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PERSPECTIVES IN MODERN CONTROL THEORY*

by

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Abstract

The purpose of this paper is to review the development of modern control theory with special emphasis on future theoretical directions as motivated by expanding areas of application and technological innovation. Of particular interest is the delineation of future research directions in the areas of

(a) large scale systems and decentralized control
(b) control using microprocessors
(c) dynamic system reliability and control under failure.

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1. INTRODUCTION

Modern system theory and its applications deal with decision making under uncertainty in both mechanistic and humanistic systems. Of particular importance, and a major source of challenges and complexities, is the case in which the outcomes of decisions are related in a dynamic context; that is, the current outcome(s) - or output(s) - of a dynamic system depend on the history of past decisions - or control inputs. For example, consider the problem of maintaining a moving submarine at a constant depth below the ocean surface. In this case the main output variable of interest, the submarine depth, depends (among other things) upon the past history of the position of the submarine control surfaces, the stern plane and the bow plane.

The development of any theory and associated computational algorithms for analysis and design almost always requires the abstraction of reality by means of approximate, yet realistic mathematical relations. In the case of control of dynamic systems these mathematical relations take the form of complex, linear or nonlinear, ordinary or partial differential equations. These differential equations relate the main system variables of interest, often called <u>state variables</u>, to the variables that can be directly manipulated, either manually or automatically, which are often called <u>control variables</u>.

In addition to the inherent complexity associated with multivariable dynamic systems whose behavior is described by complex differential equations, the control engineer must also deal with the issues of uncertainty. There are several sources of uncertainty that are of crucial importance in both analysis and design which arise due to

(a) errors in modelling a physical system by means of mathematical equations

(b) errors in the parameters that appear in differential equations of motion, e.g. the submarine hydrodynamic derivatives

(c) exogeneous stochastic disturbances that influence the time evolution of the system state variables in a random manner, e.g. the effects of the surface waves upon submarine depth

(d) sensor errors and related noise in measurements.

Such uncertainties are modelled as random variables and/or random processes. Thus, the complete description of any real physical system requires the use of stochastic differential equations. Figure 1 shows a visualization of the key elements of a stochastic dynamic system.

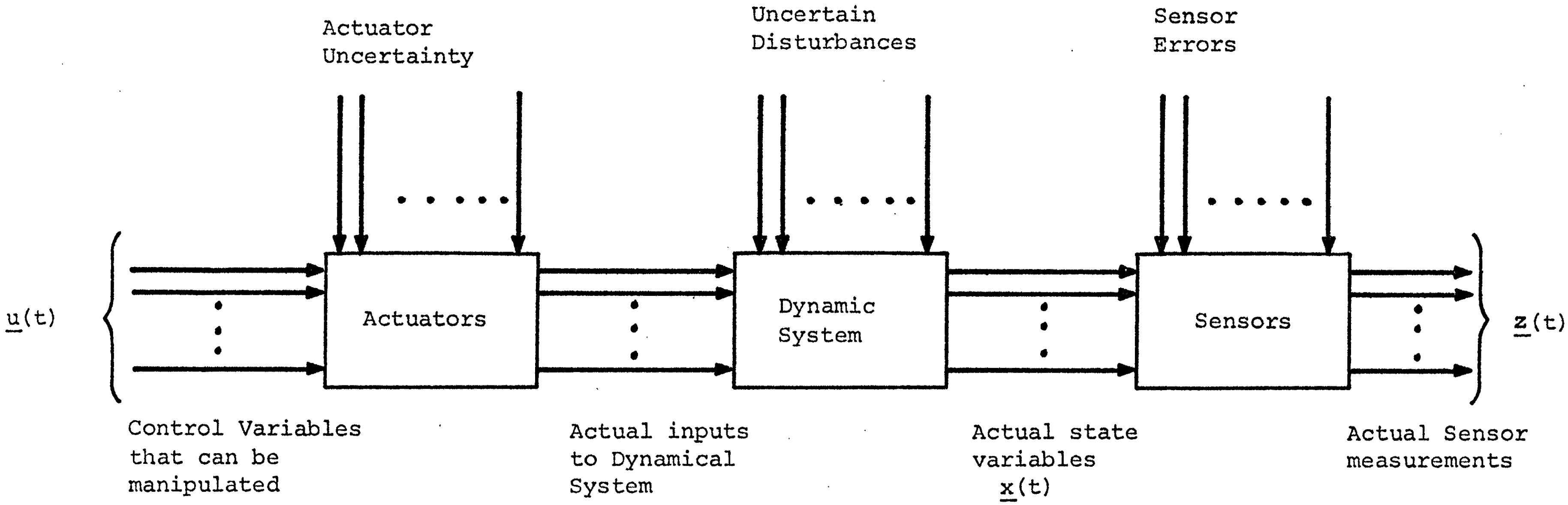


Figure 1. Block Diagram of a Realistic Stochastic Dynamic System

From a pragmatic point of view the only variables available for realtime measurement are the control inputs $\underline{u}(t)$ and the sensor measurements, $\underline{z}(t)$

