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ANALYSIS OF SYSTEMATIC AND RANDOM COORDINATE ERRORS OF VISUAL LANDMARKS AND THEIR EFFECT ON POSITIONING ALGORITHM ACCURACY

Abstract. Visual landmark-based positioning systems are becoming increasingly popular in mobile robotics, autonomous vehicles, and indoor navigation technologies. One of the key factors determining their accuracy is the correctness of landmark coordinates, which in practice can be distorted by both systematic offsets and random noise. This requires a quantitative assessment of the impact of such errors on the operation of positioning algorithms. **Subject of research**: analysis of the impact of systematic and random errors in determining the coordinates of visual landmarks on the accuracy of positioning algorithms. The research addresses the assessment of sensitivity in different positioning algorithms to offsets and noise in landmark data and to identify critical factors that most affect localization accuracy. **Methods applied:** simulation modeling with the ability to vary the parameters of systematic and random errors, reproduction of four scenarios (no errors, only bias, only noise, combination). The mean absolute error (MAE) and root mean square deviation (RMSE) were used to assess accuracy. **The following results were obtained.** Even small errors in the coordinates of landmarks significantly reduce the accuracy of positioning. It was found that systematic errors have a more critical impact on the results compared to random noise. The centroid and weighted centroid methods were the most resistant to errors, while lateration showed high sensitivity to systematic shifts.

Keywords: systematic errors; random noise; visual landmarks; positioning algorithms; localization accuracy; simulation modeling; RMSE (Root Mean Square Error); MAE (Mean Absolute Error).

Introduction

Positioning systems based on visual landmarks are a key element of modern navigation and spatial reference technologies in robotics, autonomous transport and indoor localization tasks. Unlike classical approaches based on radio signals, the use of visual landmarks allows achieving higher accuracy in complex environments where there are obstacles or global navigation systems are absent. At the same time, the correct operation of positioning algorithms significantly depends on the accuracy of specifying the coordinates of these landmarks. In practice, coordinates can be determined with errors due to measurement inaccuracies, calibration errors or deformations of the environment map.

The problem is that even small systematic biases or random noise in determining the position of landmarks can significantly affect the results of positioning algorithms. This is especially important for applications where high accuracy and stability are critical, for example, in medical robotics, autonomous transport control or augmented reality systems. To assess this impact, it is advisable to use simulation modeling, which allows you to vary the error parameters and conduct multiple experiments for statistical analysis. This approach allows you to compare the stability of different algorithms and draw conclusions about their suitability for use in conditions of systematic and random errors in the data on the coordinates of visual landmarks.

Literature analysis. Early in the development of intelligent transportation systems [1], key challenges related to the integration of artificial intelligence, automated control, and localization methods were identified. These developments laid the foundation for further research, where increasing attention is paid to the accuracy and robustness of positioning in complex environments. In subsequent works, the main emphasis was placed on visual localization. Reference [2] provides a review of of modern vision-based positioning technologies with an emphasis on changing illumination, map scalability, and noisy data processing. As discussed in [3], three-dimensional indoor localization systems, which emphasize the importance of integrating visual landmarks into multi-sensor architectures. The review [4] is devoted to the navigation of unmanned aerial vehicles using vision, while [5] focuses on the reliability of the obtained results and the challenges associated with controlling their reliability.

Traditional algorithms also remain important. In [6, 7] it is shown that even advanced localization methods remain sensitive to errors in the environment map. In [8] an approach to building compact semantic maps is proposed, which demonstrates the critical role of accurate landmark descriptions.

Work on sensory integration has also been developed. In [9], a method of combining visual data and additional sensory channels to improve accuracy in rooms is proposed. In [10], an example of underwater navigation of autonomous vehicles is described, where the correctness of determining the coordinates of landmarks is a key condition for completing tasks.

In the field of computer vision, methods for detecting and tracking landmarks are actively being researched. In [11], aircraft localization was implemented using object recognition algorithms, in [12] a method for positioning in large-scale environments was developed, in [13] the possibility of high-precision manipulation using vision was demonstrated, and in [14] an algorithm for industrial scenarios was created. All these examples confirm that even small errors in determining the coordinates of landmarks significantly affect the final result.

