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METHODS AND ALGORITHMS OF BUILDING A 3D MATHEMATICAL MODEL OF THE SURROUNDING SPACE FOR AUTOMATIC LOCALIZATION OF A MOBILE OBJECT

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ABSTRACT

Context. The task of automating the positioning of a mobile object in a closed space under the condition of its partial or complete autonomy is considered. The object of study is the process of automatic construction of a 3D model of the surrounding space.

Objective. The goal of the work is the develop an algorithm for creating a 3D model of the surrounding space for further localization of a mobile object in conditions of its partial or complete autonomy.

Method. The results of the study of the problem of localization of a mobile object in space in real time are presented. The results of the analysis of existing methods and algorithms for creating mathematical models of the surrounding space are presented. Algorithms that are widely used to solve the problem of localization of a mobile object in space are described. A wide range of methods for constructing a mathematical model of the surrounding space has been researched – from methods that use the comparison of successive point clouds of the object of the surrounding space to methods that use a series of snapshots of characteristic points and comparison of information about them in different snapshots at points that are as similar as possible according to the parameter vector.

Results. The method for three-stage construction of a 3D model of the surrounding space is proposed for solving the problem of localization of a mobile object in a closed space.

Conclusions. The conducted experiments have confirmed the possibility of the proposed algorithm for three-stage construction of a mathematical model of the environment to determine the position of a mobile object in space. The methods used in the algorithm allow obtaining information about the surrounding space, which allows localizing a mobile object in a closed space. Prospects for further research may lie in the integration of information flows about the position of the object from different devices, depending on the type of data acquisition, into a centralized information base for solving a wide range of tasks performed by automatic mobile objects (robots).

KEYWORDS: mathematical 3D model, localization method, SLAM method algorithms, position determination, mobile object.

ABBREVIATIONS

DATMO is a detection and tracking of movingobjects;
EKF is a extended Kalman filter;
ICP is a iterative closest point;
NDT is a normal-distributions transform;
NNS is a nearest neighbor search;
LS3D is a least squares 3D surface matching;
ML-NDT is a multi-layered NDT;
PCL is a point cloud library;
PMD is a photonic mixer device;
RANSAC is a random sample consensus;
SLAM is a simultaneous localization and mapping;
SURF is a speeded up robust features;
ToF is a time-of-flight.

NOMENCLATURE

T_n is a environmental space;

x_n is a scan area size along the x-axis;

y_n is a scan area size along the y-axis;

z_n is a scan area size along the z-axis;

$z_{t,n}$ is a beam data obtained using a laser range scanner;

$c_{t,n}$ characterizes the erroneous measurements in the data;

k is a field covered by the beam;

m is a model that maximizes the probability of the data;

x_t is a robot position at a certain point in time;

f is a function that returns for each position x_t of the robot, each beam with number n and each field $k \leq z_{t,n}$.;

ζ is a indicator variables that are equal to 1 if and only if $z_{t,n}$ is the maximum value of the range, otherwise – 0;

s_i is a given point in space R^3, for which it is necessary to find the shortest distance to the set T;

τ is a the point that gives the smallest value to the functional S;

τ_j is a nearest pair of points for point s_i;

J is a functional for a given displacement vector t and rotation matrix R;

R is a real orthogonal matrix with a determinant equal to one, that is, it belongs to a special orthogonal group of rotation $S0(3)$;

t is a vector representing the displacement of a set of points along vector $[x,y,z]^T$;

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$\|\cdot\|_2^2$ is a square of the norm or the square of the Euclidean distance between two points;

S_i is a point cloud block;

ε is a point cloud threshold;

$T_7(p,x)$ is a spatial transformation function;

p is a vector;

t is a displacement;

r is a axis of rotation;

ϕ is a angle of rotation.

INTRODUCTION

Today, there is a rapid development of mobile autonomous systems. Such systems, for the most part, are increasingly based on the use of intelligent systems. One of the main functions of modern intelligent mobile systems is their autonomous navigation. Implementation of such a function is possible with a clear understanding of the surrounding environment, that is, it is necessary to transform information about the surrounding world into a mathematical model convenient for processing by these systems.

