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The Use of Frame-Based Microprograms for Planning the Behavior of an Intelligent Unmanned Aerial Vehicle in an Uncertain Environment

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In the paper we consider a model for the representation and processing of procedural knowledge of an intelligent unmanned aerial vehicle (UAV) that is based on the logic of condition-dependent predicates. Condition-dependent predicate calculus provides logically valid inferences in an arbitrary subject area by isolating monotone regions. The proposed knowledge model contains a set of frame-based microprograms of behavior (FMP) and overcomes certain disadvantages of known logic models. Procedures for planning purposeful behaviour of an unmanned aerial vehicle in underdetermined environment are proposed.The automatic planning of the purposeful UAV behavior in an underdetermined environment comes down to: substitution of objects for subject variables that implement slots functions in condition-dependent predicates and form the structure of FMP body; planning of purposeful activity through verification of conditions that determine possibility of efficiently performing operations included in the FMP structure and by selection of typical elements of procedural knowledge. In the experimental part of the paper we simulate UAV purposeful behaviour in a perturbed environment.

Key words and phrases: UAV, frame-based microprogram, planning, predicate, behaviour, underdetermined environment, procedural knowledge.

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1. Introduction

The analysis of state-of-the-art foreign and domestic researches on the planning behavior of robotic systems, including unmanned aerial vehicles (UAVs), identifies separate fields of research and subject area problems. Trajectory motion of a UAV in a perturbed environment is one of the central themes of the modern researches. In the paper [1] the authors consider an intelligent motion control system of mobile robots based on rules, which is able to respond rapidly to changes in the real dynamic environment. The problem of synthesis of the quadrocopter motion control is discussed in [2].The authors propose a new approach to the synthesis of control systems of mobile robots based on the principles and methods of synergetic control theory. In papers [3, 4] the problem of trajectory tracking of an unmanned aerial vehicle is solved by adjusting the fuzzy PID controller. Two-loop control system that uses adaptive neural networks to compensate external disturbances is considered. An overview of modern intelligent control systems of robotic aircrafts with a special focus on autopilots for small unmanned aerial vehicles is performed in [5]. We remark the presence of a large number of papers in the area of motion planning of robotic systems in an environment with obstacles. In [6, 7] the authors discuss construction of control and planning systems for autonomous agents (robot systems) in a non-deterministic environment. In [8, 9] the authors solve 3D-trajectory planning problems for an aircraft in the presence of uncertainty. The authors use a spatial grid as a model of the environment and propose heuristic search algorithms on graph models.

One of the central problems of creating an effective intelligent solver for an unmanned aerial vehicle that can function purposefully in an uncertain environment is the development of a model for representation and processing of knowledge in a general form. The necessity of such a representation of knowledge for an intelligent UAV is determined by the impossibility to form a detailed model of regularities in the environment. Due to that, in an underdetermined environment UAVs have to adapt to the current operating conditions that entails knowledge representation given in a general form. It is required to represent UAV knowledge in such a form that allows specifying them and adapting to the current environmental conditions in the process of purposeful activity, taking into account the nature of objects.

First-order predicate logic is one of the most common approaches associated with the representation and processing of knowledge in multi-purpose intelligent systems [10–12]. However, the effective application of this model for the representation and processing of knowledge in the problem of planning purposeful activity of an intelligent UAV in underdetermined environment is limited for the following reasons:

1. To derive solutions a detailed knowledge representation model should be build [13];
2. Second-order and higher-order predicates cannot be used in knowledge models, thereby functionality of intelligent problem solvers is significantly reduced [14];
3. The laboriousness of the approach for deriving solutions to complex problems of knowledge processing, which is reduced to theorem-proving by the resolution rule [15]. This follows from the fact that in knowledge models based on the logic of first-order predicates for the formal description of objects, events and regularities, semantic component is not used.

A significant contribution to the solution of the problem of the exponential complexity in deductive inference was made in [16]. In this paper the authors propose deduction algorithms based on the transformation of semantic networks, which provide the possibility of organizing several types of parallel inference and reducing the complexity of the theorem proof process. Decision-making procedures organized in this way allow building effective solvers of complex problems, but do not remove the rest of the above-mentioned limitations associated with the usage of first-order predicate logic for planning purposeful UAV activities in a non-deterministic environment.

