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MULTI - MODEL PARTITIONING THE MULTI - MODEL EVOLUTIONARY FRAMEWORK FOR INTELLIGENT CONTROL

Dr. Demetris G. Lainiotis
Professor Emeritus
Department of Computer Engineering and Information
University of Patras
Rio-Patras, Greece 26500

e-mail: dlainiot@otenet.gr
Fax: +30.61.991-909

I. INTRODUCTION

The nature of control problems of great current interest is highly complex, nonlinear, stochastic, time-varying, and partially known at best. The difficulties of control design are compounded further because the control goals and control laws may not be completely defined either because they are not known at design time or because they change unexpectedly [1 - 11].

As such, the modern control engineering design problems to be solved are highly complex, large-scale, and computationally intractable. Their practical solution requires system/algorithms that are: a) adaptive, in order to cope with significant unmodeled and unanticipated changes in the plant, in the environment and in the control objectives; b) learning, in order to increase its knowledge of the plant and its environment; and c) intelligent and autonomous. Moreover, the resulting intelligent controls must be realizable in decentralized/parallel/distributed processing implementations. Indeed, for the complex control problems of today, the modular, parallel/distributed processing architectures are absolutely necessary in order to meet, at reasonable cost, the time-processing constraints imposed by the complexity of the applications.

The design of optimal controls, especially for large-scale, complex applications, depends integrally on the model of the physical problem. Indeed, the model constitutes the vital link between the “physical” problem in which the optimal control will be used, and the mathematical realm in which it must be designed. The effectiveness, and applicability of the designed system depends strongly on the realism with which the associated mathematical model represents the underlying “physical problem. However, the more realistic the model, the greater its complexity, and consequently the greater the difficulty of the associated control design problem, and the greater is the difficulty in implementing the designed control. The difficulties are compounded further by the fact that as the model realism increases so does the ignorance of the model. In most applications, complete knowledge of complex models is neither available nor readily forthcoming and one is confronted with the design of an optimal control in the face of incomplete model knowledge. To fully account for this model uncertainty, necessitates increasing the model complexity even more, e.g. augmenting the state-vector with the unknown parameter vector (for parametric model uncertainty), thus substantially increasing the effective dimensionality and complexity, e.g. nonlinearity, of the problem.

The classical approaches to the control design problem have been to assume the model, whether complex or drastically reduced, to be known, and to proceed with the design, if it is computationally feasible, bearing the consequences of practically unrealizable controls if the model is complex, or the consequences of ineffective controls if the model complexity is reduced unrealistically. Furthermore, the classical approaches do not confront the problem of unmodeled, and unanticipated changes in the plant, in the environment, and in the control objectives. They do not posses the "intelligence", adaptivity, and learning capacities. As such they are not autonomous. For example, they are neither capable of failure detection and identification, nor of altering their control laws to conform to unanticipated changes in the control goals.

In the late sixties and early seventies, Lainiotis [2 - 8] introduced the multi-model partitioning (MMP) methodology for the design of adaptive/intelligent systems and with his collaborators [4 – 8] applied it to the design of adaptive controls. In contrast to previous approaches, the multi-model (MMP) methodology addresses all of the above mentioned requirements for effective intelligent/adaptive/learning controls with decision-making capacities, and with computationally attractive modular/parallel/distributed processing architectures. The MMP controls have been successfully applied to numerous important applications in the last 30 years.

II. <u>MULTI MODEL PARTITIONING (MMP) METHODLOGY: STRUCTURE AND RATIONALE</u>

In contrast to previous approaches, the MMP methodology, Lainiotis [2 - 11], and Lainiotis et al [4 - 8] does not confront the complex model nor does it approximate it by a single simpler model of reduced complexity and much reduces realism. Instead it decomposes (partitions) the control problem into a set of control subproblems, the optimal or suboptimal controls of which are far easier to derive, and most importantly, they are far easier to implement. Specifically the multi-model partitioning approach consists of the selection of a parameter vector θ of the model (plant, environment etc.) each value of which specifies a particular realization of the complex model. As such, the admissible values of θ constitute a set of possible sub-models of the original complex model. This gives rise to the multi-model name for this decomposition or partitioning. The submodels may be chosen around a possible/probable operating point (set-point), e.g. flight condition of an aircraft, physiological state of a patient, operating point of a chemical reactor, a failure condition, etc., etc.

Moreover, following the Bayesian viewpoint the choice of a particular value θ_i of θ is random with a-priori probability $P(\theta_i)$ consistent with the stochastic nature of the original complex model. The probabilities $P(\theta_i)$ incorporate/represent the "relative" likelihood or frequency of this set-point (probability of occurrence) or reflect the relative significance/importance of this set-point, e.g. stall condition for an aircraft, critical condition of a patient, etc.

Conditioning on this pivotal parameter vector θ, the original complex, large-scale control problem is decomposed/partitioned into a set of control design subproblems, each corresponding to an admissible parameter-conditional model.

Given the above rationale the MMP adaptive/intelligent control proposed by Lainiotis [2 - 11] is as follows:

MMP Adaptive/Intelligent Control:

Given the performance index J the measurements $\lambda_k = \{z_1, z_2, z_3, \ldots ,z_k\}$ where $z_i = z(t_i)$, the set of N submodels M_i each corresponding to the value θ_i of θ, and the a-posteriori probability $P(\theta_i / k)$, i=1, 2, … , N, the MMP adaptive/intelligent control/ (MAIC) u_k is

$$u_k = \sum_{i=1}^{N} \hat{u}_i(k) \cdot P(\theta_i / k)$$

where

$\hat{u}_i(k)$ = is the optimal or approximately optimal control corresponding (matched) to the ith submodel Mi

$P(\theta_i / k)$ = the weight $P(\theta_i / k)$ is the a-posteriori probability of θ_i given the measurements of λ_k. It is a measure of how likely it is that the particular value θ_i corresponds to the sub-model that generated the measurements λ_k.

