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O. Ivaniuk

Ukrainian State University of Railway Transport, Kharkiv

NAVIGATION OF AUTONOMOUS SYSTEMS BASED ON SITUATION CONTROL WITH DYNAMIC REPLANNING

The solution to the problem of autonomous mobile systems navigation is a complex task, traditionally presented in the form of solving the sequence of subtasks: perception of information about the environment, localization and mapping, path planning, and motion control. A large number of scientific works are devoted to the solution of the listed subtasks. However, existing research does not pay enough attention to the integration of individual elements of the navigation cycle solutions into a single homogeneous system. This leads to an additional accumulation of errors in the process of a complex solution to the navigation problem. In previous works, a model was proposed that provides homogeneous integration, using for this a multi-level structure of representing an autonomous system's knowledge in the form of sets of fuzzy rules and facts. The five-level model represents the autonomous system's knowledge of goals, paths, an environment map, strategies, and specific controls necessary to achieve the goal. To ensure adequate processing of fuzzy rules, a modified Takagi-Sugeno-Kang fuzzy inference model is proposed. In this work, the previously proposed model is expanded. The model was tested in conditions of noisy sensor data. A method is proposed for the formation of level 2 rules, which describe an autonomous system's cartographic knowledge about the environment, using the well-known methods of global path planning. Extension of the model provides dynamic paths replanning of the autonomous system, using the processing of present knowledge about existing paths. Such replanning is effective in terms of computational time and independent of the completeness of the knowledge base of complete paths.

Keywords: *navigation, autonomous systems, situational control, dynamic replanning.*

Introduction

The purpose of mobile robotics at the cognitive level is solve the navigation problem. Navigation of an autonomous mobile system can occur with different initial knowledge about the environment. There are the following situations can be distinguished: 1) the environment is known and does not change over time (known static environment) 2) the environment is known, but can be changed – obstacles can accidentally arise in the path (known dynamic environment) 3) the environment is unknown and unchanged (unknown static environment) 4) the environment is unknown and can change (unknown dynamic environment).

Navigation of an autonomous system can have different purposes: 1) achievement of the target position (start-to-goal navigation); 2) coverage by the trajectory of the entire plane of the map (coverage navigation); 3) exploration of the environment; 4) patrolling.

In work [1], the navigation process of an autonomous robot is generally presented and described in form as a cycle (Fig. 1).

As shown in Fig. 1, the navigation process has the following components: perception of information about the environment, localization and mapping, path planning (sometimes called motion planning), and motion control.

Perception of information about the environment is the task of reading, processing, summarizing, and interpreting data obtained from the sensor systems of the robot.

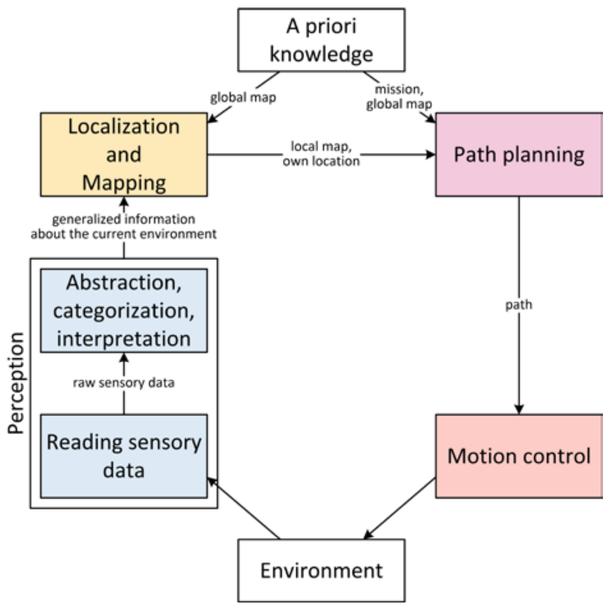


Fig. 1. The process of navigation of a single autonomous mobile robot (adapted from [1])

Localization and mapping are two interrelated tasks that link objects to an environment map (known in a priopi or self-constructed). The most important case of localization – self-localization – is the determination by an autonomous system its own position in the environment. The role of localization and mapping in the navigation cycle can be different, depending on the amount of a priori knowledge and the type of available sensory data. There are some possible situations:

1) There may be no need for mapping, and localization is greatly simplified when the environment is known in a priory and available access to the global coordinate system (GCS), such as a GPS satellite navigation system, using sensor systems.

