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Research Issues in Autonomous Control of Tactical UAVs

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Abstract

This paper summarizes the enabling technologies for an autonomous tactical UAV. Current technologies are adequate for semi-autonomous UAVs that operate in a relatively structured environment. For tactical UAVs in a rapidly changing uncertain environment the present techniques are inadequate. The essence of autonomous control is rapid in-flight replanning under uncertainty. This is cast as a large optimization or decision problem. Monolithic and decomposition techniques are discussed for the solution of large decision problems. Hierarchical decomposition is the most promising approach, but suffers from an inadequate theoretical basis. Finally, research areas are proposed to address the decomposition problem.

1 Introduction

The study objective was to determine what the research issues were in developing autonomous control systems for tactical UAV's. Specifically, what areas need further basic/applied research and what the thrust of this research should be.

The problem areas identified were not specifically control related, and none were concerned with inner-loop feedback stability and control. For example, the SAB summer study[1] identifies man-machine interface and loss of positive control as the primary issues in autonomous tactical UAV's. An AGARD study[2] cites the following issues: 1) communications—secure, unjamable data link; 2) coordination—Army, AWACS, JSTARS, etc.; 3) target identification; 4) target assignment; and 5) deconfliction.

Other references cite automated decision aiding/decision making[3, 4, 5] as one of the most difficult problems leading to autonomy. Man-machine interface, communications, and target identification are real and difficult issues, but not readily addressable by control or systems theory. The decision/control problem was selected for this investigation.

Saridis[6] has defined the next step beyond adaptive/learning control as intelligent control. This is the intersection of control, artificial intelligence (AI), and operations research (OR) as shown in Fig. 1. AI in this case can be looked at as a knowledge base, expert system, learning, or simply heuristics. What is more noteworthy is the strong role of OR, specifically planning, which can be viewed as the essence of decision making. Pilot's Associate[3], Integrated Control Avionics Air Superiority[4], and Control Automation & Task Allocation[5] are dominated by the planning/management function. The first two systems are designed as pilot aids. It is only logical that an autonomous control system would have to perform all of the functions identified, but rather than only offering advice, the advice would be acted upon as decisions, as in[5].

Decision making through planning (and planning management) appears to be the essence of the autonomous control problem, and the focus of the investigation.

2 In-flight Replanning

A typical planning problem is shown in Fig. 2. The task is to determine a path through a defended environment that satisfies all the constraints as well as the mission objectives. As can be seen, there are many levels of planning. There is pre-mission planning where all the information is static. This is the best plan that can be made based on the available information. There is the near term plan, which is executed in the air, which involves the physical flying of the aircraft, normally done by the pilot. This can be looked at as a trajectory tracking task which can be completely automated through inner loop control, autopilot design, tracking, and short term on-line trajectory generation. It is the intermediate level of planning where the desired capability of autonomous control is achieved. Near real time in-flight replanning is needed as new sensor information, commands, or intelligence is recieved by the UAV. The challenge is to optimally update the off-line plan as new information is received and/or unforseen events occur. The optimization problem is dominated by size, complexity, and uncertainty.

The computational approach to decision making as planning can be grouped as optimal or heuristic.

Optimal	**Heuristic**
enumeration	heuristic search
dynamic prog.	neural networks
mathematical prog.	simulated annealing
gradient methods	genetic algorithms
Newton methods	expert systems
	machine learning

The basic problem with optimal approaches is that the computation time explodes exponentially with problem size. An important result from planning theory[7] is that most general planning problems belong to the class NP-hard, which means that there are no known polynomial time algorithms to solve this class of problems. An alternative is to concentrate on sub-optimal solutions using heuristic techniques.

Another dimension of the problem is *monolithic* versus *decomposition*. There is a hierarchical decomposition of the problem into smaller problems that can be more easily solved. These two dimensions are illustrated in Table 1. Generally, the mission

	Optimal	**Heuristic**
Monolithic	small size coarse grain	medium size medium grain
Decomposed	medium size coarse grain	large size fine grain

Table 1: Planning Dimensions

planning problem can be decomposed spatially, as in Fig. 2, or temporally, as in Fig. 3. The size and granularity are key determinants of the practicality of solving a realistic problem in near real time. In Table 1 the upper left corner represents problems that can be solved by optimal algorithms. The coarse grain signifies that the events of importance are relatively far apart in time or space. Linear programming may be a reasonable choice here. The upper right corner signifies problems of medium size that allow a bigger search space due to the heuristics. A reasonable choice here would be simulated annealing. The bottom row is quite different. It depends on the feasibility of decomposing the problem. If the problem can be decoupled, or nearly decoupled, the sub-problems can be solved independently without worrying about interactions with other sub-problems, as in the lower left corner of the table. This is rarely the case in planning because most decisions are interrelated. The lower right represents how a realistic planning or decision problem could be addressed. This is the approach taken by PA, ICAAS, and CATA.

