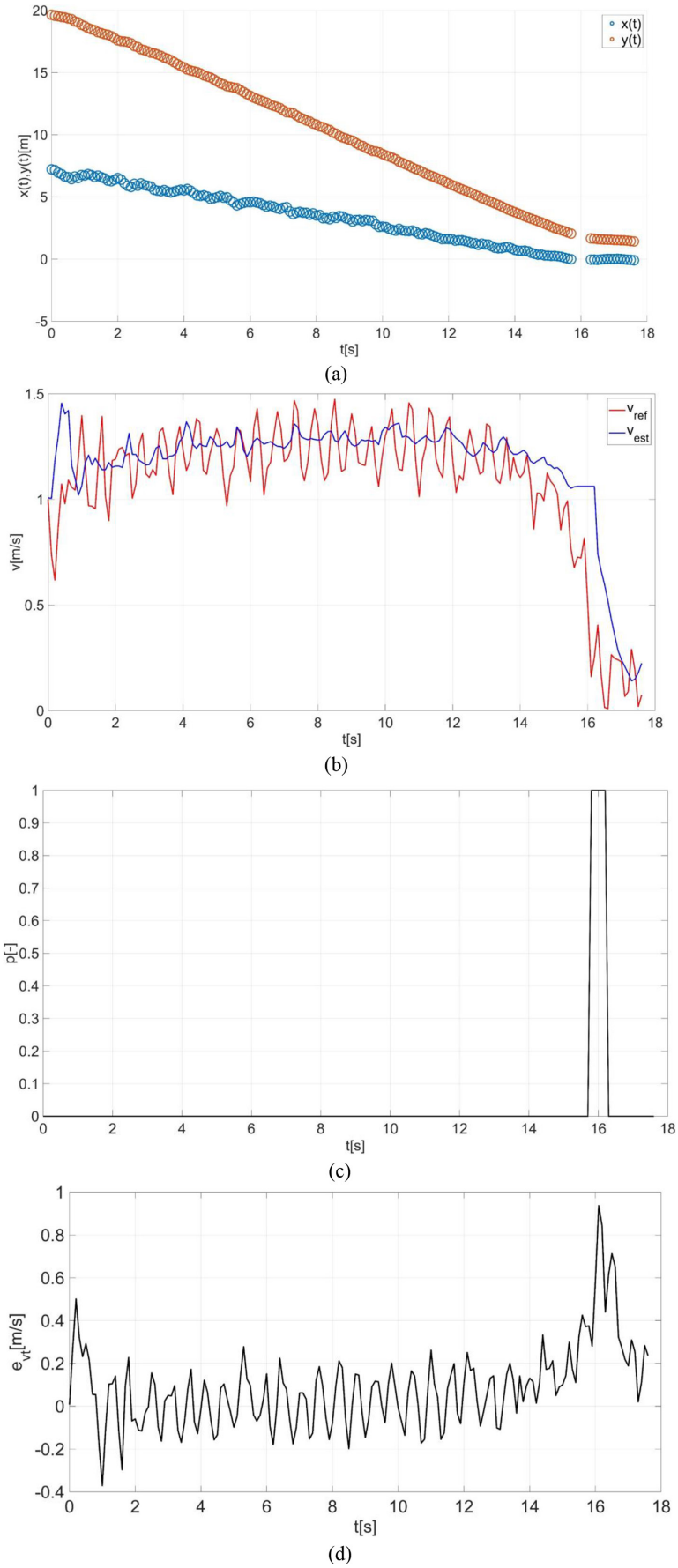
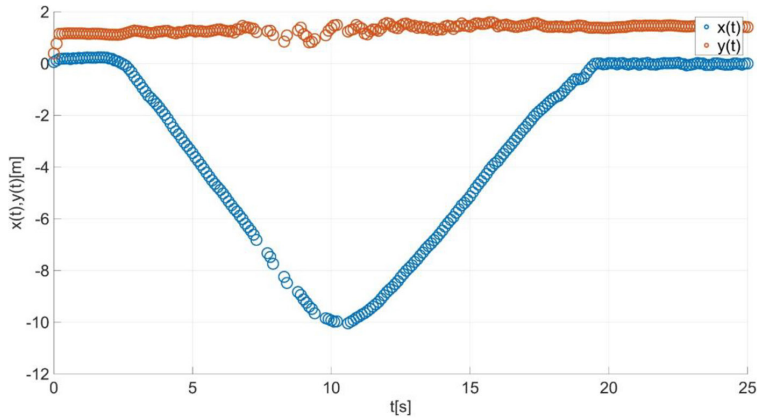
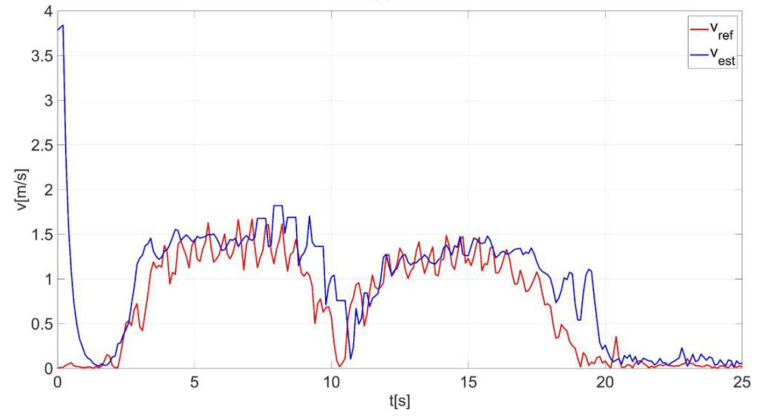


