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INTEGRATED SYSTEM SIMULTANEUS LOCALIZATION AND MAPPING

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Abstract**—***In this paper, we consider the solution of the problem of simultaneous localization and the construction of a map for an unmanned aerial vehicle (a quadrocopter). The structure of the integrated navigation system is developed on the basis of the fusion of several sources of navigational information, which allows to compensate the shortcomings of each source, which includes the following blocks: an improved system of visual navigation based on the use of EKF-SLAM, satellite navigation system GPS, barometric altimeter, radio altimeter, Strapdown inertial navigation system, the converter of modes of navigation. To improve the quality of the visual navigation system, an improved EKF-SLAM algorithm is proposed with the adaptation of the surveillance zone and local data association based on the improved ants algorithm, thereby avoiding obstacles. Recognition of landmarks is based on the use of the algorithm SURF. The EKF-SLAM algorithm is integrated through Adaptive Observation Range. Algorithms for dynamically changing the size of the observation zone and determining the redundancy of the detected landmarks are proposed. The extended Kalman filtering procedure for the problem under consideration and the proposed improvements are given. It is shown that the problem of SLAM data association can be represented as an optimization problem. As an optimization algorithm, an ant algorithm is proposed.*

Index Terms—Extended Kalman filter; simultaneous localization and mapping; integrated navigation system; strapdown inertial navigation system; landmarks.

I. INTRODUCTION

Currently, robotics has become a well-developed industry: thousands of robots working in different companies of the world, underwater manipulators have become an indispensable accessory of underwater research and rescue vehicles, space study is based on extensive use of robots with different levels of intelligence. Particular attention is paid to the automation of heavy, hazardous, tedious and monotonous work in various fields with the help of robot manipulators.

One of the main functions that an autonomous mobile robot should have is the ability to accurately determine the parameters of your own location and build maps of the terrain. It is necessary at each moment to know the location of the robot and the map of that part of the surrounding space that was available for observation from the initial moment of time to the current one. Since there is no a priori information about the position of the robot in space, its location is logical to represent in the system of local coordinates associated with its initial position. The requirements for the constructed map can be very diverse. At the same time, the main one is the ability of the robot to navigate it. Without this, the calculation of the location and the construction of the map will be carried out independently, which will lead to a continuous increase in the error. Other requirements can be: accessibility for human perception, support for large spaces, etc.

II. PROBLEM STATEMENT

A. The Localization Model

Suppose we have a mobile robot in an environment which contains beacons-points in the environment with a known exact location and which (once acquired) the robot can calculate its distance and direction from. Further suppose that after initialization the robot cannot assume to know its exact location or orientation; due to inaccuracies of the actuators it must attempt to extrapolate this information from the beacons. Our robot could theoretically navigate such an environment without too much difficulty even if the robot's actuators were not completely accurate.

Imagine that the robot starts in some known location, x_0, and has knowledge of a set P containing several feature locations. The world is exactly as our robot perceives it because the robot's (noisy) sensors have not been needed yet. When the robot attempts to move a given distance in a certain direction (i.e. the movement vector u_1) to location x_1, it will actually move along some other vector to some location which is nearby x_1. The beacons need to be relocated to determine the new robot pose. If the actuators were completely accurate the beacons could be reacquired by assuming they have moved inversely to u_1. Because the actuators are imprecise, however, the robot must search for the beacons. The search is facilitated by beginning near the expected location of the beacon and expanding outward. Fig. 2 presents the situation so far:

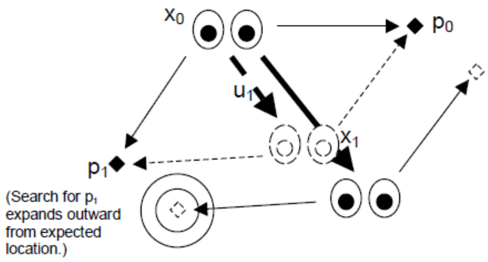

Fig. 1. Stage of localization. ⟶ is the actual movement; ▬▶ is the predicted movement; ⟶ is the actual observation; - - -▶ is the predicted observation; ◆ is the actual feature position; ◇ is the predicted feature position

Notice that x_1 as well as the movement vectors correspond to estimates rather than ground truth. Once the beacons are reacquired, a new robot location estimate, x_2, can be made, as shown in Fig. 2.