The object of study is the process of automatic construction of a 3D model of the surrounding space.

Construction of a mathematical model of the surrounding environment using modern circuit solutions is possible when using SLAM and DATMO algorithms [1].

The subject of study is methods of building a mathematical model of the environment at the expense of a set of received spatial points that give an idea of their relative location in space.

The purpose of the work is to develop a method for creating a 3D model of the surrounding space for further localization of a mobile object in conditions of its partial or complete autonomy.

1 PROBLEM STATEMENT

Let's assume that there is a mobile object (robot) that is in a closed space under conditions of partial or complete autonomy. The task facing the system of such a mobile object is that, based on the received data, it should be able to form a 3D model of the surrounding space, localize the object in space, create (or update or supplement) a "map" of movement and to decide on further actions. It should be borne in mind that many methods of creating a mathematical model of the environment are designed with powerful hardware and computing resources in mind, and this often does not depend on the complexity of the task assigned to the mobile device.

Let's assume that the environmental space T_n (x_n, y_n, z_n). For a given space, the task of determining the point clouds that characterise the objects located in the given area can be solved in two ways: the first is by directly calculating the point clouds in the entire space T_n and the second is by dividing the space into parts $T_{n/m}$, where m characterizes the share into which the space is divided (in this case, the calculation of the point clouds is carried out separately in each part). The division into parts and division options are set by the user and can look like this, for example:

– into two parts – $T_{n/2}(x_{n/2}, y_n, z_n)$ or $T_{n/2}(x_n, y_n, z_{n/2})$;

– into three parts – $T_{n/3}(x_{n/3}, y_n, z_n)$ or $T_{n/3}(x_n, y_n, z_{n/3})$;

– into six parts – $T_{n/6}(x_{n/3}, y_n, z_{n/2})$ or $T_{n/6}(x_{n/2}, y_n, z_{n/3})$;

– into nine parts – $T_{n/9}(x_{n/3}, y_n, z_{n/3})$.

This division is set by the user taking into account the possible complexity of the "contour" of the surrounding space and the available computing power. That is, the task of determining the need for division (or its expediency) should be determined by the nature of the objects in the scanning area T_n (x_n, y_n, z_n) and the degree of complexity of calculating the parts m.

So, in the final result, using the methods and algorithms of SLAM and DATMO, the mobile object system, when using limited hardware and software capabilities, should produce a convenient model of the environment for further processing.

2 REVIEW OF THE LITERATURE

The work [1] presents a description of the system operation method intended for simultaneous localization and mapping, as well as detection and tracking of objects moving in dynamic environments. It is known that for more accurate localization and mapping, it is necessary to carry out a detailed reconstruction of the surrounding environment.

All approaches to creating three-dimensional modeling ("reconstruction") are of two types: passive and active. Passives do not affect the object to be reconstructed, unlike actives. In work [2], two approaches to the reconstruction of a three-dimensional model are distinguished.

The first approach. Three-dimensional scanning, which refers to active types of reconstruction and is carried out using special scanners. This method is characterized by high accuracy and does not depend on weather conditions, but it also has disadvantages, such as expensive and hard-to-find equipment, as well as a large amount of time needed to develop the model. These problems can be solved by reducing the quality of the original 3D model for simple objects that do not have clear requirements for detail and the difference in quality will not be very noticeable.

The second approach. Photogrammetric approach, which belongs to the passive type. It consists of determining characteristic points on a series of images and comparing information about them with the points that are as similar as possible according to the vector of parameters. The approach is characterized by the ability to reconstruct complex objects of any level of complexity without the use of special equipment, but it requires a lot of time and depends on weather conditions. Reducing the influence of the number of provided reference images and weather conditions on the quality of the original 3D model can be achieved by using the stereoscopic parallax algorithm and stereo images.

Active methods [3] of obtaining a mathematical description of an object include any methods that emit

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any waves. Such methods include obtaining object characteristics using PMD-cameras, lasers, echo sounders, etc.

The principle of operation of PMD-cameras is based on ToF measurements, i.e. the measurement of the time it takes for light to move from the camera to the object and back after reflection from the object to a special light-sensitive matrix. The distance can be calculated from the equation for an ideal camera.