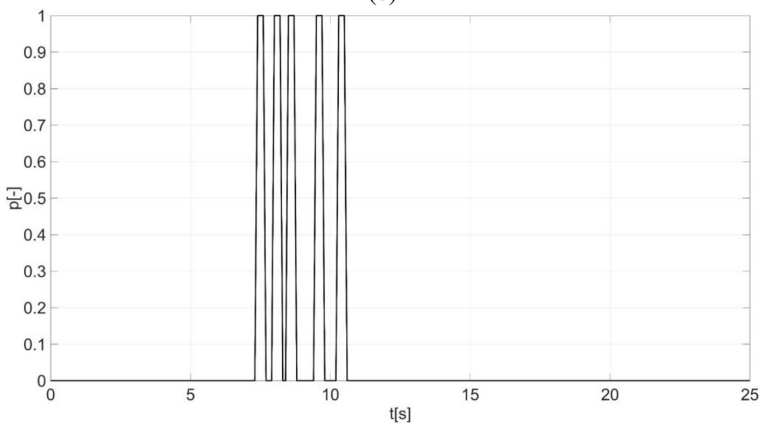
Figure 5. Test results for case No.1: (a) position coordinate waveforms, (b) velocity estimates along with the reference velocity, (c) position signal interruptions, (d) velocity estimation error



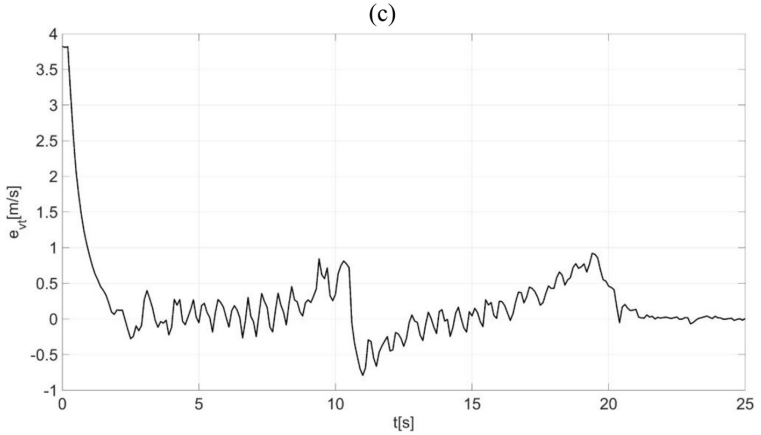
(a)



(b)



(c)



(d)

Figure 6. Test results for case No.2: (a) position coordinate waveforms, (b) velocity estimates along with the reference velocity, (c) position signal interruptions, (d) velocity estimation error