2. WHAT IS THE CONTROL PROBLEM?

The control engineer is usually given a particular physical system (a submarine, an aircraft, a power system, a traffic network, a communications system,etc.) that has been designed by others. More often than not, the performance of the original system is unsatisfactory; this may be due to the fact that the interaction of the exogeneous disturbance inputs with the natural system dynamics creates unacceptable behavior of the system state variables. For example, the system may be inherently unstable, in the absence of control, due to the complex interaction of kinetic and potential energy; this is the case with all unaugmented helicopters, missiles and certain high performance aircraft. Even if the system is stable, its response to changes in commanded inputs may be either too oscillatory or too sluggish, and hence unacceptable.

If the behavior of the unaugmented, or open-loop, system is not satisfactory then the only way that it can be made satisfactory is by the judicious manipulation of the control variables as a function of the actual sensor measurements. This is often called feedback control. The main thrust of the control system design problem is to deduce the transformation from the noisy sensor measurements to the control signals. This is illustrated in Figure 2; the device that accomplishes this transformation is called a controller or a compensator. Depending upon the nature of the physical problem and the stringency requirements for the overall system performance, the physical realization of the feedback controller can be exceedingly simple (e.g. a constant gain analog amplifier) or complex (a

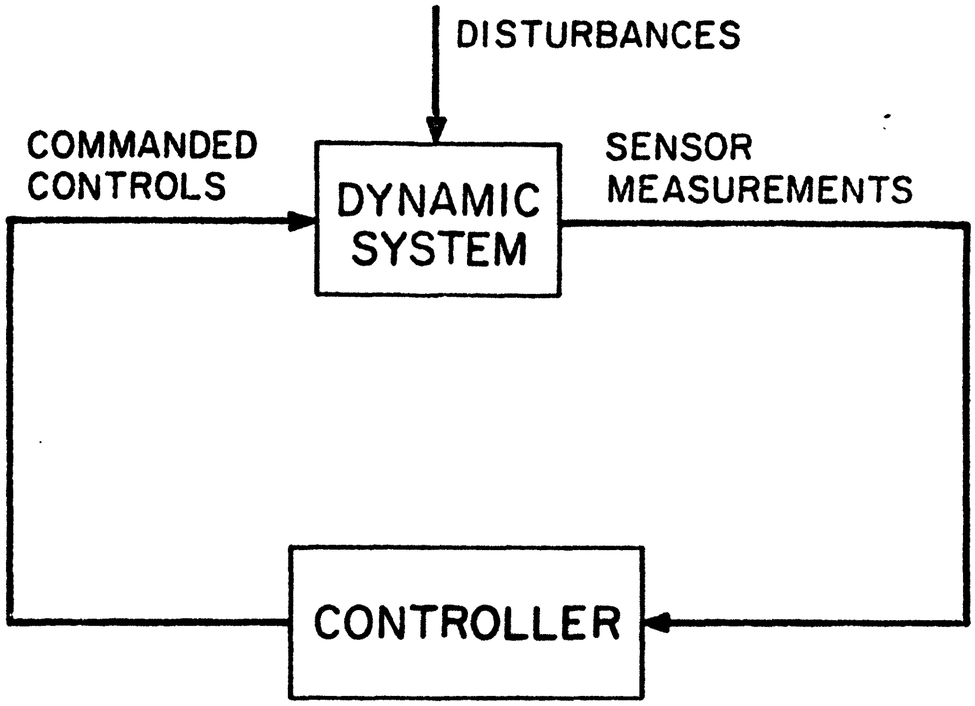


Fig. 2 Structure of Centralized Stochastic Control System

special purpose modern digital computer). The appropriate design of the feedback compensator or controller so that not only the system performance is satisfactory but, in addition, technological constraints that pertain to its implementation are observed is the essence of the control design problem. By technological constraints we mean both hardware and software considerations, cost, weight, reliability, and so on.

3. HISTORICAL PERSPECTIVE

In this section we present a very brief historical perspective of the techniques available for the design of feedback control systems. By necessity our perspective will be brief. However, we hope to convey the intimate interrelationship between the development of the theory, the motivating applications, the available computational tools, and the hardware technology for implementation.

The first phase of the development of control theory can be traced to the time period 1940-1960. At present, we refer to this brand of theory as servomechanism theory or classical control theory. During this period the theory was developed for systems described by linear differential equations with constant coefficients and characterized by a single control input. By means of the Laplace transform such systems could be analyzed in the frequency domain, so that the system dynamics could be represented by a transfer function. One of the main motivations for the development of the design methodology was the need for accurate fire control systems for both naval and surface weapons systems (see references [1] to [4]). Later on during this time period the feedback control of chemical and industrial processes also provided additional motivation for theoretical refinements.