A decomposed planning problem will generally have significant coupling. Accounting for the coupling or coordinating the sub-problems is the essence of the difficulty. Unless adhoc rules or engineering judgment is to be used to decompose the problem, this requires a theory of hierarchies.

3 Hierarchical Decomposition

A three echelon organizational hierarchy is typical of nearly all decision and planning systems—Pilots Associate for example. The lower echelon is the only one that interacts with the plant—physically controlling the aircraft and its systems. This would be the actual feedback control law. The upper levels are abstractions and represent the decision making hierarchy. These levels coordinate the efforts of the lower levels. There are feedback loops between the levels, but not within a level. The essence of the problem is determining an appropriate description or abstraction at higher and higher levels, finding a decision or cost function for each of the levels, and deriving a coordination signal that corrects the performance of sub-levels to satisfy the overall or highest level objective. This is the critical problem—the sub-problems are being solved perfectly, but the overall objective is not being achieved. A theory of coordination is presented in [9], but little guidance is given on how to derive the coordination function.

Rigorous decomposition principles which enable the off-line (and possibly, on-line) solution of large linear programming and convex quadratic programming problems are currently available - see, e.g., [10, 11, 12]. These decomposition principles exploit the special structure of the constraint matrix, such as the application area of economics, where the concept of "shadow prices" is evoked [12]. Similar decomposition principles will have to be derived for large planning optimization problems. It is expected that some structure can be found in large problems since these often arise from a linking of subproblems in either the temporal or spatial domains. Efficient modern parallel computing also rests on the proper decomposition of large-scale problems.

A heuristic optimization approach of proceeding through the solution of a hierarchy of models of varying granularity, or the application of multigrid methods, present interesting possibilities. Also, a promising approach for the solution of large scale optimization problems is advantage learning applied to local-search-based optimization [13].

One must, however, guard against the adverse effects of coupling. Simple minded decomposition approaches which hinge on the over-optimistic presumption of minimal coupling of the subproblems are doomed to failure. Conversely, the decomposition of a large-scale problem into a large number of simple subproblems does not guarantee that the large-scale system's dynamics are captured. One should also warn against the use of high gain linear feedback control to achieve decoupling, for this could cause saturation, windup, and instability.

A quote from [9] gives additional motivation for studying hierarchical decomposition:

> "There is a lack of attention given to organizational theory as evidenced by the scarcity of researchers in the field. One would assume that at present there are more researchers worrying how to "optimally" adjust parameters in feedback control systems (a problem which at best can bring marginal commercial improvement) than there are researchers worrying about quantitative aspects of control and communication processes in organizational type systems."
>
> *Mesarovic*

In summary, rigorous hierarchical decomposition is key to solving large decision problems.

3.1 Uncertainty

Uncertainty is ubiquitous in decision system problems. This uncertainty can be categorized as: 1) unknown parameters; 2) unknown dynamics; 3) disturbances; 4) noise; 5) actions of non-coperative agents; 6) actions of coperative agents; 7) unmeasured or unmeasurable information; or 8) erroneous information. Thus, in an unstructured environment, decision making is performed with incomplete, and often misleading, information.

A significant increase in the degree of uncertainty is seen when a hierarchy of higher level control objectives are postulated for the decision system, e.g.: the controlled object is required to optimally reach a prespecified waypoint, fly a specified trajectory, reach a (possibly moving, or evading) target, find a target, or complete a mission. The degree of uncertainty increases as one moves from the inner-loop to decision making. This is in part attributable to an adversary in military scenarios. Hence, the decision system is not only faced with random disturbances, but by a determined opposition.

When one considers a path planning problem, the control horizon is extended and the level of ucertainty increases. Similar to navigation, the stretching of the optimization horizon accentuates prediction error and leads to feedback. Feedback brings about additional uncertainty in the form of measurement noise. Moreover, in nonlinear estimation problems the use of control can couple into the estimation process.

Uncertainty is not confined to stochastic decision problems. As has been mentioned above, uncertainty is introduced into deterministic decision problems where an adversary agent is at work. This is the domain of game theory and, in a dynamic setting, the theory of differential games. When a solution in pure strategies does not exist, then an approach to address the uncertainty introduced by the actions of an adversary agent is to randomize, namely, have recourse to a mixed strategy. This is a viable approach provided that one is planning to perform a repetitive task, e.g., fly out a multitude of (low cost) UAVs.

4 Conclusions

Autonomous control has been shown to require complex decision making under uncertainty. The solution approach is predominently hierarchical decomposition. There are no detailed theoretical guidelines for hierarchical planning systems of three levels or more. Such theoretical results as are available are for two level planners cast as a linear programming problem that exploits a problem specific structure. There is not a "language of abstraction", the issue of feedback or coordination between levels has not been defined in detail, uncertainties are not adequately represented in the models, and, most importantly, there is no proof that the decomposed decision system will solve the original decision problem.