A special place is occupied by works devoted to adaptive approaches. In [15] an algorithm for automatic landing of aircrafts was developed, in [16] and [17] methods of adaptive localization and flight control are described, and in [18] the use of machine learning to increase the stability of navigation systems is considered. The closest to the topic of our research is the work [19], which presents an adaptive algorithm for visual positioning in the local environment. This method takes into account uncertainty and allows you to adjust the parameters in real time, which ensures stability to shifts and noise in the coordinates of landmarks. This work serves as the direct scientific foundation for our research.

In parallel, other areas related to the problem of robustness are developing. In [20] and [21], methods for controlling technical systems based on robust models and optimization are presented. Works [22] and [23] focus on reducing errors through data preprocessing and optimal methods for their use. Finally, in [24], navigation assistance systems for people with visual impairments are considered, which demonstrates a broader social context. All these studies confirm the need to study the impact of errors on positioning algorithms, but a systematic analysis of systematic and random errors of landmark coordinates is still almost absent.

Despite the significant amount of research in the field of visual positioning, there is a lack of systematic analysis of how landmark coordinate errors affect different algorithmic approaches. Most work focuses on improving individual algorithms or sensor integration, but rarely offers a controlled comparison of the sensitivity of algorithms to systematic and random errors.

Problem statement and purpose of the study. The aim of this study is to model the impact of systematic and random errors in the coordinates of landmarks on the accuracy of several common positioning algorithms. Using a simulation approach, different scenarios (ideal data, systematic bias, random noise, and their combination) are considered and the nearest landmark, lateration, centroid, and weighted centroid methods are compared. The results obtained allow us to quantitatively assess the sensitivity of algorithms to errors and determine the most robust solutions under uncertainty.

Research methodology

In order to assess the impact of systematic and random errors in determining the coordinates of visual landmarks on the accuracy of positioning algorithms, a simulation approach using multiple experiments (Monte Carlo method) was applied. At the first stage, **input data** was formed: an environment model with a given location of landmarks, measurement noise parameters, and ranges of systematic biases and random deviations (Fig. 1).

Four scenarios have been developed to control the impact of different types of errors:

- Clean (without errors),
- Bias only (systematic offsets),
- Jitter only (random noise),
- Both (combination of offset and noise).

The stages of the algorithm are presented in Table 1.

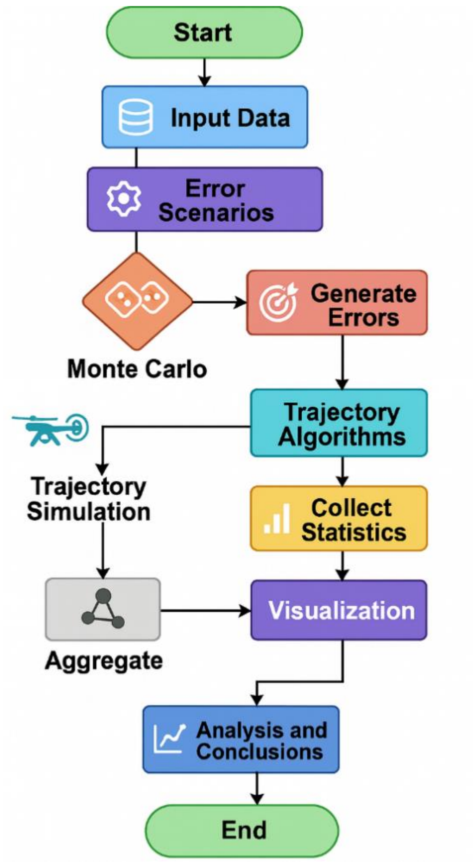

Fig. 1. Research methodology

Next, multiple simulations (Monte - Carlo) were performed, where in each experiment errors were generated according to given statistical laws (normal distribution for systematic bias and uniform distribution for noise). Based on these data, a “noisy” landmark map was constructed.