The design tools which emerged from classical control theory were, by necessity, greatly influenced by the computational tools and the simulation facilities available. Most design tools were graphical in nature (Nyquist diagrams, Bode plots, Nichol's charts, root locus plots). Closed form solutions were sought. Since the available theory could not handle nonlinear systems and stochastic effects (with the notable exception of Norbert Wieners work [5]) extensive simulations were carried out on electronic analog computers, with a great amount of "knob twisting" and common sense engineering utilized to arrive at a satisfactory design. Almost exclusively, the implementation of the feedback system was by electro-mechanical and analog-electronic devices.

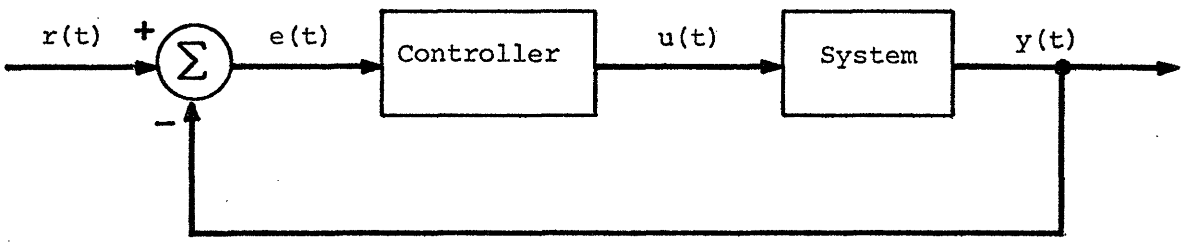
The basic development of classical control theory can be understood in reference to Figure 3. The basic idea was to have the actual output y(t) "follow" the reference input r(t) as closely as possible. The error signal, e(t), was a measure of the undesirable deviation which was then transformed by the controller into the actual control signal that was applied to the physical system. At the basic level the issue of how to design the controller so that the error signal always remains small was the key design problem.

The second phase of the development of a more sophisticated and powerful theory of control is often referred to as <u>modern control theory.</u> Its origins are acknowledged to be around 1956 and it still represents an extremely active research area. In its early stages of development, the theory was strongly motivated by the missile and aerospace age and in particular trajectory optimization. Aerospace systems can be extremely nonlinear and, in general, their motion and performance can be influenced by several available control inputs. Since classical control theory represented a scientific design methodology only for linear single-input systems, a much more general design methodology had to be developed for the stringent performance requirements of aerospace systems.

The development of modern control theory and the associated design methodologies were also greatly influenced by the appearance of the modern digital (maxi) computer in the early sixties. The digital computer greatly influenced the nature of "solutions" to control problems. To be more specific, in classical control theory one almost always sought closed form solutions; in modern control theory one accepts a recursive algorithm as a perfectly acceptable solution to the control problem. This transition from analytical solutions to algorithmic solutions opened several important new research horizons and fresh ways of thinking.

The basic new ingredient associated with modern control theory was that of optimization. This new attitude towards "optimal design" was necessitated by the fact that it is difficult to examine simultaneously several control and state variables, as they evolve in time, in order to make a clear cut scientific decision on which design is preferable. Thus, for multivariable control problems it is important to translate the desirable attributes of "good" system performance into a scalar mathematical index of performance that had to be optimized subject to the constraints imposed by the system differential equations, as well as additional constraints on the control and state variables which arise from the physical nature of the problem.

Two powerful theoretical approaches were developed during the early phases of modern control theory. The first approach represented an extension of classical calculus of variations methodology to the optimal control



r(t): reference input

y(t): actual output

e(t): error signal (e(t) = r(t) - y(t))

u(t): control input

Figure 3. The Traditional Servomechanism Problem

problem; it was developed by the Russian mathematician L.S. Pontryagin and his students and was called the maximum principle (see references [6] to [11]). The second approach, due to the U.S. mathematician R. Bellman, was based upon the so-called principle of optimality, an almost self-evident property of optimal solutions, which led to the so-called dynamic programming algorithm (see references [12] to [14]).

These two major theoretical breakthroughs in the late fifties resulted in a worldwide flurry of research during the early sixties. Several digital computer algorithms were developed which could be used for the numerical solutions of the complex nonlinear equations which define the optimal control solution and the theory was applied to a variety of complex trajectory optimization problems for both endoatmospheric and exoatmospheric aerospace systems, with a great deal of success.

Another byproduct of the initial research breakthroughs in dynamic optimization problems was the development of a systematic theory, with associated digital computer algorithms for problems of optimal stochastic estimation and optimal stochastic control.