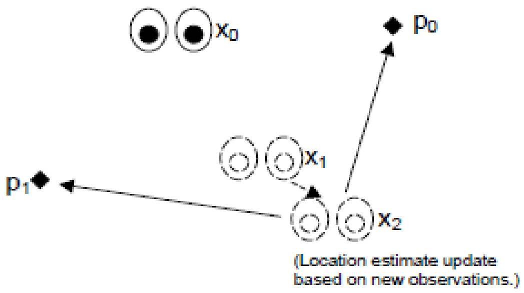

Fig. 2. New assessment of the robot's location: ⟶ is the position update vector; - - -▶ is the observation; ◆ is the feature position

Over time, the estimate of the robot pose will never diverge because the beacon locations are fixed and known absolutely; the robot pose is always calculated from the same correct data. We use beacons rather than features in this example simply because we would be more likely to know the absolute location of beacons than naturally occurring features. Note that the situation would be essentially the same if the agent began with an accurate feature map rather than beacons. The only difference would be that the agent would need to reacquire features from camera images rather than simply finding beacons.

B. The Mapping Model

Mapping, in a sense, is the opposite of the situation described above. In mapping, we assume the agent knows exactly where it is at all times – that is, we assume we either have perfect motion sensors, or an error free Global Positioning System (GPS). What the agent lacks in the mapping context is a way of knowing the absolute location of features. Notice that in contrast to localization, the agent does not begin with an accurate world view; the agent can locate features to build a map, $z_0 = \{z_{00}, z_{01} \dots z_{0n}\}$ where z_{ij} is read, "the jth feature estimate at time step i". Of course, z_0 will only contain approximations of the actual feature locations. When the agent moves, however, the map can generally be made more accurate [7].

III. OVERVIEW OF EXISTING SOLUTIONS

At the moment, in the absence of a universal solution, the simultaneous localization and mapping (SLAM) problem is solved using combinations of the above sensors and software for these sensors. Since the sensors do not always provide accurate measurements and are prone to accumuate errors over time, the robot's position estimate may differ significantly from its actual position. To overcome this disadvantage, most algorithms that implement SLAM use the following approaches: advanced Kalman filter, particle filter or SLAM on graphs.

Extended Kalman Filter (EKF). It is based on the Kalman filter – a recursive filter that estimates the state vector of a dynamic system and uses a number of incomplete, inaccurate measurements. The main disadvantage of this approach is the quadratic dependence of the complexity of the algorithm on the number of observed landmarks [8].

Particle Filter. One of the brightest representatives of methods based on particle filters is the Monte Carlo method (Monte Carlo Localization). This method is used to localize the robot in space and operates with collections of images, also known as "particles." Advantage is the logarithmic complexity.

Simultaneous localization and mapping on the graphs. This method uses the representation of the map as a sparse graph. The nodes of this graph are the locations of the robot on the map and the points of the map obtained with the range finders, and the edges are the links between the relative positions of the robot on the map and the map elements that are observed from these positions. Such an approach has less accuracy in constructing a map than previous approaches.

IV. PROBLEM SOLUTION

Each of the algorithms described above require something as input that is generally unavailable in practice. A localization algorithm outputs the robot pose but requires accurate feature locations (i.e. a map) as input every time the algorithm iterates. Conversely, a mapping algorithm generates a map but needs an undated pose as input. The fact that the (usually unavailable) input of each process is the output of the other suggests that the two problems are related, and could perhaps be combined into a single solution; it seems that if both processes are utilized together there is some hope for robot navigation without either an a-priori map or accurate GPS/odometry.