2) In the case of a fully known environment and the absence of access to GCS, the task of self-localization plays a key role.

3) In a situation of an unknown environment and available access to the GCS, the task of mapping arises. In this case, the problem is simplified and solved by algorithms of sensory data noise suppression. To solve the problem, sensory systems based on lasers, lidars, and sonar are used.

4) In the case when the environment map is completely unknown, and access to the GCS is absent, the autonomous system is faced with the task of simultaneous construction of the environment map and self-localization on it (SLAM – simultaneous localization and mapping) [2]. In such conditions, the mapping can be a self-goal, i.e. the research problem is solved without a specific goal position for movement. The task of SLAM is complex because it involves the accumulation of errors in the process of movement, due to the limited sensor systems accuracy. To solve it, various techniques are used, most of which are based on noise suppression, for example, Kalman filtration and particle filtration [3–5].

Path planning is the task of constructing the optimal, according to a certain criterion, path for the autonomous system from the start position to the goal. Depending on the amount of priory knowledge, there are global and local path planning are distinguished. Global path planning is possible in situations with a known environment. The task of local path planning is solved in cases of an unknown environment, using sensor-based data.

Motion control is a task that is to ensure the passage of the path without deviations, providing control of the speed and direction of movement of the autonomous system. To solve the problem, control systems with different controllers are used (PID controller and its variants [6], fuzzy controllers [7–9], neural network controllers [10], model predictive control [11]). Of particular importance is motion control for nonholonomic systems [1]. Many works are devoted to the study of ways of solving the above tasks, but not enough attention is paid to the issues of ensuring the functioning of mobile systems in an autonomous mode, taking into account the fuzzy and incomplete data about the environment. Functioning in such conditions leads to the need to use knowledge about the path in motion control and to replanning the path based on the situation that is formed on the basis of data from the robot sensors.

This paper aim is an integrated model of autonomous system's navigation that combines a model of situational control and a model of dynamic replanning of the path.

Statement of basic materials

Study of a navigation model based on situation control with a pre-prepared plan. To solve this problem, the navigation model of an autonomous mobile system based on knowledge stratification is used as a basic one [12]. Based on this model, it is proposed to integrate solutions of path planning, robot localization, and situational control tasks into a single system with a homogenous model for representing knowledge about the path, motion control, and the situation in the environment. The levels obtained as a result of stratification correspond to the knowledge of goals, paths, an environment map, strategies, and specific controls necessary to achieve the goal (Fig. 2). It is proposed to represent knowledge of each specific level in the form of sets of facts and rules.

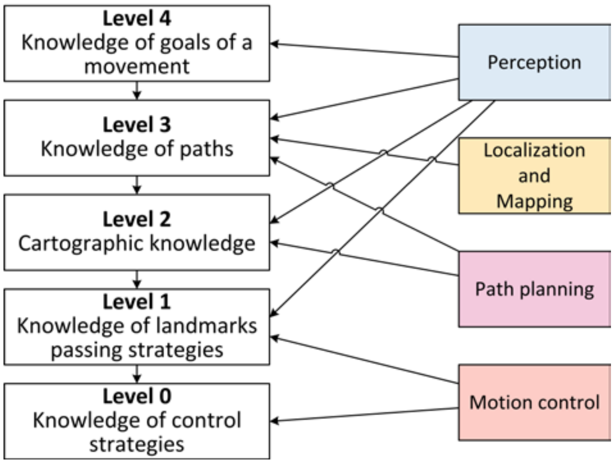


Fig. 2. Knowledge stratification of an autonomous system corresponding to the structure of the knowledge base

The facts are formed on the basis of the data perceived by the sensors of the autonomous system with subsequent processing by the abstraction mechanism. The facts have a fuzzy characteristic that shows how the content of the verbal representation of the situation (prototype) corresponds to a specific set of data from the sensors of the autonomous system. The fuzzy characteristic is a fuzzy LR-number with a Gaussian membership function. Based on the fuzzy characteristics, the confidence factor (cf) is determined [12–13].