Table 1 – **Research stages**

No.	Block from the scheme	Stage content
1	BEGINNING	Initialization of the research, definition of the task and goal
2	Input data	Setting the environment map, landmark coordinates, bias and jitter parameters
3	Error scenarios	Choosing one of four scenarios: Clean, Bias only, Jitter only, Both
4	Monte-Carlo	Multiple simulation (N experiments)
5	Error generation	Formation of a “noisy” landmark map: bias ~ Normal, jitter ~ Uniform
6	Trajectory modeling	Object movement in discrete steps (M steps) within the scene
7	Positioning algorithms	Application of methods: Proximity, Lateration, Centroid, Weighted Centroid
8	Statistics collection	Calculation of errors for each step, calculation of MAE and RMSE
9	Aggregation	Averaging of the results over all experiments, determination of the root mean square deviation
10	Visualization	Construction of radar and bar charts, preparation of tables
11	Analysis and conclusions	Comparison of sensitivity of methods, assessment of robustness, formulation of recommendations
12	END	Completion of the research, preparation of results for publication

The next stage involved modeling the trajectory in an environment where the object moved in discrete steps. For each step, the positioning algorithms were applied: Proximity, Lateration, Centroid, and Weighted Centroid. For each method, the obtained position estimates were compared with the true position.

Based on the results, error metrics were calculated: mean absolute error (MAE) and root mean square error (RMSE). These values were stored for each experiment, after which the statistics were aggregated across all replicates.

The summarized data was presented in the form of radar and bar charts, as well as tables with numerical values of mean errors and standard deviations. This allowed for a visual comparison of the robustness of different algorithms in different scenarios.

At the final stage, an analysis of the results was carried out, which determined: sensitivity of each method to systematic and random errors; scenarios where accuracy degradation is most critical; relative advantage of algorithms in terms of robustness indicators.

Simulation Software

Specialized software was developed for the research in Python 3.12. Open scientific libraries were used in the implementation, including NumPy for vector and matrix calculations, math and random for working with elementary functions and generating random variables, and matplotlib for plotting and visualizing results. In some cases, the pandas library was used to save the results in CSV tabular format.

The program code is built on a modular principle, which made it possible to isolate separate parts responsible for data generation, motion trajectory modeling, implementation of positioning algorithms, error calculation, and results visualization. At the initial stage, an environment model is formed, which includes a scene map with coordinates of visual landmarks. Next, the parameters of systematic biases and random noise are set, which allows us to reproduce various scenarios of the impact of errors. The program implements four types of scenarios: an ideal case with no errors, only systematic bias, only random noise, and a combination of these factors.

For each scenario, a series of Monte - Carlo experiments are performed. Within each experiment, a set of errors is generated: systematic bias is modeled by a random variable from a normal distribution, while random noise is reproduced by a uniform distribution. Based on these parameters, a "noisy" landmark map is formed, which is used for further calculations. After that, the object's motion trajectory is modeled, which consists of discrete steps within the scene.

At each step, positioning algorithms are applied. Four methods are implemented: Proximity, Lateration, Centroid, and Weighted Centroid. For each of them, a position estimate is calculated and compared with the true coordinates. This allows us to determine the positioning error at each stage.

The collected data is analyzed in the statistical module, where the metrics of mean absolute error (MAE), root mean square error (RMSE) and standard deviation are calculated. Aggregation across all experiments is used to summarize the results, which ensures the reliability of the conclusions obtained.

The final stage is visualization. The program builds radar charts of errors by steps, bar charts of average errors, and also generates tables with numerical results. The commands plt.plot() and plt.bar() are used to plot graphs, and plt.savefig(..., dpi=300) provides high-quality saving for later inclusion in the article. Thus, the developed software provides a full cycle of research - from modeling the environment with errors to obtaining statistical characteristics and preparing graphical results for publication.

Experimental Results

The experiments were conducted to assess the sensitivity of positioning algorithms to systematic and random errors in the coordinates of visual landmarks. For this purpose, a model environment was used in which landmarks were located at the vertices of a square area with a side of several meters. This configuration allows creating a symmetrical test scene suitable for testing algorithms in different conditions.

