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POTENTIAL APPLICATION OF ARTIFICIAL INTELLIGENCE CONCEPTS TO NUMERICAL AERODYNAMIC SIMULATION

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I. INTRODUCTION

The development of sophisticated computational fluid dynamic (CFD) tools for simulating the external flow field about complicated three-dimensional flight vehicles or internal flows within vehicle components requires vast expertise and enormous resources in terms of both human researchers and computer capacity (speed and storage). The creation of such simulation tools requires knowledge of the disciplines of numerical analysis, fluid dynamics, computer science, and aerodynamics, and the development of such tools takes an inordinate amount of time. Furthermore, the writing of software is becoming more expensive every year [1,2]. Shorter, less expensive development times resulting in more powerful, versatile, easy-to-use, and easy-to-interpret simulation tools are necessary if computational aerodynamics is to fulfill its potential in the vehicle design process. To this end, some of the concepts of artificial intelligence (AI) can be applied. It is the purpose of this paper, first, to briefly introduce these concepts and, second, to indicate how some of these concepts can be adapted to speed the numerical aerodynamic simulation process.

II. ARTIFICIAL INTELLIGENCE BACKGROUND

Artificial intelligence is a discipline of computer science concerned with the study of symbolic reasoning by a computer and symbolic representation of knowledge. The objective of applied AI is to design and construct computer programs that exhibit the characteristics normally associated with human intelligence (for example, performance, adaptability, and self-knowledge). The core elements of artificial intelligence are (1) heuristic search (rules of thumb to guide the search of the problem's solution space, as opposed to blind, exhaustive search, or an algorithmic solution procedure); (2) symbolic representation (representing knowledge by means of first-order predicate calculus or frames, for example); and (3) symbolic inference (methods of manipulating symbols to do reasoning). Research in these core areas is conducted through the study of such topics as natural language processing, formal theorem proving, concept learning, automatic programming, robot control, computer vision/perception, and problem solving and planning. Formal approaches to this research (using a formal, unambiguous language for representing facts and ideas, and a formal logic to reason about those ideas) have performed successfully on some rather simple problems. However, the elusiveness of high-level performance by formal methods on more difficult tasks led many AI researchers to an approach that emphasizes the importance of knowledge in expert problem solving [3]. That shift in approach has resulted in the emergence of expert systems technology.

Expert systems are knowledge-based AI programs which are capable of performing at the level of a human expert as a result of their emphasis on domain-specific knowledge and strategies. In addition to the characteristics of high-level performance and reliance on domain-dependent knowledge, expert systems are distinguished from other AI programs and computer programs in general by their ability to reason about their own processes of inference, and to furnish explanations regarding those processes [3]. These distinguishing characteristics are made possible by the underlying architecture common to most expert systems. There are two major components [4]: a knowledge base (domain-dependent facts, rules, heuristics) and a separate inference procedure. Knowledge acquisition and input/output components are usually included.

Expert systems are particularly well suited to two generic types of problems [4]. First, there are the problems in which pursuit of an exact or optimal solution would lead to a combinatorial explosion of computation; second, there are the problems that require interpretation of a large amount of data. In addition, the domains where application of expert systems technology is most appropriate are those fields in which "the difficult choices, the matters that set experts apart from beginners, are symbolic, inferential, and rooted in experiential knowledge" [4]. Expert systems have been constructed in such domains as medical diagnosis, chemistry, symbolic mathematics, geology, circuit design, structural engineering, and computer system configuration (Refs. 3-7 contain descriptions of these systems).

Expert system techniques are currently powerful enough to produce a few successful systems, such as MACSYMA, DENDRAL, and R1 [3]. But the state of the art still falls short of ideal intelligent behavior, or a mature technology. The domain of expertise must be very narrow, the problem representation languages and I/O languages are limited, there is little self-knowledge (which affects explanation capabilities and recognition of the system's own limitations), expertise is restricted to that from a single source, and much of the knowledge and problem-solving approach incorporated into an expert system is painstakingly hand-crafted, resulting in relatively long construction times [3]. Research continues to push the boundaries of capability of expert systems outward.

III. EXPERT SYSTEMS IN CFD

The design and application of computational aerodynamic simulation tools involves the synthesis of many facets (Fig. 1), each of which requires expertise and experience for its formulation, development, and use. It is conceivable that an expert system could be designed that would act as a flow-field synthesizer; that is, act on all of the facets depicted in Fig. 1 for a CFD computation. Present expert systems techniques could be used in at least five aspects of the CFD computation that would involve some of these facets (Fig. 2): three-dimensional grid generation (a pacing item in CFD [8]); flow problem definition and initialization; construction and analysis of numerical schemes; flow-solver selection and use; and data reduction, analysis, and display. Because grid generation has been identified as having the most promise, more detail is presented below.