Suppose a robot starts from some known origin. First of all it constructs a preliminary map, then moves to a new location and updates its expected location. Finally the of the integrated EKF-SLAM algorithm is shown in Fig. 4.

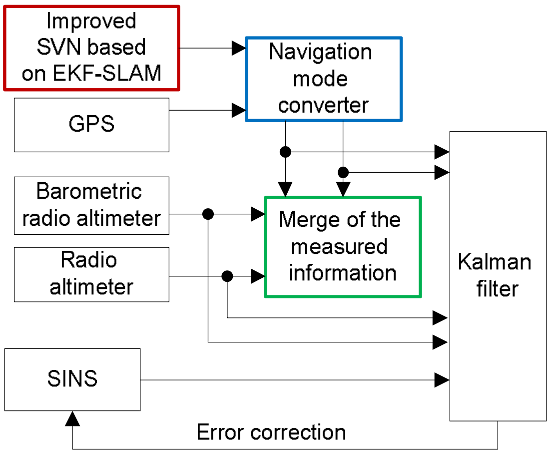

Fig. 4. The scheme of the AR-SLAM-EKF algorithm

The structure of the improved algorithm is shown in Fig. 5.

The essence of the algorithm consists in using a local circular map (instead of the usual rectangular map) for the current estimation of the coordinates of the apparatus and localization of the zone of the used landmarks in the global coordinate system, with the simultaneous updating of the global map. The principle of localization of the monitoring zone is shown in Fig. 6.

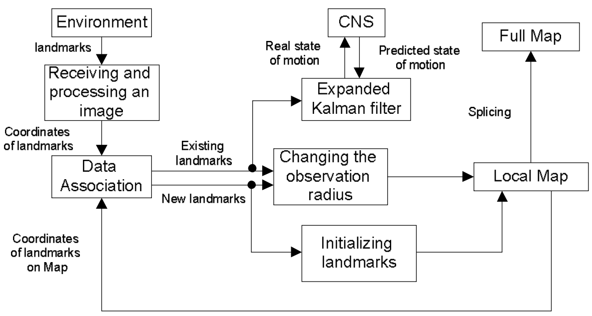

Fig. 5. The structure of the improved algorithm

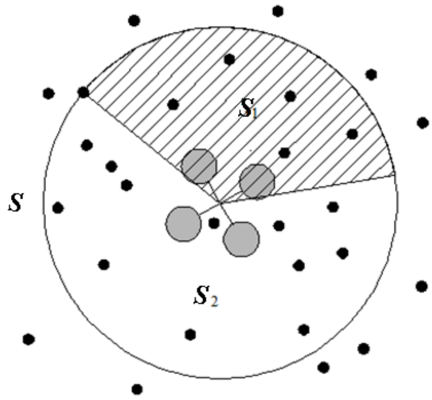

Fig. 6. Circular local map and range of observation: S is the circular local map; S_1 is the range of observation; S_2 is the additional range; black dots are landmarks

If you do not change the radius of the local map, the following problems are possible:

1) In a medium with rare reference points, the number of observed landmarks in the region S_1 may be too small, even equal to zero, because of which it is impossible to refine the positioning, i.e. the prediction error will continue to accumulate.

2) In a multi-reference environment, the number of landmarks in the S region may be too large, many of these landmarks will be redundant for positioning the robot, which will increase the dimensionality of the state vector and affect the computational speed.

3) If the observation range is too large, then the reliability of observing distant landmarks is reduced, which will affect the positioning accuracy of the robot.

