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A LOGICAL-LINGUISTIC ROUTING METHOD FOR UNMANNED VEHICLES WITH THE MINIMUM PROBABILITY OF ACCIDENTS[1]

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Abstract. Forming optimal motion control laws for unmanned vehicles (UVs) by analyzing sensory data about the choice environment is an integral part of designing their situational control systems. The weakly predictable variability of the UV operating environment and the imperfection of measuring means reduce the possibility of obtaining comprehensive information about the environment state. Therefore, routing to minimize travel time and the probability of an accident is performed under uncertainty. An effective way to solve this problem is using logical-probabilistic and logical-linguistic models and algorithms. This paper is intended to develop new optimal routing methods for UVs with estimating the probability of an accident based on the logical-linguistic classification of route segments. For this purpose, the rows of parameters and characteristics of reference route segments are created and compared with the logical-probabilistic and logical-linguistic parameters and characteristics of classified route segments considering their significance for routing. After processing sensory and statistical data, the proposed logical-probabilistic and logical-linguistic methods are used to estimate the probabilities of accidents and minimize a performance criterion. As a consequence, the accuracy and speed of optimal routing for UVs are both increased. The results of this research can be used in the central nervous system of intelligent robots to classify route segments obtained by analyzing sensory and statistical data, which will improve the quality of motion control in an uncertain environment.

Keywords: optimization, control laws, the probability of an accident, sensory and statistical data, the attributes of reference route segments, logical-probabilistic and logical-linguistic analysis and classification.

INTRODUCTION

The development of unmanned vehicles (UVs), including unmanned aerial vehicles (UAVs), has recently become in high demand [1, 2]. The R&D works on UVs are determined by the following key problems:

1) extending the duration of autonomous operation;

2) improving navigation systems;

3) increasing payload;

4) raising the degree of autonomy based on artificial intelligence.

The fourth problem has recently been associated mainly with using neural network technologies [3–7].

Among their significant drawbacks, note the controversial problems of choosing a sufficient learning sample without overtraining the neural network and the problem of covering as many choice situations in decision-making as possible [8]. In addition, when forming control principles and algorithms, researchers and engineers consider information security problems for UVs [9] but often neglect motion safety issues of optimal routing [10, 11]. However, the prevention of accidents is the main operating principle of motion control systems for UVs and other robotic devices capable of moving in an automatic mode [12]. To implement this principle, it is necessary to develop algo-

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rithms for estimating the probability of an accident on a route and select the safest route under the existing constraints. Moreover, when solving the motion control problem, it is necessary to consider additional complexities due to the coordination of all motion participants: each participant must satisfy the corresponding kinematic equations and the existing state-space constraints, including dynamic constraints [13, 14] to minimize the probability of collision and related risks.

Risk assessments are predictive in nature since their uncertainty is associated with many factors that cannot be accurately estimated. The uncertainty of predictable risks causes situations reducing the probability of UV's accident-free motion along a route.

Qualitative and quantitative methods [15–17] are used to assess risks under uncertainty. The qualitative approach consists in determining all possible types of accident risks on a route and identifying their areas of occurrence and sources [18]. Further, this approach can serve for obtaining quantitative risk assessments. The quantitative approach allows calculating the value of individual risks on route segments and the entire route [19, 20]. Note that methods of probability theory and mathematical statistics are often used. In this case, it is necessary to study scenarios that simulate and analyze the simultaneous consistent change of all factors on route segments considering their interdependence. The conditions of implementing UV control algorithms are described by an expert through scenarios (e.g., pessimistic, optimistic, and most probable ones) or a system of constraints on the main parameters of the route and the corresponding indicators characterizing the probability of an accident.

This approach involves expert assessments obtained by complex procedures [21], starting with the selection of the number and qualification levels of experts. The results of the multi-step procedure are processed by statistics and qualitative analysis methods. Regression and correlation analysis tools are used for comprehensive risk analysis, and methods of the logical-probabilistic approach are employed for detailing and analyzing structurally complex routes [22].