One of the most important facets required to solve accurately a three-dimensional CFD problem using finite-difference procedures is the proper location of the nodal points in the flow region to be resolved. There are basically two decision stages and a feedback stage involved in the discretization process. The two decision stages involve (1) the grid topology and (2) the grid-generation scheme; the feedback stage involves an analysis and modification of the grid based on the geometric derivatives, the flow-solver algorithm employed, and the flow solution generated. Although grid generation is intrinsically complex, the elements of the decision stages are well understood by experts in the field and the feedback stage is currently receiving attention. Grid generation is, therefore, likely to offer the greatest potential for an early successful design of an expert system in computational fluid dynamics.

The schematic of an expert grid-generation system (EGGS) shown in Fig. 3 is based on some of the major components of an expert system; it depicts in detail the essential ingredients of some of those components. Input consists of three groups of information: (1) flow parameters such as the Mach number, angles of attack and yaw, and Reynolds number (these would determine, for example, whether planes of symmetry can be used, the position of the outer computational domain, and the nodal point clustering near surfaces); (2) geometric data (for external flows, the multiple, time-varying body coordinates at the inner boundary of the computational volume); and (3) qualitative program control information such as the level of accuracy required (e.g., calculations for understanding complicated fluid physics might require a fine grid, whereas those for performing preliminary engineering design might require a coarse grid), and the permissible level of expense to be incurred.

The knowledge base consists of facts (grid-generation schemes and grid-analysis theory) and heuristics (experience and good judgment regarding grid topology decisions, for example). Modern grid-generation philosophy concerned with three-dimensional discretizations dictates that some form of a zonal grid topology be employed. There currently exists no theory that can determine the zoning or grid patchwork for either two- or three-dimensional problems, so heuristics are used. It is hoped that theory can eventually replace many of these heuristics. Once the flow field has been zoned, each zone can then be discretized using the procedures denoted in Fig. 3; the procedures include either algebraic or differential approaches. With the flow region discretized, various levels of grid-analysis procedures can be used to judge the quality of the resulting grid. These vary in complexity from procedures that simply look at grid parameters, such as the transformation Jacobian, geometric derivatives, and ratio of the metrics, to procedures that combine these functions with the flow-solver algorithm and flow solution to yield an improved grid.

EGGS produces as output three pieces of information to be used by the flow solver: (1) the coordinate location of the nodal points, (2) the definition of each surface of the computational cube (e.g., plane of symmetry, body, shock wave), and (3) the zonal interface control parameters. The latter piece of information tells the flow solver which parts of the zonal grid boundaries are adjacent to each other. This is required by the boundary condition routines in the flow solver.

IV. RESOURCE REQUIREMENTS

Development of knowledge-based systems requires a significant investment of time and money, and requires a new kind of professional — the knowledge engineer. One time-estimate for building an expert system is anywhere from 7 months (for simple systems in a friendly environment with existing tools) to 15 yr (for complex systems in demanding environments where new tools must be researched and developed) [9]. Although the proposed expert grid-generation system would fall toward the simple end of the spectrum, a more comprehensive expert flow-simulation system will undoubtedly be more complex, and may require more powerful AI tools than are presently available. For a discussion of the issues involved in expert system development, see Refs. 3 and 9.

V. CONCLUDING REMARKS

The techniques of artificial intelligence, in particular those of expert systems, can be applied to most facets of the numerical aerodynamic simulation process. This paper describes some of the concepts underlying those techniques, and indicates the areas of aerodynamic simulation in which those techniques could play a significant role. A proposed expert grid-generation system is briefly described which, given flow parameters, configuration geometry, and simulation constraints, uses expert knowledge about the discretization process to determine grid-point coordinates, computational surface information, and zonal interface parameters. Additional details of this and other possible CFD expert systems can be found in Ref. 10. The potential payoff from the use of expert systems in the numerical aerodynamic simulation process is worthy of attention and warrants the allocation of resources as an investment in the future. Expert systems in CFD will promote the fusion, preservation, and distribution of aerodynamic knowledge, and will streamline research and design by managing the complexities of those processes. The users of these future systems will be freed from attending to the details of numerical simulation, and allowed to explore, innovate, and create at a higher level of abstraction.