Each experiment involved the generation of errors in the coordinates of landmarks, which were described by two components: a systematic bias and random noise (jitter). The systematic bias was modeled by a normally distributed random variable with a mean of 0.25 m and a standard deviation of 0.08 m (negative values were truncated to zero). Random noise was described by a uniform distribution in the range from 0 to 0.15 m.

For each scenario, N = 100 Monte - Carlo experiments were conducted. The influence of RSS measurement noise, which was modeled by a normal distribution with a standard deviation of 6.0 dB, was taken into account. The average values of the errors of the true and estimated position for one experiment were 2.8 m and 2.0 m, respectively.

The positioning results were compared based on four algorithms: Proximity, Lateration, Centroid and Weighted Centroid. For each method, the mean absolute error (MAE), root mean square error (RMSE) and standard deviation were calculated. Visualization was carried out in the form of radar diagrams with a maximum radius of 3.0 m and divisions every 0.5 m, which allowed us to clearly assess the nature of the distribution of errors in different conditions (Table 2, 3).

Table 2 – **Average absolute error (MAE)**

No.	Scenario	Proximity		Lateration		Weighted Centroid		Centroid	
		mean, m	std, m	mean, m	std, m	mean, m	std, m	mean, m	std, m
1	clean	1.1652	0.0258	0.8818	0.0190	0.8800	0.0207	1.8152	0.0000
2	bias_only	1.2130	0.0556	0.9261	0.0353	0.9285	0.0401	1.8218	0.0072
3	jitter_only	1.1665	0.0262	0.8830	0.0209	0.8840	0.0220	1.8162	0.0027
4	both	1.2176	0.0586	0.9339	0.0428	0.9322	0.0418	1.8238	0.0107

Table 3 – **Root Mean Square Error (RMSE)**

No.	Scenario	Proximity		Lateration		Weighted Centroid		Centroid	
		mean, m	std, m	mean, m	std, m	mean, m	std, m	mean, m	std, m
1	clean	1.3666	0.041428	1.0110	0.0266	1.0081	0.0285	1.9365	0.0000
2	bias_only	1.4158	0.070112	1.0551	0.0400	1.0598	0.0454	1.9453	0.0100
3	jitter_only	1.3655	0.039901	1.0100	0.0272	1.0111	0.0296	1.9377	0.0028
4	both	1.4211	0.072643	1.0665	0.0489	1.0639	0.0469	1.9481	0.0145

Table 2 shows the mean absolute error (MAE) values and their standard deviations for the four positioning algorithms in different error impact scenarios. In the baseline scenario (clean), when systematic and random errors are absent, the best accuracy was demonstrated by the lateration (0.88 m) and weighted centroid (0.88 m) methods, which practically coincided in terms of error. The nearest landmark method showed slightly worse results (1.16 m), while the least accurate was the simple centroid method (1.82 m).

When introducing a systematic offset (bias_only), the error increased for all methods, but this was most pronounced for the lateration and weighted centroid methods, where the MAE increased to ~0.93 m. For the nearest landmark method, the error increased from 1.16 m to 1.21 m. The centroid method remained the most sensitive to landmark distortion (1.82 m).

Adding only random noise (jitter_only) did not change the overall picture much: the results are close to the scenario without errors. This indicates that short-term noise in the landmarks coordinates has less impact on accuracy than systematic shifts.

The worst case scenario is a combination of both factors (both), where the MAE increased the most: up to 1.22 m for the nearest landmark method and up to 0.93 m for the lateration and weighted centroid methods. At the same time, the centroid method consistently showed the worst result (1.82 m), reacting little to additional noise or displacement. Thus, the results obtained confirm that systematic errors in determining the coordinates of landmarks have a more significant impact on the accuracy of positioning algorithms than random ones, and the lateration and weighted centroid methods were the most resistant to influences.

Table 3 shows the root mean square errors (RMSE) and their standard deviations for the four positioning algorithms in different scenarios.