In risk prediction under limited statistical data, it is reasonable to create a database of reference route segments that contains their qualitative attributes and quantitative expert assessments (the values of their membership functions and the values of their significance factors), as proposed in the logical-linguistic classification [23]. Within the scenario approach, which uses fuzzy set methods to calculate the values of the membership functions, it is then possible to rank the set of admissible routes by comparing a given route with the reference routes from the database [24]. In this case, the probability of an accident on reference route segments can be estimated by simulating UV's motion under uncertainty [25] and the available statistical data. Simulation modeling generates hundreds of possible accident combinations. After analyzing the simulation results and statistical data, it is possible to obtain distributions of the probabilities of accidents on reference route segments and give an integral assessment of the control efficiency and intelligence level of the UV [26] after optimal routing. In particular, this approach has been applied to determine the probabilities of accidents on reference route segments when forming the reference database in the proposed logical-linguistic method. The problem is to develop a method for an automatic control system (ACS) to select an optimal route of the vehicle that moves under uncertainty using logical-linguistic classification of route segments to certain reference models with the risk assessments or probabilities of accidents determined previously.

1. THE ROUTES RANKING PROBLEM

When searching for the best combinations of UV's motion control laws, the common problem is to find an optimal control minimizing the performance criterion

$$J_i = k_T T_i + k_R P_i,$$

where: $T_i = t_{if} - t_{i0}$ is the time to transfer the ith UV ($i=1,2,...$) located at the time instant t_0 in an initial point s_i of a bounded space $L^3 \subset E^3$ to a target point f_i of this space by the time instant t_f; E^3 denotes the three-dimensional Euclidean space; k_T is the significance factor of the goal achievement rate, adjusted by an expert or a group of experts; P_i is the estimated probability of an accident involving the ith UV while moving along the route during the time T_i; finally, k_P is the significance factor of the estimated probability of an accident, also adjusted by an expert or a group of experts.

In the proposed ACS, it is first necessary to determine UV's travel time on all possible routes. Under the existing logical-probabilistic, logical-linguistic, and other constraints, to calculate the product $J(R_v) = k_T T_i$ on each UV's route R_v, the ACS should evaluate the functional [3]

$$J(R_v) = k_T \left(\sum_{i,j} a \frac{L_{ij}}{V_{ij}} + \sum_{i,j} b \frac{\Psi_{ij}}{W_{ij}} + \sum_{i,j} c\tau_{i,j} \right), \quad (1)$$

where: a, b, and c are preference coefficients; V_{ij} and W_{ij} are the linear and angular velocities, respectively, which depend on the environment (e.g., air humidity and temperature); τ_{ij} is the delay time at an intersection depending on its type and load; Ψ_{ij} are the turning angles at an intersection; finally, L_{ij} are the lengths of segments between intersections.

As shown in [23], (i,j) is an element of the ordered set describing a given route from the starting point to the terminal point.

After evaluating the functional (1) for all possible UV's routes from point s_i to point f_i, the routes can be ranked by the time of arrival to point f_i. However, the fastest route may also turn out to be the most accident-prone. Therefore, the next step in optimal routing should be ranking of the routes R_v by the probability of an accident, $P_i(R_v)$.

2. THE DATABASE OF REFERENCE ROUTE SEGMENTS

Within the proposed method, when determining the probability of accidents on UV's routes and the product $k_R P_i$, we apply a logical-linguistic classification algorithm of route segments, which attributes a given route segment to a reference one. As shown in [23], this algorithm has high speed and efficiency. For implementing the algorithm, a database of reference route segments is created when developing the ACS for the UV. This database contains rows with the parameters (attributes) of reference route segments and the probabilities of an accident on such segments, determined in advance based on simulation modeling and statistical data. The presence of an attribute is indicated by one and its absence by zero.

Each route contains one or several segments at an intersection and one or several segments between intersections. Therefore, the database includes rows characterizing motion at an intersection and between intersections. Tables 1–8 show an example of reference rows from the database.

2.1. The Database of Reference Rows for Intersections

Table 1

Intersections

Database row	Type of intersection, direction of motion	Probability of accident
C_1 = /10000000000/	┤ with passage to the right	P_{C1} = 0.12
C_2 = /01000000000/	┤ with passage to the left	P_{C2} = 0.15
C_3 = /00100000000/	┬ with passage straight	P_{C3} = 0.13
C_4 = /00010000000/	┬ with passage to the right	P_{C4} = 0.11
C_5 = /00001000000/	┴ with passage straight	P_{C5} = 0.14
C_6 = /00000100000/	┴ with passage to the left	P_{C6} = 0.17
C_7 = /00000010000/	┼ with passage straight	P_{C7} = 0.18
C_8 = /00000001000/	┼ with passage to the right	P_{C8} = 0.16
C_9 = /00000000100/	┼ with passage to the left	P_{C9} = 0.20
C_{10} = /00000000010/	L with passage to the left	P_{C10} = 0.10
C_{11} = /00000000001/	Γ with passage to the right	P_{C11} = 0.09