The article [4] compares distance determination methods using a PMD-camera and stereo vision. Possible deviations of the distance depending on the angle of inclination of the cameras are indicated. In conclusion, the distance is determined more accurately by the PMD-camera, the disadvantages are the low resolution of the PMD-camera, which leads to a lower quality of information compared to stereo vision, therefore, for the purposes of surface reconstruction, the use of both methods would be desirable.

The work [5] is devoted to the combination of active and passive methods of determining object coordinates, that is, the use of both PMD-cameras and stereo vision.

In [6], it is proposed to use a combination of a PMD-camera with a high-resolution RGB camera to improve the quality of object visualization. The accuracy of using PMD-cameras is considered, but the accuracy of the resulting combination is not specified.

The authors of [7] conduct a comparison of different ToF cameras, based on the distance determination error, depending on the installation angle, as well as the quality of the averaged frames at each distance.

The application of the laser is described in detail in the works [8, 9] for the composition of spectral portraits of objects, use for navigation of a mobile robot and for 3D modeling of an object when using a system of four cameras, respectively. The use of lasers is associated with the high accuracy of determining the points of the object's surface, but this leads to a significant increase in the price of the system for finding coordinates, modeling and visualization of objects.

3 MATERIALS AND METHODS

At the moment, there are many different SLAM algorithms, which differ both in the type of input information, the representation of the surrounding space in the form of a map, and in the methods of processing this information. The work [10] presents the classification of localization algorithms according to the dimension of the fixed space:

– two-dimensional localization on the plane (2D-SLAM);

– three-dimensional localization in space (3D-SLAM);

– color localization by R, G, B image components (RGB-D SLAM);

– color three-dimensional localization in space (6D-SLAM).

These characteristics depend directly on the type of sensor used. For example, when using simple laser rangefinders, the input information about the surrounding space is a set of grid maps, accordingly, 2D-SLAM is used for processing. In the presence of an additional scanning axis, a set of spatial points can be obtained, which gives a representation of the objects of the room taking into account their relative location in space, so 3D-SLAM can be applied here. Color localization algorithms evaluate the state of the robot based on the image from the color video camera installed on it. 6D-SLAM algorithms are used when using sensors that allow obtaining a three-dimensional color image of objects for the purpose of localization and map construction. It should be noted that the vast majority of localization algorithms on the plane can be extended to three-dimensional space.

An important feature of SLAM is that most of the algorithms can be implemented only in a static environment, that is, the room or area where the robot is located should not change.

The 2D-SLAM algorithm is used, as a rule, in application of laser rangefinders. But when processing the received data, especially in the presence of dynamic objects, it is also necessary to take into account the probability of their position changing [11]:

$$p(z_{t,n} \mid c_{t,n}, x_t, m) = \left[\prod_{k=0}^{z_{t,n}-1} (1 - m_{f(x_t,n,k)})\right]^{\zeta_{t,n}} \times$$
$$\times \left[[m_{f(x_t,n,z_{t,n})}]^{c_{t,n}} \times [1 - m_{f(x_t,n,z_{t,n})}]^{(1-c_{t,n})} \times \right.$$
$$\left. \times \prod_{k=0}^{z_{t,n}-1} (1 - m_{f(x_t,n,k)}) \right]^{(1-\zeta_{t,n})}.$$

The first term in this equation determines the probability that the distance specified by the beam is the maximum scan range. In such a situation, the probability is calculated as the product of the probabilities that the beam covered the region from 0 to $z_{t,n-1}$.The second term of the equation indicates what to do in the case when the maximum range of the beam is not displayed. If $z_{t,n}$ is not reflected by a dynamic object, i.e. $c_{t,n}$=1, then the probability is equal to $m_{f(x,n,k)}$. If, on the contrary, $z_{t,n}$ is reflected by a dynamic object, then probability takes value is $1 - m_{f(x,n,k)}$.

The built model, when using this approach, should take into account the probability of the appearance of false measurements when building the map.