The rules have common structure, corresponding to the modified Takagi-Sugeno-Kang (TSK) model [12]:

$$\begin{aligned} R_i^l \quad & IF\ event(f_i^l)\ and \\ & CF\_{}^{sat} f_i^l\ is\ high\ and \\ & CF\_{}^{sat} f_j^{l+1}\ is\ high \\ & THEN\ cf\_{}^{sat} f_k^l = 1, \\ & cf\_{}^{sat} f_i^l = -1, \\ & [cf\_{}^{sat} f_j^{l+1} = -1]. \end{aligned} \quad (1)$$

where l – level of abstraction;

f_i^l – i-th fact of l-th level;

$cf\_f_i^l$ – confidence factor of fact f_i^l;

${}^{sat}f_i^l$ – fact-satellite of fact f_i^l, that expresses the measure of expectation of fact f_i^l appearance;

$CF\_f_i^l$ – name of a linguistic variable that fuzzy represents the numerical value of the confidence factor cf of fact f_i^l using three terms (high, low, zero).

The above rule is activated by an event $event(f_i^l)$ that is generated by the appearance of data from sensors about features of i-th landmark (LM) of the path, provided that the current subgoal of movement is achieved, as evidenced by the activity of the satellite of this fact $CF\_{}^{sat}f_i^l$ *is high*. A condition $CF\_{}^{sat}f_j^{l+1}$ *is high* in the rule indicates the current subgoal of the $l+1$-th level and associates this rule with the current context (the rule represents the phase of the current top-level plan). When activated, the rule changes the subgoal of l-th level after reaching the actual subgoal of this level and optionally (when the last subgoal of l-th level is reached) deactivates the subgoal of $l+1$-th level $[cf\_{}^{sat}f_j^{l+1}=-1]$ [12].

For each of the levels shown in Fig. 2, the general form of the rule has been adapted.

Modification of the TSK model is as follows:

1) A rule in the ***IF*** field can have a term $event(f_i^l)$. This means that the rule is used by the TSK inference mechanism if the event occurs: the confidence factor $cf\_f_i^l$ of the fact f_i^l at the current step of processing take the value $cf\_f_i^l > \varepsilon$, and in the previous step this condition was not fulfilled. When at the current step no event occurs with the fact f_i^l, the rule is not used in processing by the TSK mechanism.

2) If the fact-satellite ${}^{sat}f_i^l$ is activated $cf\_{}^{sat}f_i^l > \varepsilon$ (the current goal is activated), then the context mechanism pays more attention to identification of the event $event(f_i^l)$. This is realized by reducing the threshold ε in the event condition: $cf\_f_i^l > \varepsilon - \Delta$, where Δ is an experimentally selected constant [12].

For example, for the particular case considered in [12], the level of the model corresponds to knowledge about the strategies of landmarks passing is represented by a set of rules:

R_1^{1-2} *IF* $event(f_{Line})$ *and*
$CF\_{}^{sat}f_{Line\_out}$ *is high and*
$CF\_f_{Moving\_mark}$ *is high*
THEN $cf\_{}^{sat}f_{Line\_out}=-1,$
$cf\_{}^{sat}f_{U\_Moving\_mark}=1,$
$cf\_{}^{sat}f_{Line\_in}=1;$

R_2^{1-2} *IF* $event(f_{Line})$ *and*
$CF\_{}^{sat}f_{Line\_out}$ *is high and*
$CF\_f_{Moving\_dist}$ *is high*
THEN $cf\_{}^{sat}f_{Line\_out}=-1,$
$cf\_{}^{sat}f_{U\_Moving\_dist}=1,$
$cf\_{}^{sat}f_{Line\_in}=1;$

R_3^{1-2} *IF* $event(f_{Line})$ *and*
$CF\_{}^{sat}f_{Line\_out}$ *is high and*
$CF\_f_{Moving\_azim}$ *is high*
THEN $cf\_{}^{sat}f_{Line\_out}=-1,$
$cf\_{}^{sat}f_{U\_Moving\_azim}=1,$
$cf\_{}^{sat}f_{Line\_in}=1.$

In the rules, the fact f_{Line} corresponds to the reaching of a start-stop line by an autonomous system; facts-satellites ${}^{sat}f_{Line\_out}$, ${}^{sat}f_{Line\_in}$ corresponds to expectation of reaching an exit and an entry start-stop line, respectively; facts f_{Moving_mark}, f_{Moving_dist}, f_{Moving_azim} corresponds to the type of motion control (by marking, by distance to the obstacle, by azimuth); facts-satellites ${}^{sat}f_{U\_Moving\_mark}$, ${}^{sat}f_{U\_Moving\_dist}$, ${}^{sat}f_{U\_Moving\_azim}$ corresponds to launching an appropriate motion control strategy.