Table 2

Turning angles

Database row	Angle and direction of turn	Probability of accident
Ψ_1 = /100000000/	–180° (left)	$P_{\Psi 1}$ = 0.11
Ψ_2 = /010000000/	–135° (left)	$P_{\Psi 2}$ = 0.12
Ψ_3 = /001000000/	–90° (left)	$P_{\Psi 3}$ = 0.13
Ψ_4 = /000100000/	–45° (left)	$P_{\Psi 4}$ = 0.14
Ψ_5 = /000010000/	0° (straight)	$P_{\Psi 5}$ = 0.06
Ψ_6 = /000001000/	+45° (right)	$P_{\Psi 6}$ = 0.10
Ψ_7 = /000000100/	+90° (right)	$P_{\Psi 7}$ = 0.09
Ψ_8 = /000000010/	+135° (right)	$P_{\Psi 8}$ = 0.08
Ψ_9 = /000000001/	+180° (right)	$P_{\Psi 9}$ = 0.07

Table 3

Angular velocities

Database row	Angular velocity, deg/s	Probability of accident
W_1 = /1000/	2	P_{W1} = 0.10
W_2 = /0100/	4	P_{W2} = 0.11
W_3 = /0010/	6	P_{W3} = 0.12
W_4 = /0001/	8	P_{W4} = 0.13

Table 4

Number of lanes

Database row	Number of lanes	Probability of accident
S_1 = /1000/	1	$P_{S1} = 0.10$
S_2 = /0100/	2	$P_{S2} = 0.12$
S_3 = /0010/	3	$P_{S3} = 0.13$
S_4 = /0001/	4	$P_{S4} = 0.14$

2.2 The Database of Reference Rows for Route Segments between Intersections

Table 5

Linear velocities

Database row	Linear velocity, m/s	Probability of accident
V_1 = /1000/	5	$P_{V1} = 0.10$
V_2 = /0100/	10	$P_{V2} = 0.11$
V_3 = /0010/	15	$P_{V3} = 0.12$
V_4 = /0001/	20	$P_{V4} = 0.13$

Table 6

Number of lanes

Database row	Number of lanes	Probability of accident
S_1 = /1000/	1	$P_{S1} = 0.10$
S_2 = /0100/	2	$P_{S2} = 0.12$
S_3 = /0010/	3	$P_{S3} = 0.13$
S_4 = /0001/	4	$P_{S4} = 0.14$

Table 7

Time of day

Database row	Time of day	Probability of accident
T_1 = /10000/	0 to 6 hours	$P_{T1} = 0.10$
T_2 = /01000/	6 to 10 hours	$P_{T2} = 0.13$
T_3 = /00100/	10 to 15 hours	$P_{T3} = 0.15$
T_4 = /00010/	15 to 20 hours	$P_{T4} = 0.14$
T_5 = /00001/	20 to 24 hours	$P_{T5} = 0.20$

Table 8

Route segment length

Database row	Route segment length	Probability of accident
L_1 = /10000/	very short, 200 m	$P_{L1} = 0.10$
L_2 = /01000/	short, 400 m	$P_{L2} = 0.12$
L_3 = /00100/	medium, 600 m	$P_{L3} = 0.13$
L_4 = /00010/	large, 800 m	$P_{L4} = 0.14$
L_5 = /00001/	very large, 1000 m	$P_{L5} = 0.15$

3. DETERMINING THE PROBABILITY OF AN ACCIDENT ON A ROUTE

To rank the routes R_v by the probability of an accident $P_i(R_v)$, the ACS of the UV first creates a list of intersections for each route. Next, for each list of intersections, the sensing system of the ACS determines the approximate values of their parameters corresponding to the attributes of the reference rows and fuzzifies these values to find the membership functions for the attributes of the corresponding reference rows. Then the ACS classifies the rows for intersections by comparing them with the reference rows from the database according to the algorithm described in [23]: it assigns values for the probabilities of accidents corresponding to the identified reference rows and calculates the probabilities of accidents at all intersections and the total probability of accidents at intersections along the entire route.

For example, a certain intersection is characterized by the following parameters (attributes): intersection ⊥ with passage straight, 1 lane, turning angle 30º, and angular velocity 5.6 deg/s.