Using the 3D-SLAM algorithm has a number of advantages:

– the complete vector of the position and orientation of the mobile robot in space is known;

– measurement data obtained from the sensors do not depend on the shape of the surface on which the object is moving;

– 3D reconstruction of the room in which the moving object is located is possible.

The disadvantages of this type of algorithms include the limited speed of model building, which is associated with a large flow of information from sensors and the

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need to process it. This problem can be partially solved using such algorithms as ICP, 3D-NDT, ML-NDT.

As in the two-dimensional version, the ICP algorithm is based on finding pairs of matching points between the current and reference scans.

The ICP algorithm [13] can be conditionally divided into four stages.

The first stage is finding the matching closest pair τ_j for the point s_i, such that

$$S(\tau)=\left\|\tau_j - s_i\right\|_2,$$

$$(\tau) = \underset{s_i\in S,\, \tau_j\in T}{\arg\min}\ S(\tau).$$

The second stage is calculating the displacement vector t and the rotation matrix R, which deliver the minimum functionality

$$J(R,t) = \sum_{i=1}^{N}\left\|(Rs_i + t) - \tau_i\right\|_2^2,$$

$$(R,t) = \underset{R\in SO(3),\, t\in R^3}{\arg\min}\ J(R,t).$$

The third stage is converting the block of transforming point cloud using the found rotation matrix of the displacement vector into a new point cloud

$$S_i = RS_i + t.$$

The fourth stage is repeating the entire iterative process of the algorithm until $J(R,t) \ge \varepsilon$, where the transforming point cloud is the point cloud obtained at the previous stage.

One of the main problems of this algorithm is the limited area of convergence: the algorithm works only under the condition that the point clouds are not significantly shifted from each other.

3D-NDT is an algorithm for three-dimensional transformation of normal distributions. The main difference between the 3D-NDT algorithm and the two-dimensional algorithm is the type of coordinate transformation functions $T(p, x)$ and its partial derivatives [14]. A general rotation in 3D is more complicated. A robust 3D rotation representation requires both an axis and an angle. A simple way to represent a general 3D transformation is to use seven parameters – three parameters for displacement, three for the rotation axis, and one for the rotation angle. Using a right-handed coordinate system and counterclockwise rotation, the 3D transformation of a point x by a parameter vector p can be formulated as

$$T_7(p,x) = \begin{bmatrix} er_x^2 + c & er_xr_y - sr_z & er_xr_z + sr_y \\ er_xr_y + sr_z & er_y^2 + c & er_yr_z - sr_x \\ er_xr_z - sr_z & er_yr_z + sr_x & er_z^2 + c \end{bmatrix} x + \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix}.$$

$$p = [\ t \mid r \mid \phi\ ],$$

$$t = [\ t_x, t_y, t_z\ ],$$

$$r = [\ r_x, r_y, r_z\ ],$$

$$s = \sin\phi,\ c = \cos\phi,\ e = 1 - \cos\phi.$$

In the 3D-NDT algorithm, the correct choice of cell size is very important. If the cell is too large, many other details will not be taken into account and the localization accuracy will decrease; if a very small cell is selected, it will be described quite clearly, but for the convergence of the algorithm, it is necessary to choose an initial approximation close to the real position, which cannot always be implemented. The optimal size of the cell depends on the shape and size of the room in which the moving object is located. Therefore, a structure for storing cells with normal distributions with adaptive spaces discretization, depending on the detail of the scanned areas, is needed. The work [14] presents several options for solving this problem, namely: the use of an octal tree to divide spaces into octants, additive distribution, iterative distribution, as well as the use of connected cells and cells with infinite boundaries.

ML-NDT algorithm is an extension of 3D-NDT that improves convergence speed and long-distance measurement [15]. This effect is achieved due to the automatic assignment of the cell size for each reference scan. This approach was presented as an eight-cylinder tree model, but the mathematical expectation vector and covariance matrix of each cell is stored in all layers if it contains 5 or more points. The essence of this method consists in the sequential comparison of first general forms, then more detailed and, finally, small features of the object.

In addition, a different description of the matching functions of the scan and NDT maps is presented than in the original algorithm, using the Newton and Levenberg-Marquardt iterative optimization method. The identified main drawback of the algorithm is the expansion of the necessary memory for storing layers. During experimental verification, it was found that the convergence speed increased by an order of magnitude compared to the original 3D-NDT algorithm.