In the stochastic estimation area one attempts to reconstruct estimates of key state variables and parameters of a physical system from noisy sensor data. An important class of applications that provided motivation for, and benefited subsequently by, the development of optimal stochastic estimation algorithms was the generic tracking problem of a target by radar or (active or passive) sonar. In this class of problems the radar or sonar generates noisy range and/or angle measurements; the stochastic estimation algorithms processes the noisy sensor data to obtain

(a) improved position estimates

(b) velocity estimates

(c) target classification estimates

for the target. At the present time there exists a whole variety of stochastic estimation algorithms which represent extensions of the celebrated Kalman Filter (see references [15] to [16]), the optimal stochastic estimation algorithm for linear dynamic systems subject to Gaussian uncertainties, to systems described by nonlinear equations with respect to their dynamics and measurements (see references [17] to [19]).

Stochastic estimation algorithms have been extensively used for position accuracy improvement in inertial navigation systems. Some relatively recent studies show how to couple the measurements of the inertial measurements units (IMU) to those obtained from gravitational and/or magnetic field anolmalies so as to further improve the position accuracy of a ship or submarine.

Although stochastic estimation theory, and the associated algorithms are important by themselves in a variety of application areas (such as the tracking problem and the navigation problem), they become even more important when they are coupled to the control problem. The theory and algorithms associated with <u>optimal stochastic control</u> deal with the overall problem of optimizing an overall system performance index subject to the constraints imposed by the dynamic stochastic differential equations that describe the system behavior as well as the available sensor configuration and their accuracy characteristics.

Most of the theoretical advances in optimal stochastic control have been carried out during the past decade (see references [20] to [22]). Optimal stochastic control problems are relatively well understood, since the dynamic programming algorithm can be easily extended to the stochastic case. There remain, however, certain formidable real time computational requirements associated with optimal stochastic control. This class of problems not only combines the issues of deterministic optimization and stochastic estimation, but also a considerable interaction between the two. This is the so-called dual control problem (see references [23] to [28]). Roughly speaking the problem is that in any dynamic optimization problem the present values of the control variables should cause the future values of the state variables to behave in an optimal manner. This requires, however, that a relatively good knowledge of the future system response be available. Unfortunately, especially in the case of nonlinear systems with uncertain parameters such "good" knowledge of the future is not available. It may turn out that by applying a control that excites certain modes, we could identify in real-time certain key parameters, which would improve our knowledge of future responses. On the other hand, control inputs that are good for identification may not necessarily be the best for control. The preceding argument shows the conceptual complexity of the optimal stochastic control problem. Fortunately the mathematical formulation of the problem automatically handles all of these complex tradeoffs, and provides the optimal control solution containing the correct balance between the tasks of identification and optimization of performance index as a function of time. The pragmatic difficulty is that, at the present state of the art, the real time computational requirements can be formidable for sufficiently complex nonlinear stochastic optimal control problems. To give the reader an idea of the complexity of the real time computational requirements, it suffices to state that one needs to solve in real-time coupled sets of nonlinear partial differential equations; such solutions are beyond the state of the art of current and projected maxi-computers.

The situation is not as grim, however, as one may imagine. Even if the computation of the truly optimal stochastic control cannot be accomplished, the mathematical theory provides insight into the nature of the optimal solutions. Such insight together with common sense engineering know-how about the specific physical problem, can be used to develop near-optimal solutions to several physical problems, still based upon a general design methodology. The so-called Linear-Quadratic-Gaussian (LQG) method has been extensively analyzed during the past decade (see references [29] to [31]) and has been successfully applied to several complex problems. The resultant designs show a significant degree of improvement over conventional designs. Of particular interest in naval applications one can mention the areas of submarine control (see references [32] to [33]), jet engine control (see references [34] to [37]), and super-tanker control (see reference [38]).

4. RECAPITULATION

We have attempted in the above discussion to simultaneously provide an historical perspective as well as a survey of the state of the art of classical and modern control theory. At the present time, we have a good conceptual understanding, theories, and design algorithms so that we can tackle complex control problems. Of course, there is a gap between the available theory and applications. The trend in the past five years has been to apply modern control theory to several applications. Needless to say we need many more complex applications to fully appreciate the advantages and shortcomings of modern control theory. The shortcomings can then serve as the motivating force for future relevant research at the theoretical, algorithmic, and design methodological level.

In the remainder of this paper we shall outline what are some exciting future research topics and why they are important. Needless to say the list of topics is not exhaustive; however, it represents a consensus of international opinion of the most pressing areas for future research based upon diverse application areas and the theoretical state of the art.