Above mentioned circumstances have led to the transition to a new paradigm based on the special models of knowledge representation and production rules [17, 18]. But there is a significant limitation in the effectiveness of inference when planning a UAV behavior. The main problem of using production models of knowledge representation and processing is the requirement for existence of a preliminary procedure for eliminating differences between actual and goal situations, but establishing such a procedure automatically in complex conditions is impracticable.

One of the first attempts to overcome this problem relies on using production models of knowledge representation and processing based on frame-microprograms of behavior (FMP) with the following structure: “input” “body” “output”. The input of the FMP is represented by an active fuzzy semantic network [19], vertices of such a network are labeled with specific objects in the process of purposeful behavior of an autonomous intelligent system. The input semantic network determines the situation when the intelligent system can successfully cope with the operations included in its body. The output of the FMP is given by a fuzzy semantic network describing the results of FMP operations. The disadvantage of such a model of knowledge representation intended for an intellectual UAV behavior planner (which has significant limitations on computing resources), is its cumbersomeness and the fact that it omit situations when performing all the FMP actions is not mandatory.

In this paper we propose a model for the representation and processing of procedural knowledge of an intelligent UAV for deriving solutions in the form of typical FMPs, which make it possible to overcome disadvantages of known logic models. The developed procedural model of knowledge is based on the logic of condition-dependent predicates [19], which provide the possibility to construct knowledge in a general form without using cumbersome representation structure. The automatic planning of the purposeful UAV behavior in an underdetermined environment comes down to:

1. Substitution of objects for subject variables that implement slots functions in condition-dependent predicates and form the structure of FMP body. This allows UAV to concretize the general purpose knowledge and use it to plan purposeful activities in the current operating conditions.
2. Planning of purposeful activity through verification of conditions that determine possibility to efficiently perform operations included in the FMP structure and by selection of typical elements of procedural knowledge. As a result, a chain of operations is formed allowing UAV to achieve its goal under specific operating conditions.

2. Procedural knowledge model of a UAV

The proposed model for the presentation of a UAV procedural knowledge, as it was noted earlier, is based on logic of condition-dependent predicates. In general, the range of admissible values of each object variable $y_i(X_i) \in Y, Y = y_i(X_i), i = \overline{1,m}$ in formulas is determined by a set of characteristics X_i that allows to set the acceptable constants (specific objects and events). If we describe each object or event $O = o_j(X_j), j = \overline{1,m_1}$ by the features X_j then substitution of objects or events $o_j(X_j) \in O$ for variables $y_i(X_i) \in Y$ is permissible if and only if the condition "$X_i \subset X_j$" is met. For example, the expression "To be able to fly (technical systems of Class A (strong wings, traction motor, no defects))" becomes a true statement when constants substituted into it are A class objects, for example, "aircraft KC21" has strong wings, a traction motor and no defects. Thus, in the condition-dependent predicate logic, an arbitrary multiple variable formula $M[y_1(X_1), \dots y_k(X_k), \dots y_n(X_n)]$ is true if and only if all the constants $a_k(X_{ak})$ substituted for corresponding variables $y_k(X_k) \in M$ meet the conditions "$(X_k \subset X_{ak})$" [15]. Thereby, a UAV intelligent solver in the current operating conditions is able to verify an arbitrary statement by assigning objects to subject variables.

Consider the following two formulas:

$Q_1 = P_1(UAV, y_i(X_i))$ - "To fly to (UAV, object $y_i(X_i)$)";

$Q_2 = P_2(UAV, y_i(X_i))$ - "To perform an operation (UAV, object $y_i(X_i)$)".

We combine and extend these formulas with:

1. Conditions that must be met in an uncertain environment for successful performing UAV’s operations.

2. Relevant references for transition to typical elements of procedural knowledge, that contain operations allowing to achieve necessary conditions in a non-determined environment.
3. A formalized description of the result obtained by executing corresponding operations.

The aforesaid allows us to form a standard FMP "To perform an operation b_j on a given object" given with the structure: "Identifier" "Procedures" "Exit". The identifier provides selection of an FMP by the kind of binary relations between UAVs and environmental objects. That relations can change while executing operations included in FMP procedures. FMP procedures include conditions that must be fulfilled for successful execution of the UAV operations contained in that procedures. The output of the FMP is given by the semantic network, whose edges labeled with relation values that are obtained for objects and UAVs when operations included in its procedures are processed. FMP conditions (that are determined by the values of binary relations) must be met for successful execution of the corresponding operations.