Works [16, 17] present one of the methods of implementing the color localization system based on the R, G, B components of the image – RGB-D SLAM. The work algorithm is presented in the following steps:

– extracting the SURF function from current input color images [12];

– comparing the obtained functions with the functions of previous images – obtaining characteristic points;

– evaluating image depth at the locations of characteristic points (obtaining 3D correspondence points between two frames);

– estimating the relative transformation between frames using RANSAC;

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– improving the initial estimate using the ICP algorithm [13];

– optimizing the resulting position graph.

As a result, a global consistent model of the environment is obtained, which is presented in the form of a colored point cloud.

Input information for 6D-SLAM is typically 3D laser range finder data and locations obtained using an EKF that measure odometry and metrics such as: yaw, pitch, roll, acceleration, roll rates [18].

When measuring, it is advisable to use equipment that allows you to obtain data while the robot is moving. But it is more convenient for the calculation to use a laser with a rotating profile, which requires a static 3D measurement (the robot does not move during the measurement). The initial trajectories and the 3D data associated with various positions from that trajectory are the input data for the iterative data logging component. So six registration algorithms are available:

– ICP with parallel implementation of NNS nearest neighbor procedure.

– ICP – implementation of PCL;

– ICP indicates a projection with parallel NNS;

– Semantic ICP with parallel division of points into four classes (plane, edge, floor/ground, ceiling);

– LS3D is the smallest surface area that coincides with the parallel computation of the surface representation;

– NDT – implementation of PCL.

4 EXPERIMENTS

The goal set in the work is complicated by the fact that mobile devices used indoors to capture the surrounding space use optical systems that are sensitive to the level of illumination, which increases the ambiguity of detailing the construction of a 3D model of the surrounding environment.

The research was carried out in a laboratory room with optimal filling of the space with objects of varying perceptual complexity by an optical device. The laboratory room made it possible to change the intensity of illumination of the surfaces.

A mobile object with an optical system attached to it was used during the research. The experiment was conducted at different mounting heights (from 40 to 100 cm), as well as at different tilt angles (from –30° to 40°) of the optical system.

Since it was necessary to use low-powered systems for the task at hand, i.e. the use of algorithms and methods that require minimal hardware and software resources, two systems were used:

1) a platform based on an Intel Core 2 Duo E6400 processor with a video core based on NVIDIA GeForce GT220M (1Gb), 4 Gb RAM;

2) a platform based on an Intel(R) Core(TM) i5-9300H processor with a video core based on NVIDIA GeForce GTX 1650 (4Gb), 8 Gb RAM.

5 RESULTS

The purpose of the research was to expand the capabilities of existing 2D SLAM methods to perform 3D probabilistic SLAM. The main specificity consists in supplementing the existing stages with the stages of data segmentation and scanning compliance analysis. The scanned data of the three-dimensional range is presented in the form of individual three-dimensional point clouds, which are correlated with the location of the scanning device.

The results of one of the calculations are presented in Fig. 1 and Fig. 2.

When creating the environmental model, the results of object fixation were analyzed, which were pre-ordered according to the distance from the object of movement to the object of fixation. Fig. 1 shows the results of creating a 3D model of individual elements. Fig. 1a, 1c, 1e show the results of data processing by the first computing platform. Fig. 1b, 1d, 1f show the results of data processing by the second computing platform.

Fig. 2 presents the results of data processing for all fixation components with their combination into a single 3D model. Fig. 2a shows the model built using the first computing platform, Fig. 2b – using the second computing platform.

A further study of the results showed that as the distance at which an object is fixed increases, the detail of its 3D reconstruction decreases. However, more emphasis is placed on the contours of the object. Therefore, when building a generalized model, it is advisable to use the results of calculations of individual objects with their subsequent combination. This approach will allow not only to automatically localize the mobile device in space, but also, if necessary, to analyze in more detail the objects near which it is located. This is necessary for a correct analysis of the current situation, especially for confined spaces.