In the clean scenario, the lateration (1.01 m) and weighted centroid (1.01 m) methods showed the highest accuracy, while the nearest landmark method had an RMSE of 1.37 m and the centroid method had the worst result (1.94 m). Under (bias_only) conditions, errors increase for all algorithms. This was most noticeable for the lateration and weighted centroid methods, where RMSE increased by approximately 5 cm. The nearest landmark method deteriorated from 1.37 m to 1.42 m, and the centroid method again showed the highest error (1.95 m). Adding random noise (jitter_only) had almost no effect on the results: RMSE values remained close to the clean scenario. This indicates a smaller impact of short-term random distortions of the landmarks coordinates compared to systematic bias.

The most negative impact was observed in the (both) scenario, where both noise and bias were present. In this case, the RMSE for the nearest landmark method reached 1.42 m, and for lateration and weighted centroid – about 1.06 m. The centroid method remained the least accurate (1.95 m), almost not responding to changing conditions. Thus, the RMSE results confirm the conclusions obtained from the MAE analysis: systematic errors have a more significant impact on positioning accuracy than random noise, and the most stable results were demonstrated by the lateration and weighted centroid methods.

The results of modeling the average error values under different scenarios for each method are presented in Fig. 2–5.

Analysis of the simulation results showed significant differences in the behavior of the considered positioning algorithms under different error scenarios. The nearest landmark method demonstrated stable operation, but even under ideal conditions the average error was more than one meter, which limits its suitability for tasks where high accuracy is required. All scenarios resulted in only minor changes, so this method is insensitive to random and systematic distortions, but has a high basic error.

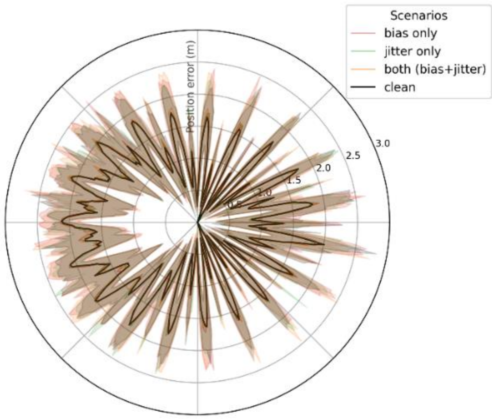

Fig. 2. Average error by the Proximity method

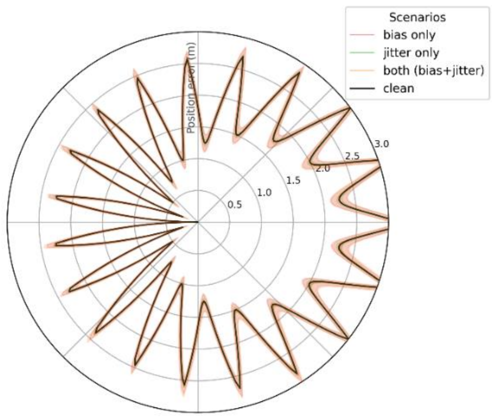

Fig. 3. Average error by Centroid method

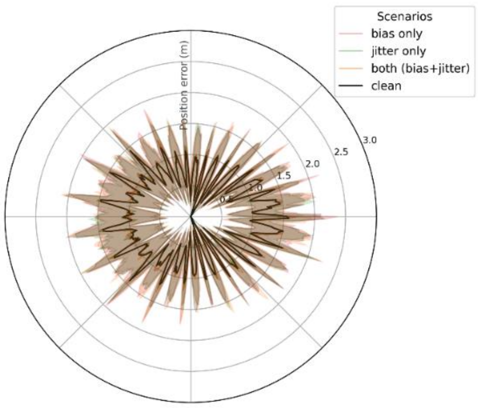

Fig. 4. Average error by Lateration method

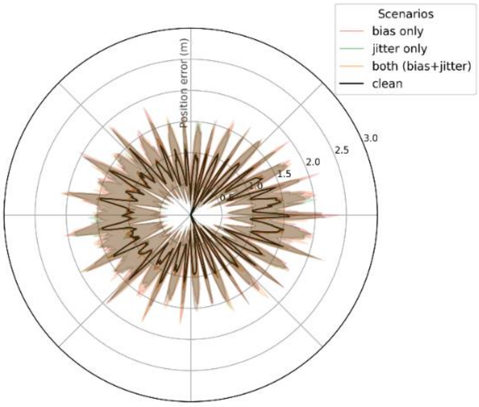

Fig. 5. Average error by Weighted Centroid method

The centroid method had the largest errors among all algorithms — about 1.8 m, and the results practically did not change regardless of the presence of offset or noise. This indicates low accuracy and at the same time low sensitivity to both random and systematic errors in determining the coordinates of landmarks.