In this case, the row characterizing intersections has the form /00001000000/; classification using the logical-linguistic algorithm [23] attributes it to the reference row C_5 with the probability of an accident P_{C5} = 0.14. The row /1000/ characterizing the number of lanes is classified as the reference row S_1 with the probability of an accident P_{S1} = 0.10. After fuzzification, the row characterizing the turning angle takes the form /0 0 0 0 0 0 0.3 0.7 0 0 0 0/, being classified as the reference row Ψ_6 with the probability of an accident $P_{\Psi 6}$ = 0.10. After fuzzification, the row characterizing the angular velocity takes the form /0 0 0.3 0.7 0/, being classified as the reference row W_3 with the probability of an accident P_{W3} = 0.12.

When passing an intersection, accidents are possible under one of the following events: C_i (i = 1, 2, ...), or Ψ_j (j = 1, 2,...), or W_q (q = 1, 2, ...), or S_g (g = 1, 2, ...). They correspond to the probabilities of an accident P_{Ci}, $P_{\Psi i}$, P_{Wq}, and P_{Sg}, respectively. According to the rules for calculating the probability of a logic function, the logic function $F_{1,2,\ldots,n}$ in the Zhegalkin algebra [27] has the form

$$F_{1,2,\ldots,n} \leftrightarrow f_1 ♀ f_2 ♀ f_3 ♀ \ldots ♀ f_n,$$

where f_1, f_2, f_3, ..., f_n are logical functions or variables (events), ♀ denotes addition modulo 2, and ↔ denotes equivalence. According to the paper [24], the probability of an accident when passing such an intersection (n = 4) is given by

$$P = (-2)^0(P_{Ci} + P_{\Psi j} + P_{Wq} + P_{Sg}) + (-2)^1(P_{Ci}P_{\Psi j} + P_{Ci}P_{Wq} + P_{Ci}P_{Sg} + P_{\Psi j}P_{Wq} + P_{\Psi j}P_{Sg} + P_{Wq}P_{Sg}) + (-2)^2(P_{Ci}P_{\Psi j}P_{Wq} + P_{Ci}P_{\Psi j}P_{Sg} + P_{Ci}P_{Wq}P_{Sg} + P_{\Psi j}P_{Wq}P_{Sg}) + (-2)^3(P_{Ci}P_{\Psi j}P_{Wq}P_{Sg}). \quad (2)$$

For a large number of logical functions ($n > 8$), it is possible to calculate the probability approximately, being restricted to 8–10 row members; for details, see [24]. If there are N intersections on the route, fuzzification, classification, and formula (2) will be used to calculate the probabilities of an accident for each intersection; after that, formula (2) gives the probability of an accident P_N at all intersections of the route.

Then for each route, the ACS of the UV first creates a list of segments between intersections. Next, for each list of segments between intersections, the ACS determines the approximate values of their parameters corresponding to the attributes of the reference rows and fuzzifies these values to find the membership functions for the attributes of the corresponding reference rows. Then the ACS classifies the rows for segments between intersections by comparing them with the reference rows from the database according to the algorithm described in [24]: it assigns values for the probabilities of accidents corresponding to the identified reference rows and calculates the probabilities of accidents on segments between intersections and the total probability of accidents on all segments between intersections along the entire route.

For example, a certain segment between intersections is characterized by the following parameters (attributes): 1 lane, travel time 8 hours, linear velocity 12.7 m/s, length 500 m.

In this case, the row characterizing the number of lanes has the form /1000/, being classified as the reference row S_1 with the probability of an accident $P_{S1} = 0.10$. The row /01000/ characterizing travel time is classified as the reference row T_2 with the probability of an accident $P_{T2} = 0.13$. After fuzzification, the row characterizing the linear velocity takes the form /0 0.45 0.55 0/, being classified as the reference row V_3 with the probability of an accident $P_{V3} = 0.12$. After fuzzification, the row characterizing the segment length takes the form /0 0.5 0.5 0 /, being equally classified as the reference row L_2 with the probability of an accident $P_{L2} = 0.12$ or reference row L_3 with the probability of an accident $P_{L3} = 0.13$. Therefore, the probability of an accident due to the length of the segment between intersections can be estimated by the average value $(P_{L2} + P_{L3})/2 = 0.125$.