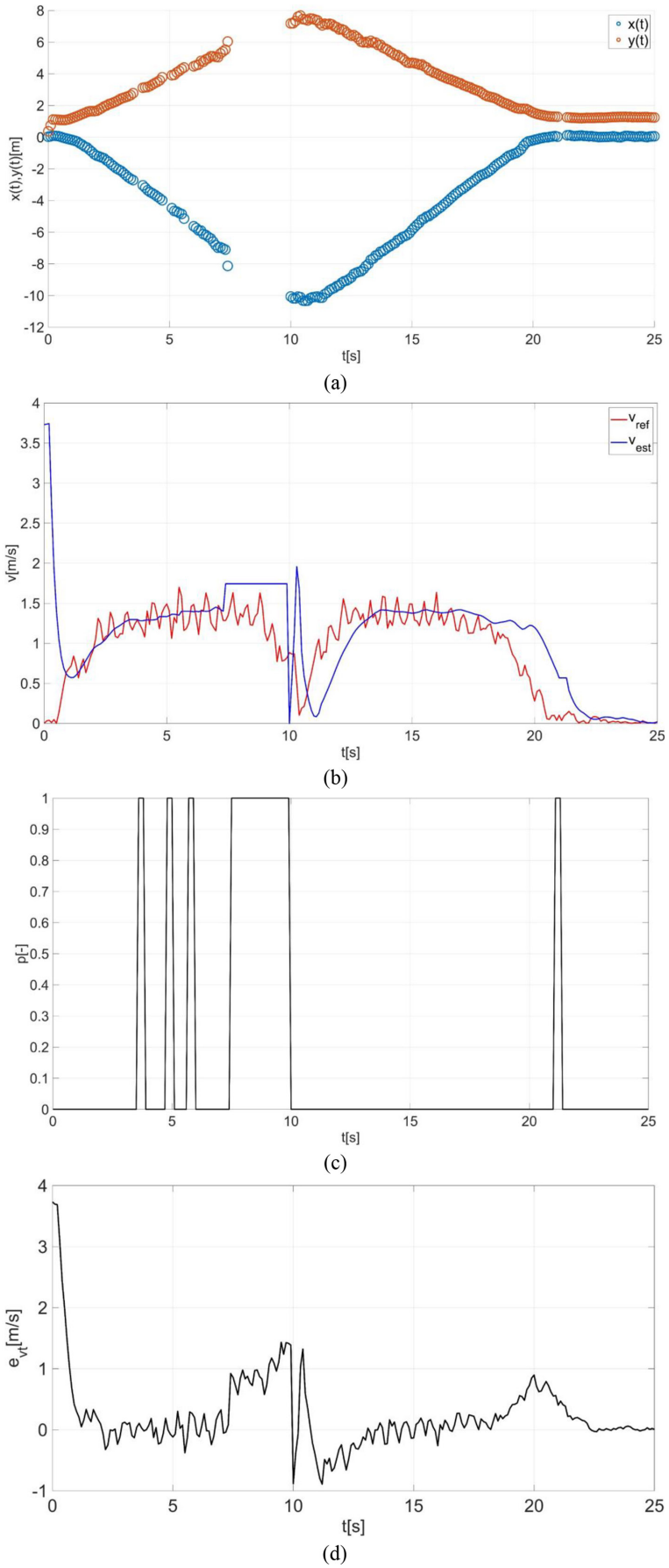


Figure 7. Test results for case No.3: (a) position coordinate waveforms, (b) velocity estimates along with the reference velocity, (c) position signal interruptions, (d) velocity estimation error