In Fig. 3 for the given rules, the example of a conclusion for a model situation is presented. Let us assume that $cf\_f_{Line} > \varepsilon$, which means that all three rules are used in processing. As shown in Fig. 3, the values of confidence factors of the facts, corresponding to the type of motion control, that need to be applied for the successful passing of landmark, differ (data noise is modeled). Based on the initial data, preference is given to the fact-satellite, which corresponds to the launch of the motion control strategy based on the distance to the obstacle.

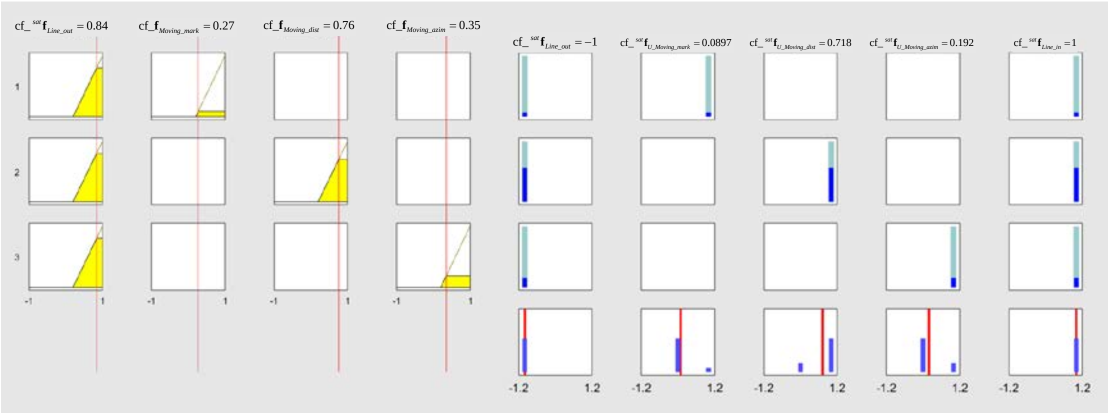
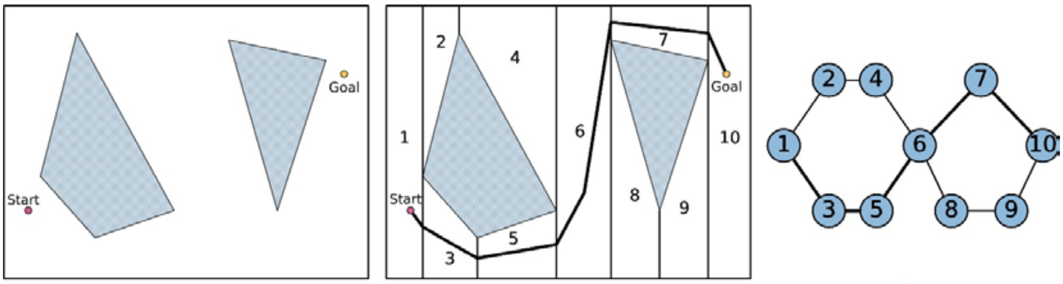


Fig. 3. Inference on the TSK model

Cartographic knowledge plays a key role in solving the problem of path planning. When the environment map is a priory known, planning a global path is considered. For this, various methods of global path planning are used, in particular: Voronoi diagrams, visibility graphs, artificial potential fields, cell decomposition, etc. [2]. A significant part of these methods, on the basis of a known environment map, builds a graph of possible paths of movement (roadmap), to which search algorithms can be applied to determine the optimal path for a certain criterion.