The analysis of the results of the work of the first and second computing platforms (described in section 4) showed that there are no significant differences that would later influence the model creation process. The main difference lies in the time required to process the database and create point cloud. According to this indicator, the first platform spends almost three times more time processing these data sets. The total data processing time on both platforms depends on two factors:

– how many objects are located on the analyzed territory and their overall dimensions;

– how detailed a 3D model of the surrounding space needs to be built.

The algorithm for recreating the surrounding space is proposed to be implemented in three stages:

– initial – small elements that are near the mobile object are recreated;

– intermediate – combining small elements into a 3D model of the space near the mobile object;

– generalized – combining all intermediate objects into a generalized scheme/system.

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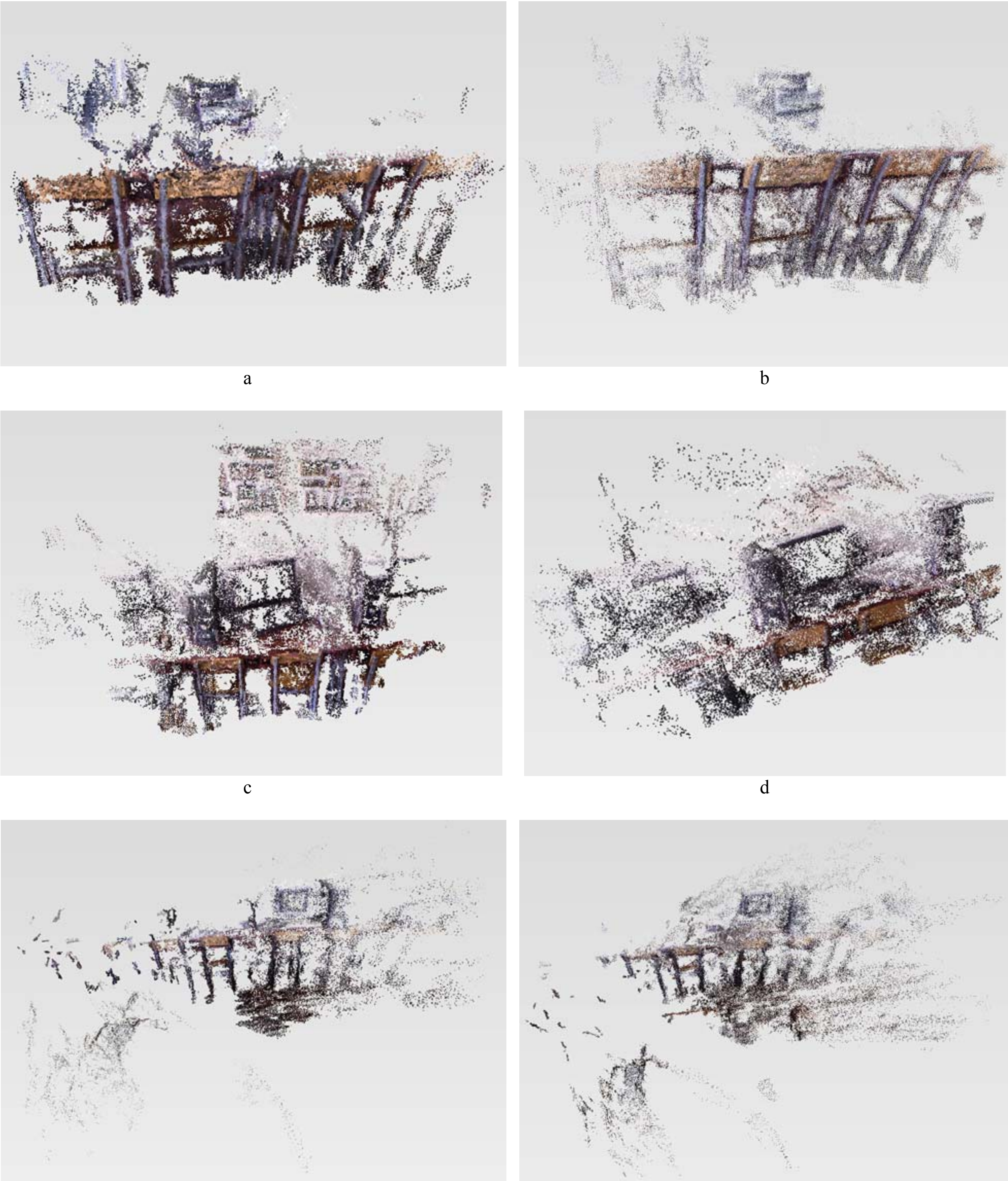