The structure of the described FMP can be represented in a form of a logic scheme [19] as follows:

$$
\begin{gathered}
Q^* \ll P_1^* \overset{1}{\uparrow} b_1(y_i(X_i)) \overset{2}{\downarrow} P_2^* \overset{34}{\uparrow\downarrow} b_2(y_i(X_i)) \overset{51}{\uparrow\downarrow} Q_1^*(y_i(X_i)) \overset{2}{\uparrow} \\
\overset{3}{\downarrow} Q_2^*(y_i(X_i)) \overset{45}{\uparrow\downarrow} \Longrightarrow \text{the goal is reached} \gg,
\end{gathered}
\tag{1}
$$

where Q^* is the FMP identifier;

P_1^* is the operator that checks the condition "There are no obstacles between UAV location and object $y_i(X_i)$ location";

$b_1(X_i)$ is the operator "Fly to the object $y_i(X_i)$";

P_2^* is the operator that checks the condition "The object $y_i(X_i)$ is located in the visibility zone";

$b_2(X_i)$ is the operator "Execute the operation b_2 on the object $y_i(X_i)$";

Q_1^* is the FMP "To plan and work out the route of convergence with the object $y_i(X_i)$ in the presence of obstacles";

Q_2^* is the FMP "Ensure fulfillment of the P_2^* condition".

The numbered arrows indicate the direction of the transition from one operator to another when the conditions P_i^* given before operator are not met.

Thus, to provide an intelligent UAV with the necessary functional capabilities, the model of procedural knowledge can be represented in the form of a set of FMPs. This model allows to significantly reduce the search space of fairly complex tasks by selecting several effective operations at each step of behaviour planning.

3. The problem of planning UAV purposeful activity

Let us consider the case when the purpose of a UAV mission in an underdetermined environement is set in a procedural form, for example, "Execute an operation b_j on an object $o_i(X_i)$", "To fly close to the object $o_j(X_j)$", etc., where X_i, X_j are sets of features correspondingly describing objects $o_i(X_i)$" and $o_j(X_j)$. In this case, FMP output is not used in the decision-making process when planning UAV's activity.

Let the the intellectual solver of the UAV's tasks in order to achieve a given goal selects FMP $F(X_i^*)$ "Perform an operation b_j on the object $o_i(X_i)$". FMP procedures in the logical form will take the following structure:

$$F(X_i^*) = P_1(h, y_i(X_i^*)) \overset{1}{\uparrow} P_2(l, y_i(X_i^*)) \overset{23}{\uparrow\downarrow} b_2(y_i(X_i^*)) \overset{4}{\uparrow}$$

$$\overset{1}{\downarrow} F_1(y_i(X_i^*)) \overset{42}{\uparrow\downarrow} P_3(N, y_i(X_i^*))(F_2(y_i(X_i^*))) \overset{3}{\uparrow} b_1(y_i(X_i^*)) \overset{3}{\uparrow}$$

$$\overset{4}{\downarrow} P_4(l, y_i(X_i^*)) \overset{41}{\uparrow\downarrow} b_3(y_i(X_i^*)) \longrightarrow \text{the goal is reached}$$

$$\overset{5}{\downarrow} P_4(N, y(X_j)) \overset{6}{\uparrow} F_2(y_j(X_j)) \overset{76}{\uparrow\downarrow} b_1(y_j(X_j)) \overset{7}{\uparrow},$$

where X_i^* are features that an arbitrary object should have for efficient processing of the operations of a given FMP $F(X_i^*)$, X_i^* = should have permissible size and weight and be immovable;

$P_1(h, y_i(X_i^*))$ is the operator that checks the condition "The object $y_i(X_i^*)$ is located higher than the zone of visibility" in order to establish if there is a difference h_i between actual and required (for succes execution of the operation $b_2(y_i(X_i^*)))$ situations;

$P_2(l, y_i(X_i^*))$ is the operator that checks the condition "The object $y_i(X_i^*)$ is located further than the zone of visibility (checks the distance l)";

$b_2(y_i(X_i^*))$ is the operator "Execute an operation b_2 on the object $y_i(X_i^*)$";

$F_1(y_i(X_i^*))$ is the FMP "To eliminate the difference h";