The best results were achieved by the lateration and weighted centroid methods. In the error-free scenario, their average error did not exceed one meter. At the same time, it was clearly recorded that systematic distortions of the coordinates of landmarks significantly worsen the accuracy of these methods: the error increased by approximately 5–6 cm in scenarios with displacement. Adding only random noise had almost no effect on the results, and the combination of noise and displacement led to the worst values among all the conditions considered. Thus, lateration and weighted centroid are the most accurate, but sensitive precisely to systematic errors, while random perturbations of the coordinates of landmarks play a secondary role (Table 4).

Overall, the results indicate that systematic errors in determining the coordinates of visual landmarks are a critical factor that can significantly reduce positioning accuracy. On the other hand, random coordinate noise can be smoothed out by statistical averaging methods and has a much smaller impact.

Comparison of the average positioning error for all considered methods in two scenarios: clean (without systematic and random errors) (Fig. 6) and both (combination of systematic bias and random noise of landmark coordinates) (Fig. 7).

Table 4 – Mean Absolute Error **(MAE)**

No	Method	Average error (clean)	Sensitivity to bias	Sensitivity to jitter	Overall rating
1	Proximity	~1.2 м	Low	Low	Stable but inaccurate
2	Centroid	~1.8 м	Very low	Very low	Least accurate
3	Lateration	~0.9 м	High	Low	Accurate, but vulnerable to systematic errors
4	Weighted Centroid	~0.9 м	High	Low	Precise, similar to lateration

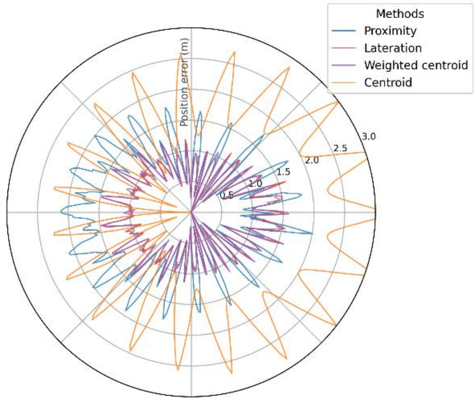

Fig. 6. Comparison of the average positioning error for all considered methods in the “clean” scenario

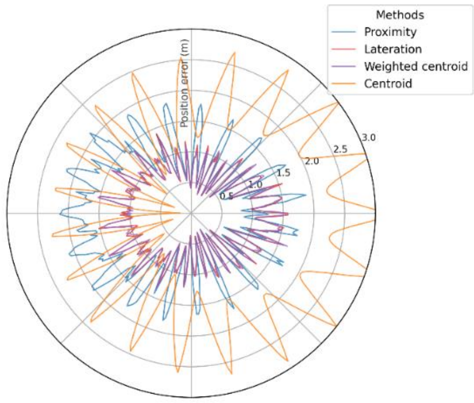

Fig. 7. Comparison of the average positioning error for all considered methods in the “both” scenario

In “clean” conditions, the lateration and weighted centroid methods provide the highest accuracy (RMSE ≈ 1.0 m), the nearest landmark method has a consistently higher error (~1.2 m), while the centroid method demonstrates the worst result (~1.8 m). In the scenario with a combination of errors, the accuracy of all methods, except for the centroid, deteriorates, especially due to the increase in trajectory instability, which indicates the dominant influence of systematic errors over random noise.