The need for future advances in control and estimation theory can only be appreciated by viewing this field of research as truly interdisciplinary applicable not only to complex defense systems but also to other complex engineering and socioeconomic systems, such as interconnected power systems, urban transportation networks, command control and communications systems (C^3), and socioeconomic systems.

5. DECENTRALIZED CONTROL AND LARGE SCALE SYSTEMS

The theory associated with both classical and modern control theory has been developed under a crucial key assumption: centralized decision making. This can be best understood in reference to Figure 2 in which the objective is to design the feedback controller. Notice that the controller (or decision maker) has access to all the measurements generated by the noisy sensors and generates all the controls. Implicit in the theory and associated algorithms is that the controller also has central knowledge of

(a) the entire system dynamics

(b) the probabilistic description of all uncertain quantities

(c) the overall index of performance.

Although such assumptions are perfectly valid in a variety of applications, it is clear that there are several complex systems that cannot be handled within the existing framework. We present two oversimplified examples that hopefully illustrate the point.

Example 1. Consider the problem of defending a fleet consisting of several vessels under attack. The overall defense objective may be to minimize the expected number of losses in terms of men and equipment. Clearly the evolution of the battle represents a stochastic phenomenon, involving real time decisions with respect to the allocation of sensor resources (radar,sonar) and defense resources (torpedoes, missiles, guns, etc). A purely decentralized strategy, i.e. each vessel only defends itself, cannot be optimal, since it does not utilize effectively the available fleet resources. On the other hand, it is unrealistic to visualize a purely centralized strategy in which the command center directs at all instants of time each and every action of the entire fleet. Conceptually a centralized strategy can be formulated, but it is unrealistic from the point of view of communication requirements and the vulnerability of the overall fleet to damage at the central command point. The proper way of handling this problem is to establish some sort of hierarchical command structure, where the overall defense objective is divided into subobjectives, as a function of the remaining defense resources.

Example 2. Consider a geographically distributed command-control-communications (C^3) system, consisting of several nodes, links of different capacities, and which is required to handle messages of different priorities. Each node represents a decision point and it has to make real time decisions on how to route the different classes of messages over the available links to their desired destinations. Under heavy demand, and especially if certain nodes and/or links become destroyed, this represents an exceedingly complex stochastic dynamic control problem. Once more a centralized control-decision strategy does not make sense. The entire resources of the network could be used to pass back-and-forth protocol and status information rather than to transmit useful messages. Once more the real time optimal decisions, say with respect to routing strategies, can only be accomplished with limited information exchange. For example, each node may be allowed only to communicate with its neighboring nodes. Hence, the optimal control strategy must be decentralized.

The above two examples represent problems of stochastic dynamic systems with distributed decision makers (or controllers) and limited communication interfaces. Several other examples such as power systems, ABM defense system, transportation networks, economic systems, have similar generic characteristics. In the control literature these are referred to as large scale systems and the methodology that has to be employed is called decentralized control.

One could go on and on describing additional large scale systems that certainly require the development of improved dynamic control strategies. However, let us pause and reflect upon their common attributes. They are

(1) topologically configured as a network

(2) they are characterized by ill understood dynamic interrelations

(3) they are geographically distributed

(4) the controllers (or decision points) are many and also geographically distributed.

This class of large scale system problems certainly cannot be handled by classical servomechanism techniques. Current designs are almost completely ad hoc in nature, backed by extensive simulations, and almost universally studied in static, or at best quasi-static, modes. This is why their performance may deteriorate when severe demands or failures occur.

We do not have a large scale system theory. We desperately need to develop good theories. The theories that we develop must, however, capture the relevant physical and technological issues. These include not only the traditional performance improvement measures but in addition the key issues of

(a) communication system requirements and costs and

(b) a new word - "distributed computation".

In addressing the problems of large scale systems and decentralized control we must also recognize that we are facing a critical technological turning point. We are in the beginning of a microprocessor revolution. These cheap and reliable devices offer us the capability of low cost distributed computation. It is obvious that relevant advances in the theory and design methodologies must take into account the current and projected characteristics of microprocessors, distributed computation, and decentralized control.

The development of a theory for decentralized control , with special attention to the issues of distributed via microprocessors, has to have the elements of a relatively drastic departure in our way of thinking.

Figure 4 shows the type of structure that we must learn to deal with. Once more we have a complex dynamic system which is being controlled by several distinct controllers. These controllers may consist of a single or many microprocessors, so that they provide means for distributed computation.