$P_3(N, y_i(X_i^*))$ is the operator that checks the condition "There are obstacles between the UAV and waypoint $y_i(X_i^*)$";

$F_2(y_i(X_i^*))$ is the FMP "To plan avoiding obstacles and work out the route to the object $y_i(X_i^*)$";

$b_1(y_i(X_i^*))$ is the operator "To get close to the object $y_i(X_i^*)$";

$P_4(l, y_j(X_j))$ is the operator that checks the condition "The object $o_j(X_j)$ is located within the zone of visibility (checks the distance l)";

$b_3(y_i(X_i^*))$ is the operator "Execute an operation b_3 on the object $y_i(X_i^*)$";

$P_4(N, o_j(X_j))$ is the operator that checks the condition "There are obstacles between the UAV and waypoint $o_j(X_j)$";

$F_2(o_j(X_j))$ is the FMP "To plan avoiding obstacles and work out the route to the object $y_j(X_j)$";

$b_1(y_j(X_j))$ is the operator "To get close to the object $y_j(X_j)$".

When a frame-based microprogram of the UAV behavior is selected, the UAV forms (relative to its location) the model of the operating area in the form of a semantic network $G = (V, E, v_0)$, where: V is a set of vertices marked with objects located in the operating area; E a set of edges, that are determined by the binary relations between the UAV and other objects; v_0 is the key vertex that correspond to the UAV. Semantic network G determines current situation and is constructed relative to key vertex.

The intelligent solver takes descriptions of goal object $o_i(X_i)$ and other objects of the operating area (that are associated with the execution of the selected FMP) and checks the condition "All the assosiated objects satisfy the requirements of substitution into the selected frame-based microprogram". If all conditions are met the decision is made that the selected FMP is feasible in the current situation and the UAV starts to implement FMP's operations. Otherwise, the intellectual solver makes a decision that none of FMPs allow performing the current task. In this case, the UAV starts planning the behavior on the basis of typical elements of the procedural knowledge model in the form of frame-based operations with the following structure: "Conditions that are necessary for execution of the operation $b_i(y_i(X_i^*))$" "Operation and description of objects' features" "Operation result".

FMPs included in the plan of a UAV behaviour are determined by identifiers that are contained in the structure of the initial frame-based microprogram. Each microprogram can include various microprograms of behavior (FMPs) that are necessary for its effective execution the current situation. To solve more complex problems UAV mission, as a rule, is given in a declarative form, for example, in the form of a semantic network S^* given in the state space.

4. Experimental research

As an experimental task, we use the problem formalized in a form (1).The problem is to reach an object in the presence of obstacles and perform an operation on the object, for example, to take some pictures. The process of UAV motion in the presence of obstacles and under wind loads is simulated in MATLAB Simulink system. Details related to the selection of the mathematical models of the flight vehicle and wind loads, as well as to the development of an intelligent control system are described in [20]. The developed simulating system contains a special module of intelligent control, realizing strategies and control rules for prompt response to changes in the external environment. The results of simulating are shown in Figure 1.

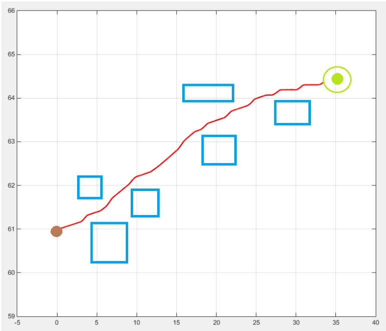

Figure 1. UAV trajectory motion

Here, UAV start point (brown color), trajectory of UAV motion (red color), impassable obstacles (cyan color) and the goal object (green color) are shown. It can be seen that the control rules enable flight vehicle to successfully cope with the mission. UAV trajectory demonstrates the effect of obstacles and wind loads on the motion. The main criterions for aircraft control quality are: integral evaluation of the deviation from the planned route in the process of motion; visual assessment of the flight trajectory.

5. Conclusions

The use of condition-dependent predicate calculus allows to represent UAV knowledge in an arbitrary subject area and organize planning various types of purposeful activity in a priori underdetermined environement. The proposed model for the representation and processing of procedural knowledge allows UAV to plan its behaviour automatically with polynomial complexity. For this purpose, a decision output tree is formed, which includes frame-based microprograms of behavior that are necessary to achieve the goal.

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