Conclusion from the comparison. In clean conditions (clean), Lateration and Weighted Centroid are the leaders. In the combination of noise and systematic bias (both), these same methods retain their advantage, but lose some of their stability, which indicates the critical role of systematic errors. Proximity remains an average option, almost unchanged between scenarios. Centroid is the least suitable for practical use: high baseline error and lack of response to additional factors.

Conclusions

A comparison of the mean absolute error (MAE) and root mean square error (RMSE) showed consistent results. In both cases, the lateration and weighted centroid methods demonstrated the highest accuracy and stability, while the centroid method consistently remained the least accurate. The nearest landmark method occupies an intermediate position, providing acceptable but not optimal accuracy.

Importantly, introducing systematic errors (bias) resulted in a more noticeable degradation of the results than adding only random noise (jitter). The scenario of combining both factors (both) confirmed the cumulative nature of their impact, but it is the systematic bias that determines the critical decrease in accuracy.

The results obtained indicate the need to compensate or correct systematic errors in the coordinates of visual landmarks to ensure the reliability of positioning algorithms. At the same time, random fluctuations are less dangerous and can be smoothed out by statistical averaging methods.

The obtained results confirm the significant impact of systematic errors in determining the coordinates of visual landmarks on the accuracy of positioning algorithms. At the same time, they open up several promising directions for further research.

First, it is advisable to develop methods for compensating and correcting systematic errors, in particular through the use of statistical models or machine learning, capable of assessing and correcting the displacement of the coordinates of landmarks during the algorithm. Second, an important task is the integration of additional sensor data (for example, inertial measurement units or data from depth cameras), which can reduce the impact of uncertainty in the location of landmarks and increase the reliability of positioning. Third, it is promising to scale the experiments to more complex environments, including dynamic scenes, external obstacles and variable lighting conditions, which will allow the simulation to be closer to real-world scenarios.

A separate direction is the development of adaptive algorithms that would automatically adjust to the characteristics of the environment and the level of errors. This may include hybrid approaches that combine classical geometric methods with modern deep learning algorithms. Another promising task is the creation of generalized criteria for evaluating the effectiveness of algorithms in the presence of different types of errors, which would allow for a systematic comparison of alternative solutions. Thus, further research should be aimed both at improving existing algorithms and at creating new methods that can effectively take into account both random and systematic errors, ensuring high accuracy and stability of positioning systems in real conditions.

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Аналіз систематичних та випадкових похибок координат візуальних орієнтирів та їх вплив на точність алгоритму позиціонування

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Анотація. Системи позиціонування на основі візуальних орієнтирів набувають все більшого поширення у сфері мобільної робототехніки, автономних транспортних засобів та технологій indoor-навігації. Одним із ключових факторів, що визначає їхню точність, є коректність визначення координат орієнтирів, яка на практиці може спотворюватися як систематичними зміщеннями, так і випадковим шумом. Це потребує кількісної оцінки впливу подібних похибок на роботу алгоритмів позиціонування. **Предмет дослідження:** аналіз впливу систематичних і випадкових похибок визначення координат візуальних орієнтирів на точність алгоритмів позиціонування. **Метою дослідження є** оцінка чутливості різних алгоритмів позиціонування до зміщень і шумів у даних орієнтирів та визначення критичних факторів, що найбільше впливають на точність локалізації. **Методи, що використовуються:** імітаційне моделювання з можливістю варіювати параметри систематичних і випадкових похибок, відтворення чотирьох сценаріїв (без похибок, лише зміщення, лише шум, комбінація). Для оцінки точності застосовано середню абсолютну похибку (MAE) та середньоквадратичне відхилення (RMSE). **Були отримані наступні результати** навіть невеликі похибки координат орієнтирів суттєво знижують точність позиціонування. Встановлено, що систематичні помилки мають більш критичний вплив на результати порівняно з випадковим шумом. Найбільш стійкими до похибок виявилися методи центроїда та зваженого центроїда, тоді як латерація показала високу чутливість до систематичних зсувів.

Ключові слова: систематичні помилки; випадковий шум; візуальні орієнтири; алгоритми позиціонування; точність локалізації; імітаційне моделювання; RMSE (середньоквадратична помилка); MAE (середня абсолютна помилка).