As shown in Figure 4, we have now several controllers or decision makers. Each controller only receives a subset of the total sensor measure-

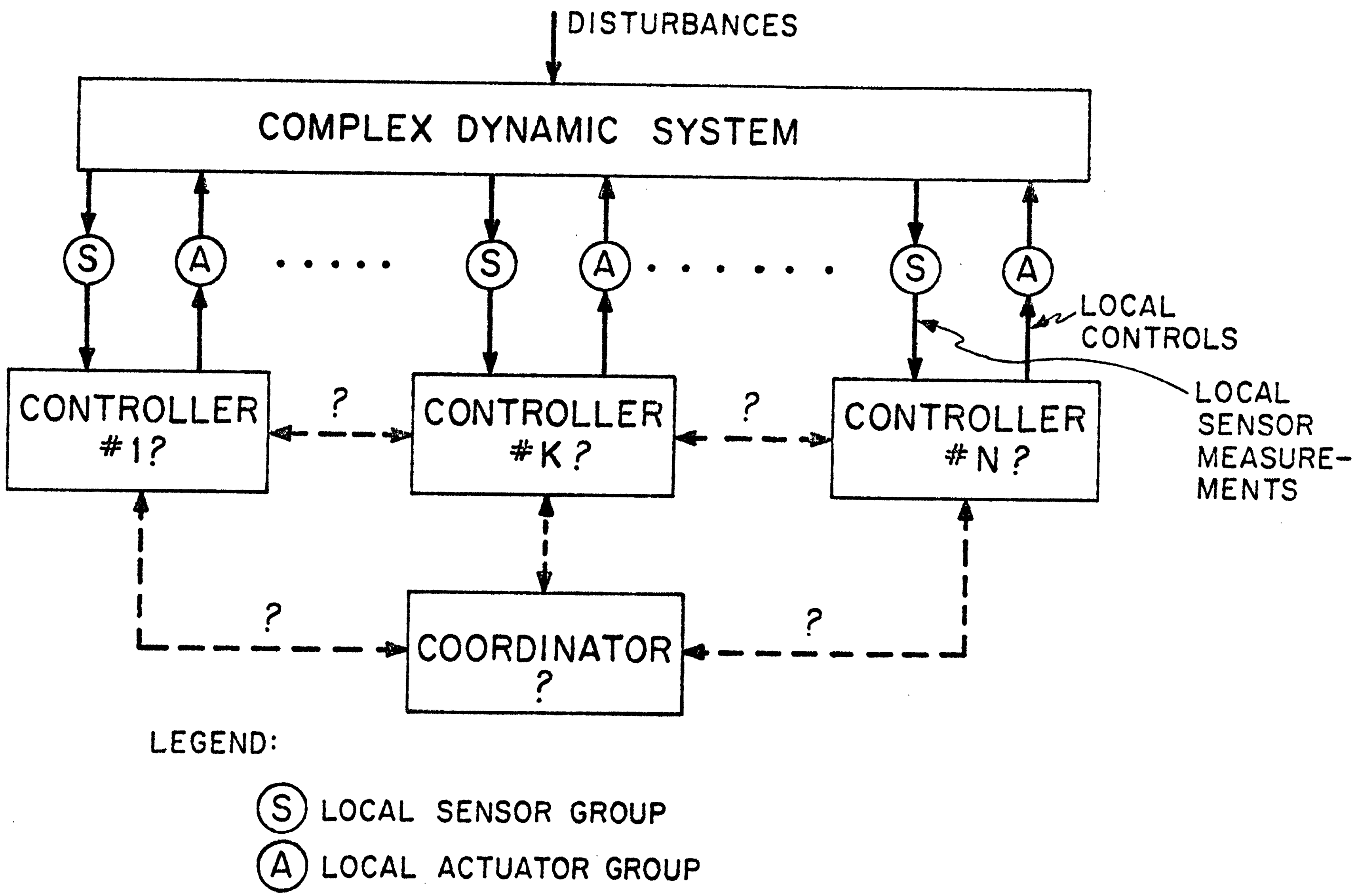


Fig. 4 Structure of Decentralized System

ments and in turn only generates a subset of the decisions or commanded controls.

The key assumption is that each controller does not have instantaneous access to the other measurements and decisions. To visualize the underlying issues involved, imagine that the "complex dynamic system" of Figure 4 is an urban traffic grid of one-way streets. Each local controller is the signal light at the intersection. The timing and duration of the green, red, and yellow for each traffic signal is controlled by the queue lengths in the two local one-way links as measured by magnetic loop detectors. In this traffic situation some sort of signal coordination may be necessary. In the general representation of decentralized control, shown in Figure 4, the dotted lines represent the communication/computer interfaces. All boxes and lines with question marks represent design variables. To systematically design the underlying decentralized system with all the communication and microprocessor interfaces, is the goal of a future large scale system theory.

The conceptual, theoretical, and algorithmic barriers that we must overcome are enormous. There are many reasonable starting ponts that lead to pitfalls and nonsense (see references [39] to [40]). Such decentralized control problems are characterized by so-called non-classical information patterns or non-nested information structure. This means that each local controller does not have instantaneous access to other measurements and decisions.