To solve these problems, the EKF-SLAM algorithm is proposed with the adaptation of the observation area depending on the state of the flow of incoming reference points. If the number of reference points Num in the observable region S_1 is less than the number of reference points $Num_{\min}$ ($Num < Num_{\min}$) that is minimally necessary for reliable correction of the predicted state vector, and the observation radius R is less than the maximum radius $R_{\max}$ of reliable observation ($R < R_{\max}$), then it is proposed to increase the radius local map. If the number of landmarks is larger than the maximum number of $Num_{\max}$ landmarks, which allows to avoid excessive redundancy of the correction ($Num > Num_{\max}$), or the observation radius is greater than the maximum radius of reliable observation ($R > R_{\max}$), it is proposed to reduce the radius of the local map. When the number of reference points is $Num_{\min} \le Num \le Num_{\max}$ and $R < R_{\max}$, the radius of the local map remains unchanged. The corresponding transition diagram is shown in Fig. 7.

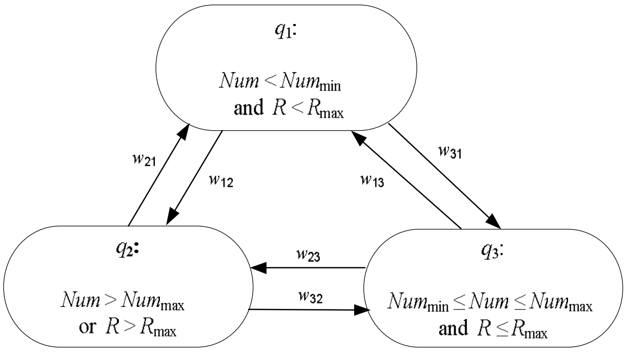

Fig. 7. Diagram of changing the radius of the local map

The set of change states for the radius of the local map $Q=\{q_1,q_2,q_3\}$, where q_1 is the increase in radius; q_2 is the decrease in radius; q_3 is the preserving the radius. The set of discrete events corresponding to the set Q, $W=\{w_{12},w_{13},w_{21},w_{22},$ $w_{31},w_{42}\}$, where w_{mn} is the switching from m to n; $m,n\in[1,2,3]$.

Algorithm of local association of SLAM data on the basis of an improved ant algorithm, implemented in two stages. At the first stage of the algorithm, we determine the reference points in the coincidence space and the observed reference points, which have the possibility of association by the criterion of individual compatibility (IC). At the second stage, coincident reference points and coordinates of coinciding observed landmarks on the set of states are determined using an improved ant algorithm.

V. RESULTS

The efficiency of the algorithm was verified by simulating unmanned aerial vehicles (UAV) flight on a square route with a side of 10 m (Fig. 8.) in a two-dimensional map. On the map, the red solid line represents the route, 88 discrete red dots represent landmarks that are evenly distributed inside and outside the route. Measuring parameters of airborne sensors: the error in measuring the angle of 0.125 radians, the error in measuring the coordinates of 0.01m, the maximum reliable distance for measurements of 3m, the angular range of measurements [-90°, 90°].

In Figure 8 blue dots represent the real positions of the UAV; blue ellipses represent covariance ellipses of landmarks and UAVs, that is – uncertainties of positions of landmarks and UAVs; the blue line represents the real trajectory of UAV flight.

Figure 9 shows that the ICOACP algorithm converges and the error and spread of orientation and localization are not large enough.

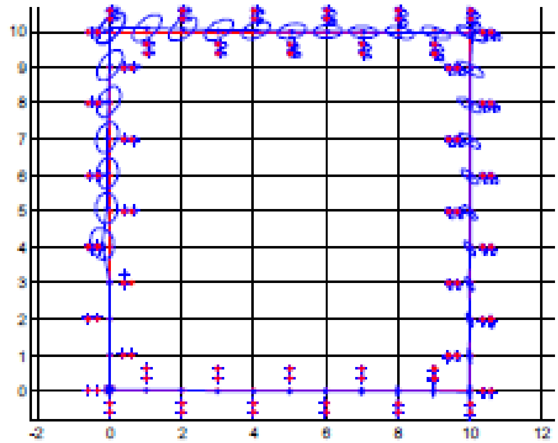

Fig. 8. Results of simulation of UAV flight trajectories using the data association algorithm