It must be noted that the weights $P(\theta_i / k)$ have the following properties:

$$\sum_{i=1}^{N} P(\theta_i / k) = 1, \quad and \quad 0 \le P(\theta_i / k) \le 1$$

III. MAIC STRUCTURE AND RELATED ADVANTAGES

Several remarks on the nature, structure, realization and related significant advantages of the multi-model, adaptive/intelligent control (MAIC) are given below:

i) Note that the MAIC is given as the weighted-sum of the model-conditional or elemental controls $\hat{u}_i(k)$, each of which is matched to a particular submodel M_i specified by parameter value θ_i, and is weighed by the a-posteriori probability $P(\theta_i/k)$ of the “true” or most appropriate submodel being specified by θ_i. Thus, the MAIC is decomposed/partitioned into a set of elemental controls which are moreover decoupled from each other. In this sense the MAIC is an approximation of the desired but inaccessible optimal nonlinear adaptive control via a set of elemental controls.

ii) The MAIC, given as the weighted-sum of the decoupled elemental controls, has a natural modular structure capable of parallel/distributed processing. This architecture makes the MAIC exceptionally fast and thus able to meet the heavy real-time processing requirements of complex, large-scale control applications.

iii) The modular structure of the MAIC has significant computational advantages. Namely the large-scale, complex, nonlinear, stochastic control is represented approximately by a set of decoupled, much smaller-size, much less complex, e.g. linear instead o nonlinear, elemental controls.

For example, for the optimal adaptive control problem with linear model of state-vector dimensionality n, and unknown parameter vector θ of dimensionality r, augmenting the state-vector with θ, we are confronted with a nonlinear model of dimensionality n+r, e.g. for n = 10, n+r could be as high as 310. So the control problem to be dealt with in the non-partitioning framework is: a) nonlinear: and b) of dimensionality 320. However, if we use the multi-model partitioning methodology we have to deal only with 310 elemental control problems which are: a) linear, and b) of dimensionality 10!!!

iv) The modular structure of the MAIC gives it exceptional ease in design, since the elemental controls are decoupled, much simpler to design than the original large-scale complex nonlinear control, and in many application, they are of identical structure differing only parametrically. Moreover, because of these significant properties, the MAIC are also readily implementable, in many cases in terms of the similar building blocks, namely the elemental controls.

IV. MAIC: EVOLUTIONARY NATURE AND RELATED ADVANTAGES

The second building block of the MAIC consists of the weights $P(\theta_i / k)$ namely the a-posteriori probabilities. These probabilities encompass several important properties and consequent advantages of the MAIC. Namely, these advantages are:

i) Learning: extensive simulations by several researchers [2 – 8, 12 – 14, 17 - 19] has shown that for time-invariant unknown parameter vectors θ, the a-posteriori probability for the submodel equal to the correct submodel generating the data converges to one, while the remaining a-posteriori probabilities converge to zero. In other words, the MAIC learns the true model and

$$u(k) \rightarrow \hat{u}_i(k) \text{ where } \theta_i = \theta^* = true\,model$$

Moreover, if the "true" model is not included in the set of submodels, then the a-posteriori probability, for the submodel Mi closest to the "true" model converges to one, while the remaining a-posteriori probabilities converge to zero. Namely, the MAIC converges to the elemental control corresponding to the submodel M_i with parameter value θ_i closest in the euclidean sense, to the "true" submodel parameter value θ^* .

ii) Adaptivity; for time-varying parameter vector θ, extensive simulations by Lainiotis et al [2 -11], have shown that the MAIC adapts to the time-varying parameters, namely it tracks their time-evolution by using essentially evolutionary/genetic algorithms first proposed by Lainiotis [2 - 11], and utilized by Lainiotis et al [4 - 8]

iii) Failure Robustness: the MAIC is very robust to failures in the plant, measurement system, even to an elementar control. This can be seen readily if one models a failure as an abrupt change in the parameter vector θ, which as was indicated above can be tracked by the MAIC.

iv) Fault Detection and Correction: the MAIC has a built-in failure detection and correction capability, because of its weighted sum structure, and the "learning" property of the a-posteriori probabilities. For example, if a failure occurs in the elemental control $u_i(k)$, the corresponding probability $P(\theta_i / k)$ approaches zero, which indicates a failure, and, moreover, the elemental control $\hat{u}_i(k)$ is removed from $u_i(k)$, which constitutes a correction

v) Intelligence: in view of the above important properties of the MAIC, namely: adaptivity, learning, self-monitoring, fault-detection and correction (decision capability, and corrective action) and the consequent autonomy, the MAIC can be considered and intelligent system.

V. MAIC PERFORMANCE AND APPLICATIONS

The critical question concerning the usefulness and applicability of the MAIC is its performance: especially in comparison to competing controls. Extensive simulations [2 – 8, 12 – 14, 17 - 19] and applications to various engineering, biomedical, economic, etc. problems have shown that the MAIC performs very well, and certainly better than competing controls, Lainiotis et al [2 –8, 12], Saridis [19], Watanbe [18],etc.

The MAIC has been extensively utilized in practical engineering, biomedical, economic applications such as chemical process control, autopilots, ship control, economic stabilization, blood pressure control, etc, etc [12 - 14].

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