In Fig. 4 shows an example of applying the vertical cell decomposition algorithm to a map of an artificial environment and the resulting graph of possible paths of movement (roadmap).



a b c

Fig. 4. An example of the vertical cell decomposition algorithm: a – the initial map of the environment; b – decomposition of the environment into cells (the path from the start point to the goal position, obtained using breadth-first search is shown); c – graph of possible paths of movement

The graph of possible paths of movement in the proposed model is represented as a set of *n* fuzzy rules. General form of such cartographic knowledge in the form of rules:

$$R_p^{map} \quad IF\ CF\_f_{LM_i}\ is\ high\ and$$
$$CF\_{}^{sat}f_{LM_j}\ is\ high$$
$$THEN\ cf\_{}^{sat}f_{Out\_dir} = 1;$$
$$p = 1, 2, ..., n;\ \ i = 1, 2, ..., m;\ \ j = 1, 2, ..., k.$$

In the ***IF*** field, the rule contains an indication to a landmark LM_i (in the form of fact f_{LM_i}) and another landmark LM_j (in the form of fact- satellite ${}^{sat}f_{LM_j}$), with which the landmark LM_i is directly related. Such a rule can be activated only if the linguistic variables (CF) corresponding to both facts, describing their confidence factors, take values *high*. So, the facts placed in the ***IF*** field describe an edge on the graph of possible paths of movement, and the totality of all pairs of facts from the ***IF*** fields of the set of cartographic rules is an exclusive list of edges of the graph of possible paths of movement.

The ***THEN*** field contains an indication of the type of the exit path linking LM_i to LM_j (in the form of fact- satellite ${}^{sat}f_{Out\_dir}$). This fact-satellite characterizes the direction of movement, for example, in the case of movement along a rectangular maze, it can take values from the set {*north*, *east*, *south*, *west*}, and in a more general case, the degree measure of deviation according to a certain (global or local coordinate system). If the rule is activated, the confidence factor of the satellite fact is given a positive value (indicated by +1), the value of which is determined on the basis of fuzzy inference on the modified TSK model.

Navigation based on situational control with dynamic path replanning. Earlier, a model of situational control of the movements of an autonomous system along a path was considered. This path must remain unchanged for the entire time until the goal position is reached. Obstacles in the process of movement and a lack of information about the state of the environment lead to the fact that the goal position along a given path cannot always be reached. This requires a dynamic replanning of a fragment of the path for achieving the goal from the current situation (the position of the autonomous vehicle and the state of the environment). The idea of situational control with dynamic replanning [14–15] regarding the task of navigation of an autonomous system is considered on the basis of the following conceptual model. The situation S_i is considered as an elementary unit, which is defined on a certain set of features. Situations are required to be distinguishable in pairs according to a certain criterion. From the point of view of control theory, a situation is a separate state in the state space, and all possible states define many different situations $\mathcal{S} = \{S_i\}$. Transitions between different states reflect transitions from one situation to another.

In fig. 5 is shown an example of a state space in the form of a graph, where each vertex is a separate situation. Situation S_1 is the start, S_{11} is the goal.

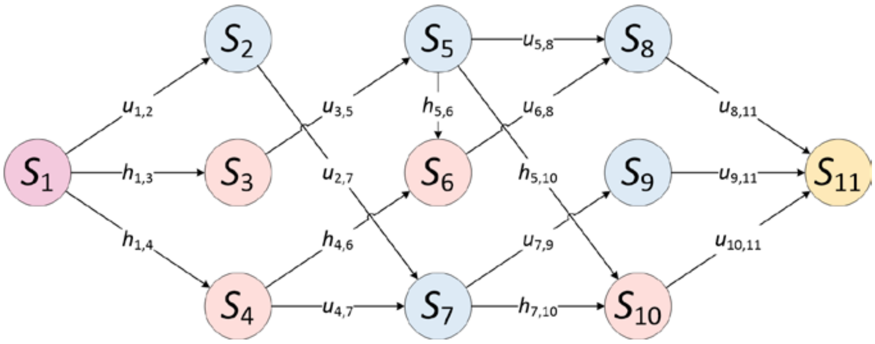


Fig. 5. Граф ситуаційної мережі

The transition from situation S_i to situation S_j is carried out by applying appropriate control $u_{i,j}$ or due to the influence of interference $h_{i,j}$. Let the previously created path provide for such a sequence of situations $(S_1, S_2, S_7, S_9, S_{11})$, however, when the autonomous system was supposed to be in a situation S_7 according to the plan, the appearance of an obstacle led to the autonomous system being in a situation S_{10}; no preliminary plan for achieving the goal S_{11} from the situation S_{10} was provided. In this case, the autonomous system, based on knowledge about the environment, must perform replanning of the fragment of the path (S_{10}, S_{11}).