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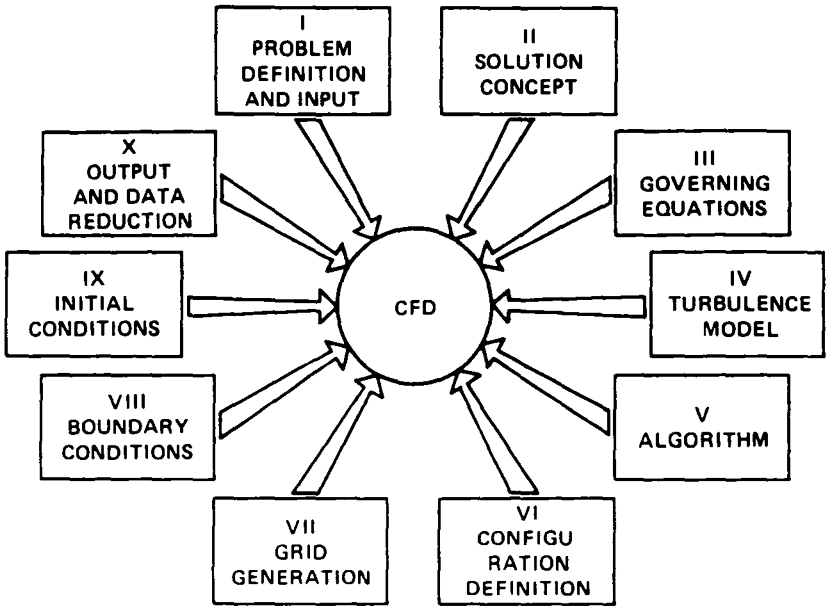

Fig. 1 Numerical aerodynamic simulation synthesizer (NASS).

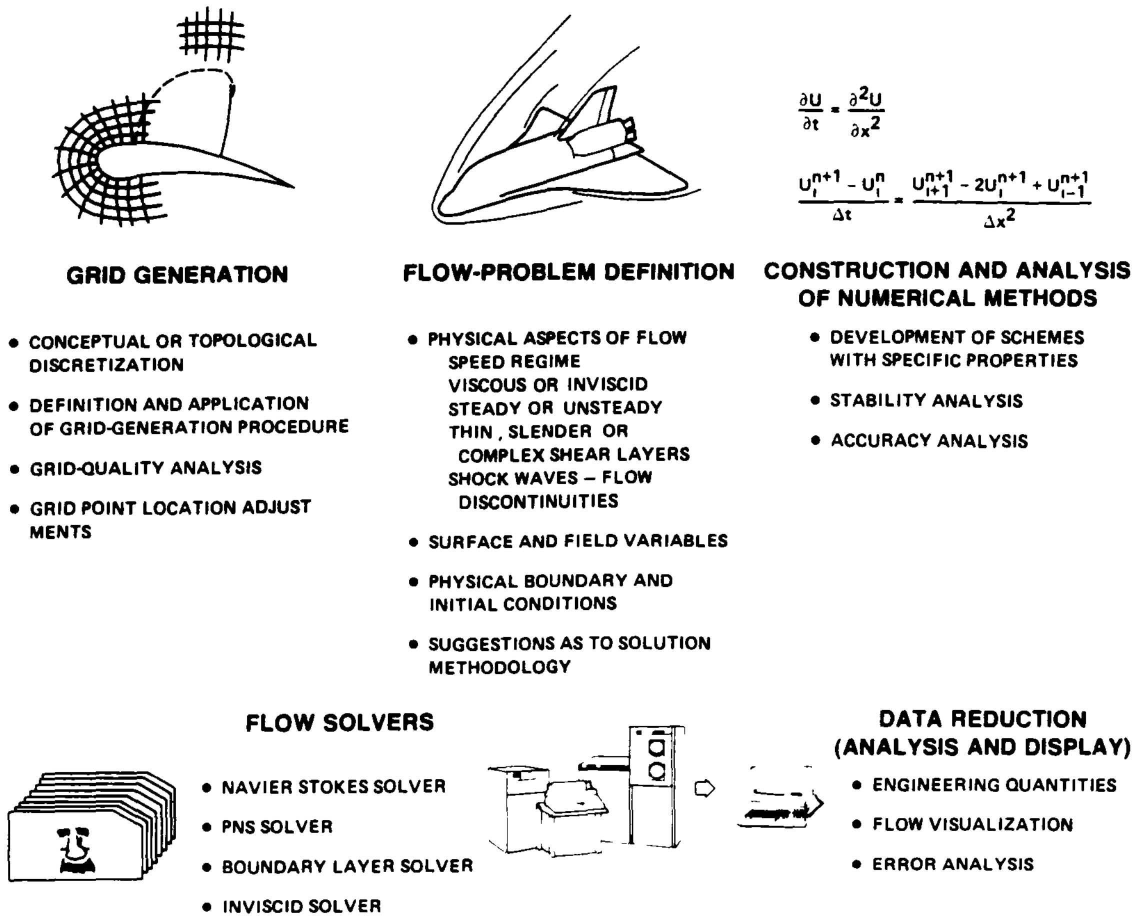

Fig. 2 Expert systems in numerical aerodynamic simulation.