Such situations can lead to complicated results. The classic paper of Witsenhausen [41] that demonstrated, via a counterexample, that a very simple linear-quadratic-Gaussian problem has a nonlinear optimal solution was an early indication of the difficulties inherent in decentralized control. Since that time some advances have been made in such fields as

(1) dynamic team theory (see references [42] to [47])

(2) dynamic stochastic games (see references [48] to [52]

which, nonetheless, have only scratched the surface. We have not seen as yet spectacular theoretical breakthroughs in decentralized control. We are at a normative stage where old ideas such as feedback are reexamined and new conceptual approaches are being investigated.

My feeling is that, concurrently with the theory, we must obtain a much better understanding of the key features associated with different physical large scale systems. Then, and only then, will we be able to obtain a deep understanding of the true generic issues associated with large scale systems, as distinct from the physical, technological and even sociopolitical peculiarities of each system.

We must answer the question of "how important is a bit of information for good control". We may have to translate or modify certain results in information theory (such as rate distortion theory) to accomplish our goals. Perhaps the deep study of data communication networks will provide a natural setting for basic understanding, since the commodity to be controlled is information and the transmission of information for control routing strategies, or protocol as it is often called, share the same resources, have the same dynamics, and are subject to the same disturbances.

In summary, the development of new theoretical directions and concepts in decentralized control promises to be one of the most exciting areas of research in the decades to come. In spite of the tremendous conceptual and technical problems, the potential payoffs in a host of application areas is enormous.

6. MICROPROCESSOR CONTROL, ALGORITHM COMPLEXITY, AND CONTROL SYSTEM DESIGN*

The potential of microprocessors for conventional control system design presents a virgin area for both theoretical and applied research. The entire development of both classical and modern control theory was never greatly influenced by computer languages and architecture for two reasons. During the early phases of development, the controller implementation was analog in nature. During the later phases the availability of special purpose minicomputers for digital control did not present any serious obstacle for implementation.

The availability of low cost and reliable microprocessors presents new opportunities for the design of sophisticated control systems. However, the peculiarities of microprocessors, their architecture and so on do present certain problems that cannot be handled by the available theory. If control theory follows its tradition of rapidly exploiting technological innovations (such as the digital computer) for novel and improved designs, then it must face the challenges presented by microprocessors.

Of paramount importance is to incorporate in the overall index of performance not only quantities that pertain to the overall behavior of the control system but, in addition, quantities that reflect the complexity of the control algorithms. In addition to the usual constraints imposed by the physical system upon the control and state variables, we must also

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* The material in this section was heavily influenced by a "white paper" recently written by one of my colleagues, Professor T.L. Johnson [53].

include constraints that reflect the use of microprocessors for signal processing and control such as memory, finite word length, interrupts and the like.

There is still another area that needs theoretical investigation in that the bulk of the existing methodology applicable to the design of digital compensators is of the synchronous type, that is the sampling of sensors and the generation of control commands is carried out at uniform time intervals. On the other hand, nontrivial applications using microprocessors will almost surely require an asynchronous operation. Hence we can see a divergence between existing theory and desired implementation. This clearly points out that the available theory has to be re-evaluated, modified, extended and perhaps we may even have to adopt a completely new conceptual framework to keep up with the microprocessor technological innovations. Perhaps the theory does not need a tremendous quantum jump, but certainly several concepts from computer science (such as computational complexity, parallel vs. serial computation, automata theory and finite state sequential machines) must be incorporated into the formulation of the control problem. To be sure, the mixing up of "continuous" and "discrete" mathematics will lead to severe theoretical difficulties that must be overcome. For example, the author is not aware of any natural and general way of incorporating discrete-valued random variables in digital compensator design. Also, computer scientists interested in the area of computational complexity have not examined in any detail the most common algorithms used in control systems (such as the Lyapunov equation and the Riccati equation). Even if such measures of computational complexity were available, it is not clear how they could be naturally incorporated either on constraints or on penalty functions in the overall performance index to be optimized. Since the mathematics have to "mesh" together, it is not clear if variational techniques could be used to solve this class of new optimization problems.

At any rate the theory underlying the optimal use of microprocessors and their interconnections for digital compensation has yet to be developed. The resultant compensators will probably be of the finite-state, asynchronous operation variety for optimal use of the computational resources. This type of structure may naturally incorporate the common implementation problems such as model aggregation, interface design, saturation, fault handling, finite state inputs and outputs, storage allocation, interrupt-handling, and alphabet and programming languages.

7. FAILURE DETECTION, CONTROL UNDER FAILURE, AND SYSTEM RELIABILITY

Another exciting area for future research deals with the overall problem of reliable control system design and operation. The motivation for studying these types of problems is self evident, since reliable opration is crucial in a variety of applications.