Following is a list of autonomous decision/control system research questions that were formulated in the course of the investigation:

- Can large monolithic optimization problems be solved in near RT using parallel computers?
- Can distributed control theory be brought to bear on the problem of hierarchical planning?
- Can one use organization theory to describe and quantify the higher levels of abstraction needed for decision making at the higher levels?
- Can you control the coupling using some feedback/coordination technique to achieve the overall performance objective?
- Can one use multigrid methods to address large scale problems?

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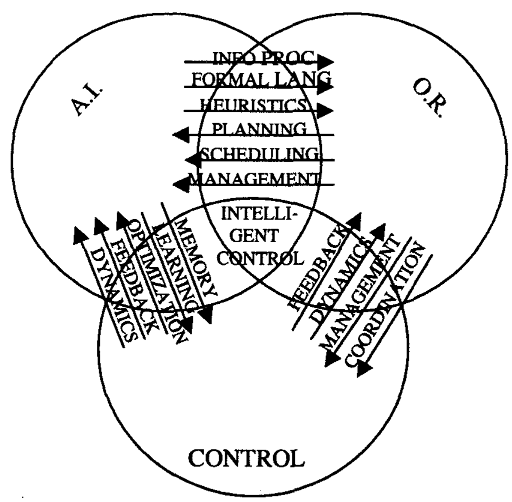

Figure 1: Intersection of Artificial Intelligence, Operations Research, and Control Theory: (Saridis, 87)

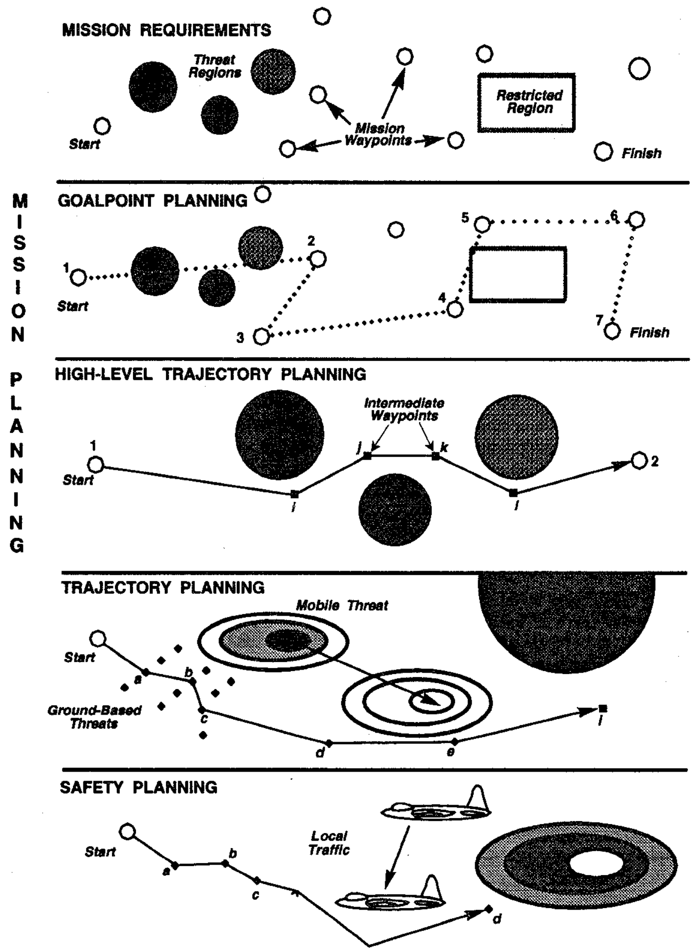

Figure 2: Planning Hierarchy with Spatial Decomposition: (Kolitz, 93)

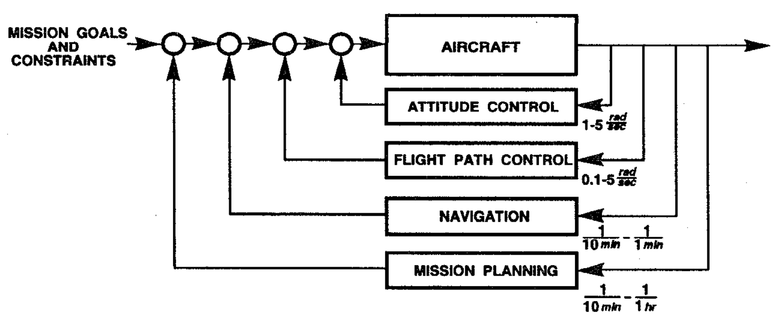

Figure 3: Planning Hierarchy with Temporal Decomposition: (Krozel, 87)