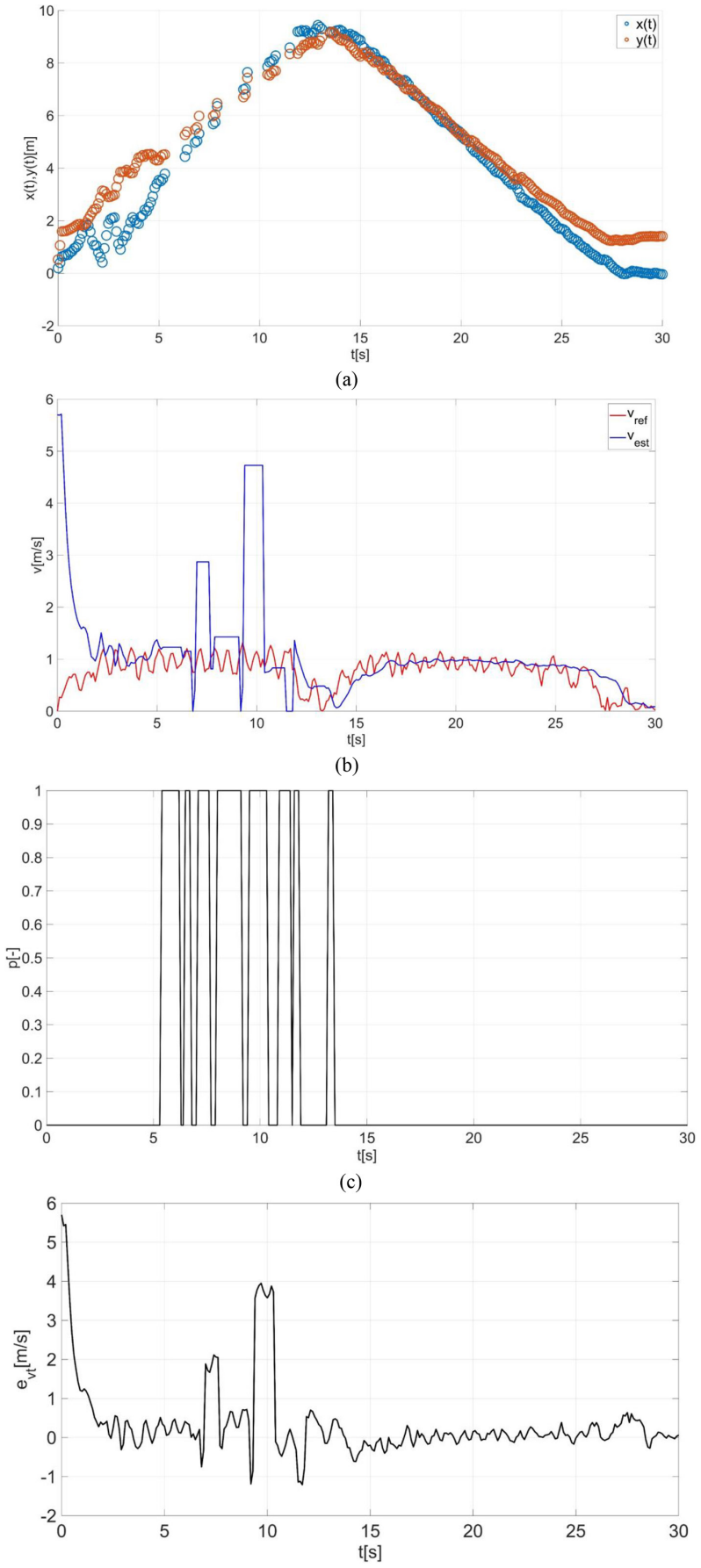


Figure 8. Test results for case No.4: (a) position coordinate waveforms, (b) velocity estimates along with the reference velocity, (c) position signal interruptions, (d) velocity estimation error

x(t) and y(t) are depicted for the respective cases. The results of the velocity estimates in the respective cases are shown in Figures 5b, 6b, 7b, and 8b. Conversely, disruptions in the guide's position are presented in Figures 5c, 6c, 7c, and 8c. Furthermore, the velocity estimation error is demonstrated in Figures 5d, 6d, 7d, and 8d.

The maximum velocity estimation error occurs at the beginning of the test period (Figures 5d, 6d, 7d, and 8d), which is related to the initialization of the Kalman filter itself. The findings further demonstrate that the presence of signal gaps in the position data (Figures 5c, 6c, 7c, and 8c) leads to an increase in estimation errors (Figures 5d, 6d, 7d, and 8d). The Kalman filter has been demonstrated to be capable of estimating values in the case of short-term interruptions, with the process of compensation via filter prediction. However, in the case of long-term interruptions, there is a significant increase in estimation errors. Subsequent to the restoration of the measurement signal, the Kalman filter requires a period of time to resume tracking the current velocity value (Figures 5b, 6b, 7b, and 8b). The root mean square (RMS) errors exhibited variability, attaining low values in instances 1, 2, and 3 (<0.6 m/s), thereby substantiating the efficacy of the Kalman filter. The lowest RMS error values are observed in case 1, which is associated with the shortest duration of motion.

In case No.1 (single short interruption), the Kalman filter operates mainly in prediction mode, and the velocity estimation error remains low throughout the entire run (Table 1). The RMS error in this case is the lowest across all scenarios (approx. 0.21 m/s). Cases No.2 and 3 are characterized by more frequent interruptions (duration shorter than T = 1 s), so they are handled by prediction steps without the need for hard resets. Consequently, the RMS errors remain below 0.6 m/s in most runs, and the mean absolute errors (MAE) are only slightly higher than in scenario 1. This indicates that the estimation technique in the mentioned cases can compensate for moderate levels of missing data.