Figure 1 – The result of the initial stage of creating a 3D model of a separate object:
a, c, e – the result of data processing by the first computing platform;
b, d, f – the result of data processing by the second computing platform

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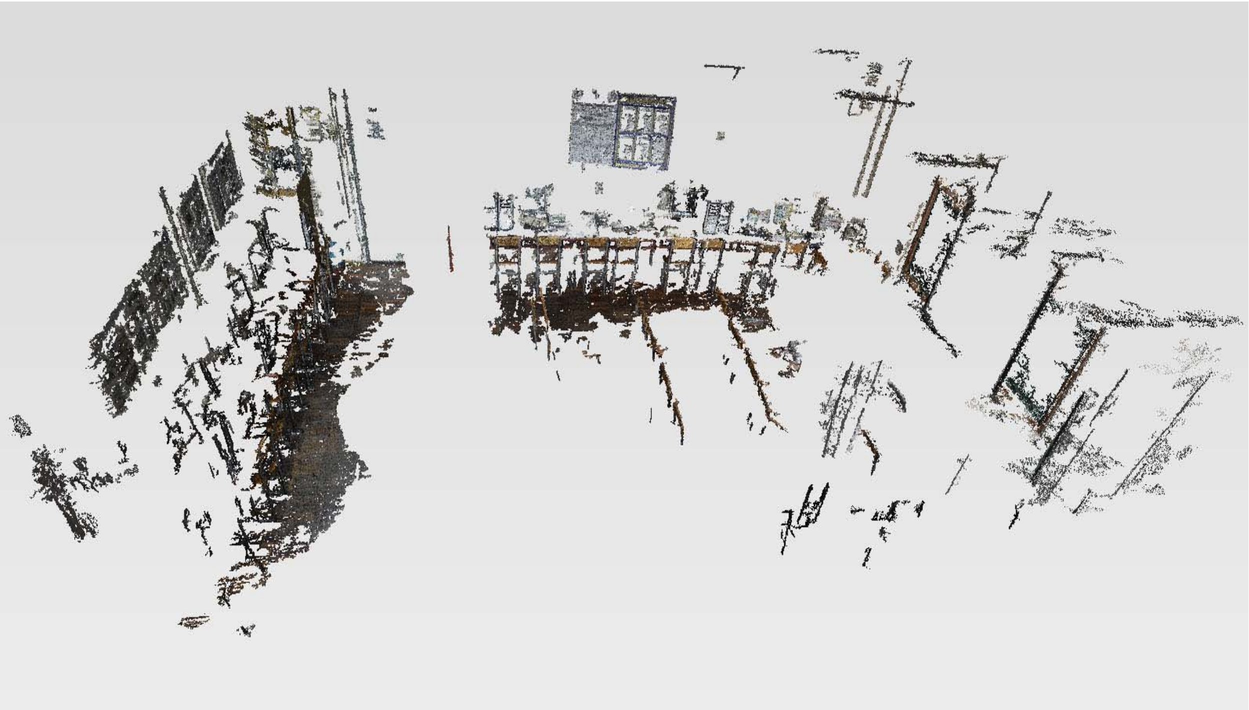
a



b

Figure 2 – The result of the intermediate stage of creating a generalized 3D model of the surrounding space:
a – the result of data processing by the first computing platform;
b – the result of data processing by the second computing platform

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This approach will make it possible to obtain not only a generalized result of object localization, but also, if necessary, more detailed information about a separate small element of space. The difference in the results of data processing at these stages lies in the details. That is, at the initial stage, we receive more detailed information about small objects, but there is no general information about the position of the mobile object. At the generalized stage, generalized information about individual elements of the surrounding space is obtained, but there is information for accurate localization of the mobile object.