At the present time, we do not have a systematic methodology or theory for handling such problems. Reliability theory, as a discipline of its own, does not appear to be well suited for dealing with the complex dynamic and stochastic situations that one is faced with in control.

Although we do not have as yet a general theory, there are several theoretical investigations and results which are emerging in the literature that appear to represent promising entries to this very important problem. Several of these concepts were presented at a workshop held at MIT, and funded by the NASA Ames Research Center, on Systems Reliability Issues for Future Aircraft in August 1975. The proceedings of this workshop will be published as a NASA Special Publication in the summer of 1976. It was evident from the presentations in that workshop that the present state-of-the-art in constructing reliable designs is to use triple or quadruple redundancy in crucial actuators, sensors, and other key components.

With respect to future high performance systems (such as aircraft, ships, etc.) the trend is to utilize a greater amount of control devices and sensors, which will be under complete automatic control. If each new sensor and actuator is constructed to be quadruply redundant, this will result in a prohibitively expensive design. The idea is then to try to arrive at systematic means for designing the control system such that the redundancy requirements are reduced, while in the case of sensor/actuator failures (when recognized), one can reorganize the control system so that the operative sensors and controllers can still maintain safe system operation.

Failure detection and isolation is then of paramount importance and some extremely important work has been done in this area during the past four years. The field is well surveyed in a recent paper by Willsky [54]. Essentially, the idea of failure detection and isolation relies very heavily upon the blending of dynamic stochastic estimation concepts (e.g., Kalman filters) with hypothesis testing ideas. Under normal operating conditions the residuals (innovations) of Kalman filters are monitored. A failure exhibits itself as a change in the statistical properties of the Kalman filter residuals. Once a failure has been detected one can formulate a set of alternate failure modes, and through the use of generalized likelihood ratios one can isolate the failed component.

Within the next five years we are going to see two or three case studies which will give us a great insight into the entire issue of failure detection and isolation, and obtain a much better understanding of the inevitable tradeoffs associated with the

(a) rapidity of failure recognition

(b) rapidity of failure isolation and classification

(c) false alarm probabilities

(d) computational complexity.

Failure detection and isolation is only the tip of the iceberg in the broad area of designing reliable systems. The whole issue of alternate ways of reconfiguring and reorganizing the control system, in real time, following the onset of a failure is a wide open research area. Much research at both the theoretical and the applied level needs to be carried out during the next decade. Of particular importance is the problem of what to do between the time that a failure has been declared and the time that the failure has been isolated. During this critical transient one can certainly expect a degraded operation of the control system, but its stability (under non-catastrophic failures) must be guaranteed.

It is imperative, in the author's opinion, that such a unified theory that deals with failure detection and isolation be developed. The current trend is to concentrate primarily upon sensor failures, but the theory and methodology has to be extended to other types of failures such as abrupt changes in the system dynamics, actuator failures, and computational failures. To be sure, redundancy of certain critical components is still going to be important. However, for military combat systems such as high performance surface effect ships, as well as for aircraft, it is desirable to distribute the redundant sensors on the vehicle so as to minimize the probability that the entire group of crucial redundant sensors (such as gyros and accelerometers) be destroyed by enemy fire. However, the geographical distribution of such redundant sensors presents additional problems since their readings will be influenced by their location. Hence kinematic and structural dynamics must be taken into account in order to have even simple majority rule voting procedures in triply redundant sensors. Thus, the short term dynamics of the ship and aircraft, as well as important bending and vibrational modes must be known relatively accurately so as to minimize the effects of false failure alarms.

In the long run we need a general theory of dynamic system reliability for the design of fail-safe, fail-operational, and fail-degradable control systems. We must develop a methodology that starts with an overall desired measure of reliability and control system performance, and provides us with systematic computer-aided design techniques that determine the type of sensors and actuators, their accuracy, their inherent reliability, their redundancy level, their geographical distribution and their back up (especially in the case of sensors) by software (based upon stochastic estimation techniques) which can reduce the level of redundancy. Furthermore such a theory must incorporate the real time reconfiguration of the control system, following the onset of one or more non-catastropic failures, so as to maintain acceptable system performance. To the best of our knowledge very little has been done in formulating in a precise mathematical way this class of problems, and several conceptual barriers have to be overcome before a useful set of theoretical tools can be developed.

8. CONCLUDING REMARKS

We have attempted to define three major future research areas in control and estimation theory. Such future theoretical directions build upon a solid theoretical foundation available today, and are motivated by both significant application areas and technological advances. It is important to stress that the theoretical issues and the technical details that must be overcome are extremely difficult and diverse. For the development of relevant theoretical and algorithmic tools one can envision significant interdisciplinary efforts by groups of control engineers, mathematicians, and computer scientists as well as the great need for advanced applications so that the advantages and disadvantages of the new theories can be rapidly tested.

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