Case No.4 represents the most complex scenario, with longer and more frequent interruptions. In this case, the duration of subsequent interruptions is longer than T = 1 s, which causes more frequent hard resets of the estimator. The velocity estimation error in this case increases, and the RMS errors reach higher values than in the other scenarios. After each interruption, the filter needs some time to re-estimate the velocity value after resuming measurements (Figure 8b–8d). However, the estimator maintains limited error values due to the applied reset strategy.

DISCUSSION

Experimental results show that the proposed loosely coupled Kalman filter with a UWB localization system is able to accurately estimate the guide's velocity when position signal interruptions occur. For case No. 1, which was characterized by a single interruption, the estimator achieves low RMS velocity errors (<0.6 m/s), confirming that the simple CV model is sufficient when UWB measurement interruptions occur sporadically. For cases No. 2-4, in which the number of interruptions is longer and more frequent, the velocity estimation accuracy decreases. The estimator handles short-term interruptions well through its prediction stage, whereas long-term interruptions necessitate hard resets and result in larger velocity estimation errors.

As part of the literature review, it was found that available articles focus mostly on position accuracy in indoor environments [26] or on simulation studies with idealized noise models [36]. Many works describe tightly coupled EKF or UKF architectures that fuse UWB with IMU [14], odometry [32] or GNSS [7], and report position errors under favorable conditions, but typically do not isolate the velocity estimation problem for a human guide in a follow-me UGV scenario [4]. The present study assessed the feasibility of velocity estimation using only data obtained using UWB technology and a loosely coupled Kalman filter under realistic signal interference conditions without relying on additional onboard sensors or other fusion architectures. It provides a computationally lightweight, easy-to-implement approach that is suitable for follow-me UGV applications with limited hardware and sensor availability.

The velocity estimator described in this article has several limitations that must be considered. The use of a CV model limits its applicability to situations where the guide's motion is linear (quasi-linear). High dynamics of

guide motion with rapid accelerations can significantly increase velocity estimation errors. The concept of a loosely coupled architecture, which processes only UWB-derived locations and does not utilize raw transmitter-receiver distance data, reduces the system's ability to compensate for NLOS conditions. Furthermore, the reset strategy used, based on a single fixed parameter (interruption time), is not optimal for various operating environments.

Furthermore, the experiments were conducted in an outdoor environment and with a specific UWB system configuration (four anchors attached to a stationary UGV, one tag on the guide). While many repetition runs were considered, the results may not directly generalize to other anchor configurations or indoor environments. Despite the limitations described, the estimator proposed in this paper offers several advantages. Its linear, loosely coupled structure is computationally lightweight and suitable for real-time implementation on mobile platforms with limited computational resources. It relies solely on UWB-based position estimation and a simple CV kinematic model, which significantly simplifies integration with UGVs. Furthermore, the implemented simple reset strategy ensures the estimator maintains limited velocity errors even in the presence of significant signal interruptions.

However, the use of only a single sensor (UWB) makes the estimator sensitive to the geometry of the transmitter/receiver deployment and varying NLOS conditions. In cases where the guide moves at higher velocities in a dense, complex environment, it may be beneficial to combine the proposed estimator with additional sensors (e.g., IMU, LiDAR) within a sensor fusion framework. Furthermore, more complex Kalman filter variations, such as EKF or UKF, could be used, potentially minimizing speed estimation errors at the cost of increased computational complexity. One area of future research is applying tight Kalman filter coupling with nonlinear variants, such as the EKF, or UKF. This combination is computationally much more complex and allows for higher velocity estimation accuracy, albeit at the cost of filter instability. One interesting area of further research could be hybrid adaptive coupling strategies, which can select the degree of integration based on available UWB signals and the object's kinematics and dynamics.

CONCLUSIONS

This article investigates the estimation of the moving guide velocity problem in a follow-me UGV scenario, using only UWB-based relative positioning and a loosely coupled Kalman filter. No additional on-board sensors, such as IMUs or odometry, were used in the study. The study relies on experimental data validated against a reference GNSS-RTK system and specifically analyzes the estimator's behavior under realistic UWB signal interference patterns. The Kalman filter can be used to estimate the motion parameters of objects under conditions of full or partial observation availability. The loose coupling technique signifies a trade-off between the precision of estimation and the stability of the system.