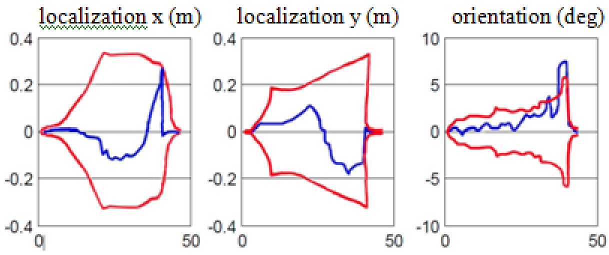

Fig. 9. Error (blue lines) and covariance (red lines) of the orientation and localization of the UAV in the x and y directions using the data association ICOACP algorithm

VI. CONCLUSIONS

The software of navigation system for UAV was developed on the basis of the improved EKF-SLAM algorithm with an adaptive observation range and a local data association, which allows to increase computational speed and navigation accuracy.

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В. М. Синєглазов, М. С. Писарюга. Інтегрована система одночасної локалізації і відображення

Розглянуто вирішення проблеми одночасної локалізації та побудови карти для безпілотного літального апарату (квадрокоптера). На основі комплексування декількох джерел навігаційної інформації розроблено структуру інтегрованої навігаційної системи, що дозволяє компенсувати недоліки кожного джерела, які містять у собі такі блоки: вдосконалену систему візуальної навігації, засновану на використанні EKF-SLAM, супутникову навігаційну систему глобального позиціонування, барометричний альтиметр, радіовисотомір, інерціальну навігаційну систему Strapdown, перетворювач режимів навігації. Для поліпшення якості візуальної навігаційної системи запропоновано вдосконалений алгоритм EKF-SLAM з адаптацією зони спостереження та локальною асоціацією даних. Розпізнавання орієнтирів базується на використанні алгоритму SURF. Алгоритм EKF-SLAM інтегровано через адаптивний діапазон спостереження. Запропоновано алгоритми для динамічної зміни розмірів зони спостереження та визначення надмірності виявлених орієнтирів. Запропоновано процедуру фільтрації Калмана для розглянутої проблеми та запропоновані вдосконалення. Показано, що проблему асоціації даних SLAM можна представити як задачу оптимізації.

Ключові слова: розширений фільтр Калмана; одночасна локалізація та відображення; інтегрована навігаційна система; інерціальна навігаційна система Strapdown; орієнтири.

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В. М. Синеглазов, М. С. Писарюга. Интегрированная система одновременной локализации и отображения
Рассмотрено решение задачи об одновременной локализации и построении карты беспилотного летательного аппарата (квадрокоптера). Структура интегрированной навигационной системы разработана на основе комплексирования нескольких источников навигационной информации, что позволяет компенсировать недостатки каждого источника, которая включает в себя следующие блоки: усовершенствованную систему визуальной навигации на основе использования EKF-SLAM, спутниковую навигационную систему глобального позиционирования, барометрический высотомер, радиовысотомер, инерциальную навигационную систему с обтеканием, конвертер режимов навигации. Для улучшения качества визуальной навигационной системы предложен усовершенствованный алгоритм EKF-SLAM с адаптацией зоны наблюдения и локальной ассоциацией данных. Распознавание ориентиров основано на использовании алгоритма SURF. Алгоритм EKF-SLAM интегрирован через адаптивные зоны наблюдения. Предложены алгоритмы динамического изменения размера зоны наблюдения и определения избыточности обнаруженных ориентиров. Дана расширенная процедура фильтрации Кальмана для рассматриваемой проблемы и предложены улучшения. Показано, что проблема объединения данных SLAM может быть представлена как проблема оптимизации.
Ключевые слова: расширенный фильтр Калмана; одновременная локализация и отображение; интегрированная навигационная система; инерциальная навигационная система Strapdown; ориентиры.

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