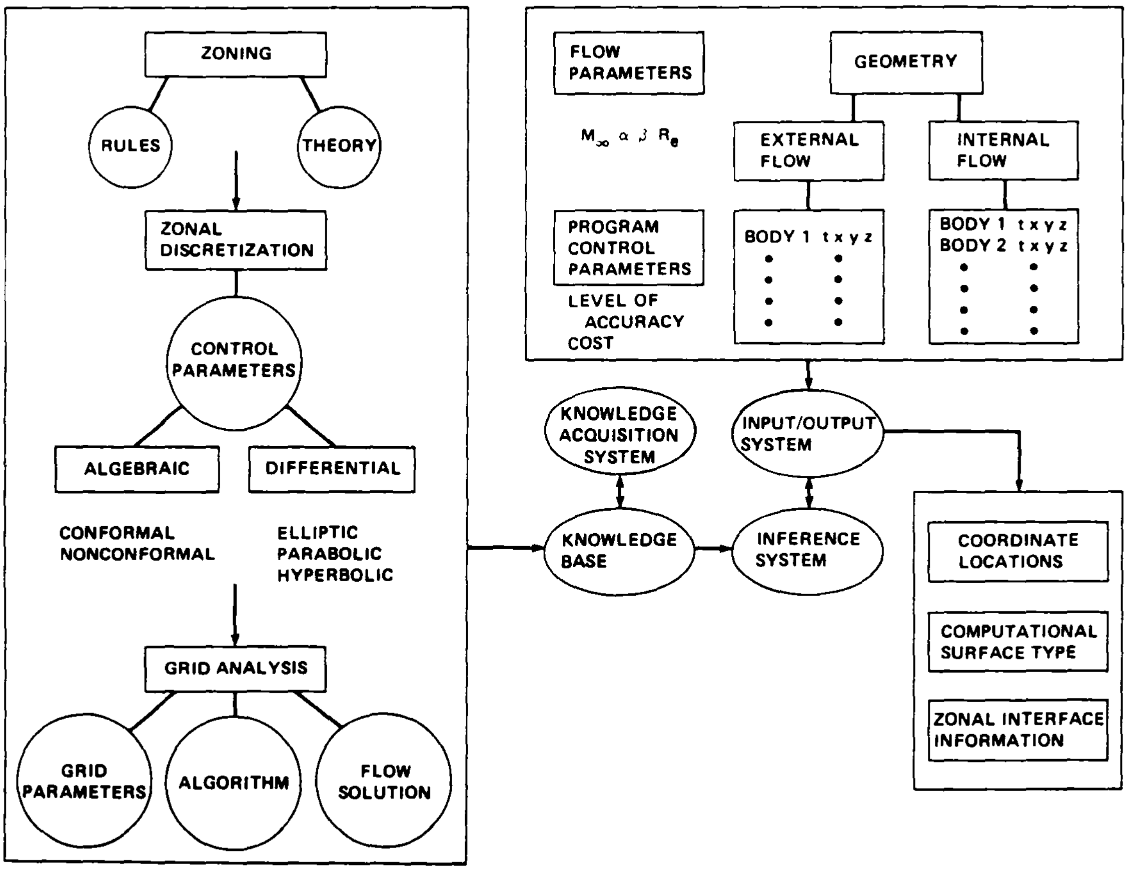

Fig. 3 Expert grid-generation system (EGGS).

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16 Abstract

Computational fluid dynamics simulation tools that are less expensive to develop, more powerful, versatile, easy-to-use, and easy-to-interpret than currently available tools are necessary if computational aerodynamics is to fulfill its potential in the vehicle design process. To this end, some of the concepts of artificial intelligence can be applied.

This paper briefly introduces these concepts, and then it indicates how expert systems developed from some of them can be adapted to speed the numerical aerodynamic simulation process. A proposed expert grid-generation system is briefly described which, given flow parameters, configuration geometry, and simulation constraints, uses knowledge about the discretization process to determine grid point coordinates, computational surface information, and zonal interface parameters. It is concluded that the potential benefit from the use of expert systems in the numerical aerodynamic simulation process is worthy of attention.

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