The occurrence of position signal dropouts reduces the quality of velocity estimates. The degree of degradation is directly related to the duration and frequency of the dropouts, and full recovery of tracking accuracy using the Kalman filter requires a transition period after signal recovery. A significant limitation of the proposed method is that its accuracy depends on the continuity of the UWB signal and the transmitter-receiver geometry. The constant velocity motion model used may not generalize complex, high-velocity motions. The proposed Kalman filter-based estimator is computationally lightweight and easy to implement on mobile platforms with limited computational resources. Further work will focus on the application of tightly coupled nonlinear Kalman filters, i.e., EKF or UKF.

Acknowledgments

This work was financed by the Military University of Technology under research project UGB 22-104/2026 (531-000104-W100-22).

REFERENCES

1. Michalski K., Nowakowski M. The use of unmanned vehicles for military logistic purposes. Zeszyty Naukowe Szkoły Głównej Gospodarstwa Wiejskiego w Warszawie. Ekonomika i Organizacja Logistyki, 2020, 5(4), 43–57.
2. Nowakowski M., Kuryło J., Dąbrowski P. Object tracking based follow me for optionally Unmanned Ground Vehicles. Defence Science Journal, 2025, 75(2), 199–205.

3. Sadeghi-Tehran P., Andreu J., Angelov P., Zhou X.: Intelligent leader-follower behaviour for unmanned ground-based vehicles. Journal of Automation Mobile Robotics and Intelligent Systems, 2011, 5, 36–46.
4. Rykała Ł., Typiak A., Typiak R. Research on developing an outdoor location system based on the ultra-wideband technology. Sensors, 2020, 20(21), 6171.
5. Rykala, Ł. Shaping the Guide Location System in Terms of Determining the Route of the Unmanned Ground Vehicle. Ph.D. Thesis, Military University of Technology, 2022, Warsaw, Poland.
6. Xu B., Jia N., Wang Z. Indoor acoustic localization with IMU for UGV. In 2022 9th International Forum on Electrical Engineering and Automation (IFEEA), 2022, IEEE, pp. 568–572.
7. Liu O., Yuan S., Li Z. A survey on sensor technologies for unmanned ground vehicles. In: 2020 3rd International Conference on Unmanned Systems (ICUS), 2020, pp. 638–645, IEEE.
8. Islam MJ, Hong J, Sattar J. Person-following by autonomous robots: A categorical overview. The International Journal of Robotics Research. 2019, 38(14), 1581–1618.
9. Bakar M. N. A., Amran M. F. M. A study on techniques of person following robot. International Journal of Computer Applications, 2015, 125(13).
10. Liu Q., Li Z., Yuan S., Zhu Y., Li X. Review on vehicle detection technology for unmanned ground vehicles. Sensors, 2021, 21(4), 1354.
11. Leitch S. G., Ahmed Q. Z., Abbas W. B., Hafeez M., Lazaridis P. I., Sureephong P., Alade T. On indoor localization using wifi, ble, uwb, and imu technologies. Sensors, 2023, 23(20), 8598.
12. Laneurit J., Chapuis R., Debain C. TRACKBOD, an Accurate, Robust and Low Cost System for Mobile Robot Person Following. In: International Conference on Machine Control & Guidance (MCG); Irstea: Vichy, France, 2016; pp. 1–6.
13. Tran Q. K., Ryoo Y. J. Multi-sensor fusion framework for reliable localization and trajectory tracking of mobile robot by integrating UWB, odometry, and AHRS. Biomimetics, 2025, 10(7), 478.
14. Long L., Wu J. Research on indoor fusion positioning based on EKF for UWB_Imu. Academic Journal of Science and Technology, 2023, 8(1), 156–160.
15. Wang C., Han H., Wang J., Yu H., Yang D. A robust extended Kalman Filter applied to ultrawideband positioning. Mathematical Problems in Engineering, 2020(1), 1809262.
16. Versano G., Klein I. A hybrid neural-assisted unscented Kalman filter for unmanned ground vehicle navigation. arXiv preprint arXiv:2603.11649, 2026.