When passing a segment between intersections, accidents are possible under one of the following events: T_i ($i = 1, 2, ...$), or V_j ($j = 1, 2,...$), or L_q ($q = 1, 2, ...$), or S_g ($g = 1, 2, ...$). They correspond to the probabilities of an accident P_{Ti}, P_{Vi}, P_{Lq}, and P_{Sg}, respectively. According to [12], the probability of an accident on such a segment ($n = 4$) is given by

$$P = (-2)^0(P_{Ti} + P_{Vj} + P_{Lq} + P_{Sg}) + (-2)^1(P_{Ti}P_{Vj} + P_{Ti}P_{Lq} + P_{Ti}P_{Sg} + P_{Vj}P_{Lq} + P_{Vj}P_{Sg} + P_{Lq}P_{Sg}) + (-2)^2(P_{Ti}P_{Vj}P_{Lq} + P_{Ti}P_{Vj}P_{Sg} + P_{Ti}P_{Lq}P_{Sg} + P_{Vj}P_{Lq}P_{Sg}) + (-2)^3(P_{Ti}P_{Vj}P_{Lq}P_{Sg}). \quad (3)$$

If there are M segments between intersections on the route, fuzzification, classification, and formula (3) will be used to calculate the probabilities of an accident for each segment between intersections; after that, formula (3) gives the probability of an accident P_M on all segments between intersections of the route.

Finally, the probability of an accident on all routes R_v is calculated by the formula

$$P(R_v) = P_N(R_v) + P_M(R_v) - 2P_N(R_v)P_M(R_v).$$

4. RANKING AND OPTIMIZATION OF ROUTES

Due to the uncertain environment of the UV moving on a route, when calculating the performance criterion (1), it is necessary to consider the constraints in the form of logical and probabilistic modulo 2 equations [25]. As shown in [14], these constraints can be reduced to logical-interval ones. In this case, two values of the performance criterion (1), min $J(R_v)$ and max $J(R_v)$, are obtained for each route R_v. For the chosen values of the significance coefficient k_p, we calculate the two values below for each route to rank the routes R_v:

$$\min J_v = \{\min\{k_T J_T(R_v)\} + \min\{k_P P(R_v)\}\}; \quad (6)$$

$$\max J_v = \{\max\{k_T J_T(R_v)\} + \max\{k_P P(R_v)\}\}. \quad (7)$$

Usually, the values $\min\{k_P P(R_v)\}$ and $\max\{k_P P(R_v)\}$ coincide whereas $\min\{k_T J_T(R_v)\}$ and $\max\{k_P P(R_v)\}$ do not. Therefore, the ranking is performed by the minimum and maximum or the average value

$$J_v = 1/2(\max J_v + \min J_v).$$

The choice of an optimal route for the UV may depend on the opinion of an expert or a group of experts.

CONCLUSIONS

When selecting an optimal route for unmanned vehicles, it is necessary to minimize the probability of an accident. For this purpose, various algorithms are developed to assess accident risks at each route planning stage considering the “observed” area of the terrain.

Risk assessments are predictive in nature since their uncertainty is associated with many factors that cannot be accurately estimated. Therefore, when creating a database of reference route segments, the probabilities of an accident on such segments are determined at the ACS design stage based on simulation modeling and statistical data. Under limited statistical data, it is reasonable to predict accident risks using logical-linguistic and logical-probabilistic methods. For this purpose, databases of reference route segments are created, containing the qualitative attributes of segments and the probabilities of an accident obtained after modeling.

When the ACS of the UV determines the probability of an accident on a route, its sensory system obtains the quantitative values of attributes on route segments. After their fuzzification, the ACS finds the values of the membership functions for the specified attributes and creates rows similar to the reference rows of the database. For each route segment, the ACS identifies the closest reference row from the database and assigns to this segment the probability of an accident corresponding to the reference row. Using these probabilities of accidents on route segments, the ACS calculates the probability of accidents on the entire route using appropriate rules (calculating the probability of logical OR functions).

When selecting an optimal route, a trade-off between travel time and the probability of an accident must be observed by minimizing the following performance criterion: the sum of travel time and the probability of an accident, multiplied by given significance factors. These significance factors are adjusted by experts and entered into the ACS database at the formation stage. Usually, the performance criterion has an interval value, so the choice of an optimal route will depend on the expert's preferences.

Along with traditional approaches, the problems under consideration will require artificial intelligence technologies for determining the probabilities of accidents on reference segments. We emphasize that previously, optimal routing problems were considered without the probabilities of accidents.

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