The paper proposes to introduce the following mechanisms into the situational control model based on a previously prepared plan [12], which was discussed above:

1. A model is introduced to represent the path in the form of a sequence of facts-satellites of facts describing the LM through which the path passes.:

$$({}^{sat_1} f_i^l, {}^{sat_2} f_g^l, {}^{sat_3} f_d^l, \ldots, {}^{sat_N} f_v^l). \qquad (2)$$

For this, a set of statuses is introduced in which facts-satellites can be, namely ${}^{sat_k} f_i^l$, where k – the status identifier of the fact-satellite ${}^{sat} f_i^l$. For the first LM in the path, the status of the fact-satellite is indicated $k = 1$, for second LM is $k = 2$ etc. For the goal LM status of its satellite is $k = N$, where N is the length of the path in LM.

Let us assume that situations are shown in Fig. 5 are described by facts f_i^l, which are formed on the basis of sensory data of the autonomous system, then the path $(S_1, S_2, S_7, S_9, S_{11})$ will be represented by a sequence of facts-satellites: $({}^{sat_1} f_1, {}^{sat_2} f_2, {}^{sat_3} f_7, {}^{sat_4} f_9, {}^{sat_5} f_{11})$, and a fragment of the path (S_{10}, S_{11}) will be represented as $({}^{sat_1} f_{10}, {}^{sat_2} f_{11})$.

2. Because of the response time to a situation is critical for autonomous systems, it is impossible to check the remaining part of the plan to achieve the goal at each step of the movement when making control decisions. This operation is shifted to algorithms for processing sensory data, which form the values of the confidence factors cf of facts f_i^l in (1). A situation tracking mechanism based on data from sensors switches the fact-satellite, which describes the characteristics of the LM's passage, into a certain status, for example, for a situation where passage is impossible $k = -1$. This status of the satellite when performing the recalculation of the confidence factor of the fact-satellite that is the first in the current fragment of the plan, gives a value that indicates $cf < 0$. In this case, the mechanism of replanning of a fragment of the path is started.

3. Replanning of a fragment of a path is a conditional concatenation of chains of type (2) representing knowledge about possible connections between land-

marks in the environment. The operation of conditional concatenation takes into account the effect of interference on environmental situations and the availability of information about the current situation. The key role in the reduced computations that must be performed in real-time during replanning is played by the mechanism of switching the statuses of the facts-satellites.

4. The situational control mechanism remains the same as in the navigation model based on a pre-prepared plan. Its integration with the replanning mechanism is performed using the plan presentation model (2). The knowledge about the paths (the third level in Fig. 2), which is used by the situational control mechanism, is specified by rules of the type [12]:

$$
\begin{aligned}
R^4_{j,p}\quad & IF\ event(f_{LM\,j,p})\ and \\
& CF\_^{sat} f_{LM\,j,p}\ is\ high\ and \\
& CF\_^{sat} f_{Route_j}\ is\ high \\
& THEN\ cf\_^{sat} f_{Route_j} = -1, \\
& cf\_^{sat} f_{LM\,j,p} = -1, \\
& cf\_^{sat} f_{Start_1} = 1, \ldots, cf\_^{sat} f_{Start_{n\_s}} = 1; \\
i = 1,2,\ldots,p;\ & j = 1,2,\ldots,n\_r.
\end{aligned} \tag{3}
$$

In this rule instead of the term $CF\_^{sat} f_{Route_j}\ is\ high$, that specifying the path, the first element of the current plan is used (2), namely $CF\_^{sat1} f_j\ is\ high$. In addition to these advantages in reducing computing resources, the proposed approach does not require the storage of all current paths and the autonomy of the system does not depend on the completeness of the knowledge base of complete paths.

Conclusions

This paper modified the navigation model of an autonomous system based on situational control. The possibilities of situational control in conditions of incomplete and fuzzy information are expanded due to:

– the modified Takagi-Sugeno-Kang model for calculating confidence factors characterizing the current control decision for the current situation;

– the model of dynamic replanning of the path of movement of the autonomous system, taking into account the current situation;

– integration of situational control models and dynamic replanning of the path on the basis of a single multi-level structure of knowledge.

The proposed model provides a reduction in computation time, which is necessary for real-time navigation and expands the situations in which the requirement for the autonomous functioning of the mobile system is fulfilled.