17. Haq H. U., Qureshi A., Khan A. Q. Kalman filter–based sensor fusion for navigation of holonomic unmanned ground vehicles. Journal of Field Robotics, 2026.
18. Taffetas S.G. Introduction to mobile robot control, Elsevier, 2014
19. Gabela, J. et al. Experimental evaluation of a UWB-based cooperative positioning system for pedestrians in GNSS-denied environment. Sensors, 2019, 19(23), 5274.
20. Krasuski K., Bakuła M., Miduch P., Przybyłek, P. Implementation the GPS+ EGNOS data for desiignation the accuracy of car vehicle coordinates in road transport. Advances in Science and Technology Research Journal, 2026, 20(5), 345–359.
21. Hyun, J., Myung, H. NR-UIO: NLOS-robust UWB-inertial odometry based on interacting multiple model and NLOS factor estimation. Sensors, 2021, 21(23), 7886.
22. Li, Y., Gao, Z., Xu, Q., Yang, C. Comprehensive evaluations of NLOS and linearization errors on UWB positioning. Applied Sciences, 2023, 13(10), 6187.
23. Styła M., Gnaś D., Bogusz A., Wójcik D., Adamkiewicz P., Rymarczyk T., Kłosowski G. Implementation of a multi-sensor platform for resource localization using ultra-wideband and time-of-flight measurement methods. Advances in Science and Technology Research Journal, 2026, 20(5), 254–267.
24. Volpi, A., Tebaldi, L., Matrella, G., Montanari, R., Bottani, E. Low-cost UWB based real-time locating system: development, lab test, industrial implementation and economic assessment. Sensors 2023, 23, 1124.
25. Volpi, A., Montanari, R., Tebaldi, L., Mambrioni, M. Low-cost real-time locating system solution development and implementation in manufacturing industry. J. Sens. Actuator Netw. 2023, 12, 54.
26. Zhang, H., Wang, Q., Yan, C., Xu, J., Zhang, B. Research on UWB indoor positioning algorithm under the influence of human occlusion and spatial NLOS. Remote Sens. 2022, 14, 6338.
27. Jourdan, D. B., Dardari, D. and Win, M. Z. Position Error Bound for UWB Localization in Dense Cluttered Environments, 2006 IEEE International Conference on Communications, Istanbul, Turkey, 2006, pp. 3705–3710.
28. Kramarić L., Muštra M., Radišić T. The influence of ultra-wideband anchor placement on localization accuracy. Sensors, 2025, 25(16), 5115.
29. Hölzke F., Ghojal M., Danielis P., Timmermann D., Golatowski F. Comparison of Ultra-Wideband Range Processing and Filtering for Indoor Localization. In 2020 IEEE Conference on Industrial Cyberphysical Systems (ICPS), 1, pp. 123–128, IEEE.
30. Krapež P., Vidmar M., Munih, M. Distance measurements in UWB-radio localization systems corrected with a feedforward neural network model. Sensors, 2021, 21(7), 2294.
31. Nguyen D. T. A., Lee H. G., Jeong E. R., Lee H. L., Joung J. Deep learning-based localization for UWB

systems. Electronics, 2020, 9(10), 1712.

32. Liu, A., Lin, S., Wang, J., Kong, X. A novel loosely coupling fusion approach of ultra-wideband and wheel odometry for indoor localisation. Electronics 2023, 12, 4499.
33. Zou A., Hu W., Luo Y., Jiang P. An improved UWB/IMU tightly coupled positioning algorithm study. *Sensors*, 2023, 23(13), 5918.
34. Hu C., Huang P., Wang W. Tightly coupled visual-inertial-UWB indoor localization system with multiple position-unknown anchors. IEEE Robotics and Automation Letters, 2023, 9(1), 351-358.
35. Rykała Ł., Typiak A., Typiak R., Rykała M. Application of smoothing spline in determining the unmanned ground vehicles route based on ultra-wideband distance measurements. Sensors, 2022, 22(21), 8334.
36. Rykała Ł, Przybysz M, Cieślik K, Krogul P, Typiak R, Typiak A. Research on selected location algorithms for the UGV operating in a follow-me scenario based on ultra-wideband positioning system. Advances in Science and Technology Research Journal. 2025, 19(1), 1–14.
37. Welch G., Bishop, G. An Introduction to the Kalman Filter, ACM, University of North Carolina, 2001.