6 DISCUSSION

The results show that when the position of the scanning device changes, that is, a new 3D point cloud is formed and fixed at that position, odometry provides mutually exclusive transformations between them. The intermediate transformations can then be used to augment the delayed-state EKF with additional degrees of freedom. After each state change, successive point clouds can be registered together, using the odometry as an initial estimate, using a 6 degrees of freedom registration algorithm. High-precision transformations can later be used to update the EKF state.

It is recommended to use an integrity check to determine the coincidence of scans approaching false local minima. This factor is especially important when the initial estimates of the transformation are erroneous.

To extend the methods described above, integrity check quality metrics have been added to the registration process itself. This step can deepen the convergence volume reading to the desired convergence properties.

CONCLUSIONS

The urgent task of determining the optimal method and algorithm for building a mathematical 3D model of the surrounding space for automatic localization of a mobile object in space is solved.

The scientific novelty of the obtained results is that a method of three-stage construction of a 3D model of the surrounding space is proposed to solve the problem of localization of a mobile object in a closed space. This method will make it possible to direct information flows about the object's position from different devices, depending on the type of data acquisition, into a centralized information base for solving a wide range of tasks performed by automatic mobile objects (robots). Combining information flows will allow creating a centralized information base, which will not only position the mobile object in space, but also allow mapping and localization on the terrain with great accuracy.

The practical significance of the obtained results is that the proposed method of building a mathematical model of the environment for determining the position of a mobile object in space allows, regardless of the complexity of the task set before the mobile device and the use of limited hardware and software capabilities, to ultimately produce an easy-to-process model of the environment.

Prospects for further research lie in studying the proposed method to extend the capabilities of existing 2D SLAM methods to perform 3D probabilistic SLAM.

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МЕТОДИ ТА АЛГОРИТМИ ПОБУДОВИ МАТЕМАТИЧНОЇ 3D-МОДЕЛІ НАВКОЛИШНЬОГО ПРОСТОРУ ДЛЯ АВТОМАТИЧНОЇ ЛОКАЛІЗАЦІЇ МОБІЛЬНОГО ОБ'ЄКТА

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АНОТАЦІЯ

Актуальність. Розглянуто задачу автоматизації позиціонування мобільного об'єкта в замкненому просторі при умові його часткової або повної автономності. Об'єктом дослідження є процес автоматичної побудови 3D-моделі навколишнього простору.

Мета роботи – розробка методу створення 3D моделі навколишнього простору для подальшої локалізації мобільного об'єкта в умовах його часткової або повної автономності.

Метод. Приведено результати дослідження проблеми локалізації мобільного об'єкта в просторі в реальному часі. Приведено результати аналізу існуючих методів та алгоритмів створення математичних моделей навколишнього простору. Описані алгоритми, які широко використовуються для вирішення проблеми локалізації мобільного об'єкта в просторі. Проведено дослідження широкого спектру методів побудови математичної моделі навколишнього простору – від методів, які використовують співставлення послідовних хмарин точок об'єкта навколишнього простору до методів, які використовують серії знімків характеристичних точок та порівнянні інформації про них на різних знімках в точках, максимально схожих за вектором параметрів.

Результати. Запропоновано метод трьохетапної побудови 3D моделі навколишнього простору для вирішення задачі локалізації мобільного об'єкта в замкненому просторі.

Висновки. Проведені експерименти підтвердили можливість запропонованого алгоритму трьохетапної побудови математичної моделі навколишнього середовища для визначення положення мобільного об'єкта у просторі. Методи, які використовуються в алгоритмі дозволяють отримати інформацію про навколишній простір, що дозволяє провести локалізацію мобільного об'єкту в замкненому просторі. Перспективи подальших досліджень можуть полягати в інтеграції інформаційних потоків про положення об'єкта з різних, за типом отримання даних, приладів в централізовану інформаційну базу для вирішення широкого спектру задач, які виконують автоматичні мобільні об'єкти (роботи).

КЛЮЧОВІ СЛОВА: математична 3D-модель, метод локалізації, алгоритми методу SLAM, визначення положення, мобільний об'єкт.

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