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Відомості про автора:

Іванюк Олександр Ігорович
аспірант
Українського державного університету
залізничного транспорту,
Харків, Україна
https://orcid.org/0000-0002-4007-2215

Information about the author:

Oleksandr Ivaniuk
Doctoral Student
of Ukrainian State University
of Railway Transport,
Kharkiv, Ukraine
https://orcid.org/0000-0002-4007-2215

НАВІГАЦІЯ АВТОНОМНИХ СИСТЕМ НА ОСНОВІ СИТУАЦІЙНОГО УПРАВЛІННЯ З ДИНАМІЧНИМ ПЕРЕПЛАНУВАННЯМ МАРШРУТУ

О.І. Іванюк

Розв'язання проблеми навігації автономних мобільних систем є комплексною задачею, що традиційно представляється у вигляді вирішення послідовності завдань: сприйняття інформації про оточення, локалізація та побудова карти оточення, побудова маршруту руху, управління рухом. Вирішенню перелічених завдань присвячена велика кількість наукових робіт. Однак, існуючі дослідження недостатньо уваги приділяють інтеграції рішень окремих елементів навігаційного циклу в єдину однорідну систему. Це зумовлює додаткове накопичення помилки в ході комплексного розв'язання проблеми навігації. В попередніх роботах запропоновано модель, що забезпечує однорідну *інтеграцію, використовуючи для цього багаторівневу структуру представлення знань автономної системи у вигляді наборів нечітких правил та фактів. П'ятирівнева модель представляє знання автономної системи про цілі, маршрути переміщення, карту оточення, стратегію і конкретні керівні впливи, необхідні для досягнення цілі. Для забезпечення адекватної обробки нечітких правил запропоновано модифіковану модель нечіткого виводу Такагі-Сугено-Канга. В даній роботі виконано розширення раніше запропонованої моделі. Виконано перевірку роботи моделі в умовах зашумлення сенсорних даних. Запропоновано спосіб формування правил рівня 2, що описують картографічні знання автономної системи про оточення, використовуючи відомі методи побудови глобальних маршрутів руху. Розширення моделі забезпечує динамічне перепланування маршруту руху автономної системи, використовуючи обробку наявних знань про існуючі маршрути. Таке перепланування є ефективним за показником часу обчислень та незалежним від повноти бази знань.*

Ключові слова: *навігація, автономні системи, ситуаційне управління, динамічне перепланування.*

НАВИГАЦИЯ АВТОНОМНЫХ СИСТЕМ НА ОСНОВЕ СИТУАЦИОННОГО УПРАВЛЕНИЯ С ДИНАМИЧЕСКИМ ПЕРЕПЛАНИРОВАНИЕМ МАРШРУТА

А.И. Иванюк

Решение проблемы навигации автономных мобильных систем является комплексной задачей, которая традиционно представляется в виде решения последовательности подзадач: восприятие информации об окружении, локализация и построение карты окружения, построение маршрута движения, управление движением. Решению перечисленных задач посвящено большое количество научных работ. Однако, существующие исследования недостаточно внимания уделяют интеграции решений отдельных элементов навигационного цикла в единую однородную систему. Это обуславливает дополнительное накопление ошибки в ходе комплексного решения проблемы навигации. В предыдущих работах предложена модель, которая обеспечивает однородную интеграцию, используя для этого многоуровневую структуру представления знаний автономной системы в виде наборов нечетких правил и фактов. Пятиуровневая модель представляет знания автономной системы о целях, маршрутах перемещения, карте окружения, стратегиях и конкретных управляющих воздействиях, необходимых для достижения цели. Для обеспечения адекватной обработки нечетких правил предложено модифицированную модель нечеткого вывода Такаги-Сугено-Канга. В данной работе выполнено расширение ранее предложенной модели. Выполнена проверка работы модели в условиях зашумления сенсорных данных. Предложен способ формирования правил уровня 2, описывающие картографические знания автономной системы об окружении, используя известные методы построения глобальных маршрутов движения. Расширение модели обеспечивает динамическое перепланирование маршрута движения автономной системы, используя обработку имеющихся знаний о существующих маршрутах. Такое перепланирование является эффективным по показателю времени вычислений и независимым от полноты базы знаний.

Ключевые слова: *навигация, автономные системы, ситуационное управление, динамическое перепланирование.*