P. J. Antsaklis, "Intelligent Control for High Autonomy in Unmanned Underwater Vehicles," P r oceedings of t he N SF/ISR W orkshop o n ' Undersea R obotics a nd I ntelligent C ontrol ' , pp. 25-32, Lisboa, Portugal, March 2-3, 1995.

Intelligent Control for High Autonomy in Unmanned Underwater Vehicles

by

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Introduction

The complexity and the uncertainty in the models of unmanned underwater vehicles (UUV) require sophisticated control methods. The need for real time control necessitate fast algorithms and the use of simpler models; and this leads to methodologies such as hybrid control. Hybrid control is of course an important part of intelligent control, where different levels of abstraction are used. The need for high degree of autonomous behavior, in Autonomous Underwater Vehicles (AUV), makes intelligent control methodologies necessary; intelligent learning control, failure diagnosis and reconfiguration methodologies become important.

Unmanned autonomous underwater vehicles represent an important class of highly uncertain, complex systems that must be controlled. The control requirements dictate the use of intelligent control methodologies. Learning will be necessary as the mission of the vehicle becomes increasingly demanding.

In the following, several ideas are brought forward regarding the control of highly uncertain systems such as AUVs. The research experience of the author and his collaborators in this area is briefly described. References of relevant published works are given.

Unmanned Underwater Vehicles (UUV)

The dynamics of motion of unmanned underwater vehicles (UUV) are typically highly nonlinear and highly uncertain. Nonlinearities arise from hydrodynamic forces as well as crosscoupling between vehicle states. Uncertainties arise due to changes in the environment that interacts with the vehicle, for example changes in the current and water conditions. They also arise due to poorly known mass and hydrodynamic properties. The mass may be uncertain when for example the UUV retrieves a large object of unknown mass. The hydrodynamic coefficients, that reflect the hydrodynamic properties in the model, typically are complex functions of vehicle geometry, speed, orientation and water conditions and as a consequence cannot be characterized exactly in advance; their values are determined using empirical techniques. In view of this, together with the limited available energy resources for control, it is apparent that the control of the motion of UUV is a highly challenging problem. In [17], the stabilization of a AUV's dive plane dynamics using learning control is discussed. An adaptive variable structure controller is designed, where the changing switching control surfaces are identified on line using an inductive inference algorithm and ellipsoidal update methods; this algorithm allows convergence after a finite number of updates, with convergence time bounded in a polynomial manner by plant complexity.

Proc. of the NSF/ISR Workshop on 'Undersea Robotics and Intelligent Control', Lisboa, Portugal, March 2-3, 95.

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Intelligent Control

To meet highly demanding control specifications in complex systems a number of methods have been developed that are collectively known as *intelligent control methodologies*. They enhance and extend traditional control methods. Intelligent controllers are envisioned emulating human mental faculties such as adaptation and learning, planning under large uncertainty, coping with large amounts of data etc in order to effectively control complex processes; and this is the justification for the use of the term intelligent in intelligent control, since these mental faculties are considered to be important attributes of human intelligence; see for example [1-3] and the references therein.

In the minds of many people, particularly outside the control area, the term "intelligent control" has come to mean some form of control using fuzzy and/or neural net methodologies. This perception has been reinforced by popularized articles and interviews mainly in the nonscientific literature. However intelligent control does not restrict itself only to those methodologies. An alternative term is *Autonomous Intelligent Control.*; it emphasizes the fact that an intelligent controller typically aims to attain higher degrees of autonomy in accomplishing and even setting control goals, rather than stressing the (intelligent) methodology that achieves those goals. Intelligent Control is *interdisciplinary,* combining methodologies from areas such as Control Systems, Computer Science and Operations Research. Applications of Intelligent Control range from manufacturing and chemical processes, to communication networks and IVHS; from space antennas to land and underwater vehicles.

Recently a IEEE Control Systems Society task force discussed what is meant by the term Intelligent Control and its uses and implications in the control area. Its findings have been reported in [4]. The report contains, in its first section, a brief introduction to the types of control problems the area of intelligent control is addressing and of its relation to conventional control. Definitions of intelligent systems and of degrees of intelligence are given in the second section, and the role of control in intelligent systems is explained. The different characteristics or dimensions of intelligent systems such as autonomy, learning and hierarchies are then discussed. The third section contains edited versions of some of the email exchanges and additional comments by the task force members, together with some references for further reading; they are meant to supplement the material in the second section and to provide some guidance and references in exploring the area of Intelligent Control.

Reconfiguration in response to anticipated and unanticipated changes

In systems where there is high uncertainty, such as a UUV for example, the actual plant may behave differently than predicted due to inadequacies in the model or changes in the plant and the environment. Model inadequacies may have occured because of inability to obtain a good model of the UUV and its environment in advance. Changes occur because of component and structural failures, because of evolution of the plant, and of degradation due to aging, because of changing water and current conditions. To deal with these changes it is useful to classify them as anticipated or non anticipated.

Anticipated changes can perhaps be dealt with by having a number of appropriate models and controllers the system switches to or interpolates among when it is instructed to do so. That is, when certain conditions exist, and this has to be sensed, appropriate action is taken chosen from a list stored on board. This approach can be very useful when quick response to drastic sudden changes, or failures, is needed. Conventional control methods,

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neural networks or other techniques may be used to derive the appropriate controllers that may be stored for example in expert systems or associative memories.

Certain changes may be considered as unanticipated because of finite memory capacity which makes it difficult to have a preprogrammed response to all changes we can think of. If a change is destabilizing and a quick reaction is of essence then it should be classified as anticipated and be dealt with via a prestored response. This was the case for example in our approach discussed above as to how to deal with reconfiguration when only incomplete information.is available. For most of the unanticipated changes, the failure detection (FDI) system, or some change detection system (CDI), must provide the information needed for appropriate reconfiguration to be possible. Neural networks may be used to identify the new model (perhaps being trained as an add on, in parallel with, to an existing model) or some other inferential techniques. Note that related work in neural networks by our group, addressing some of these problems can be found in [5-11]. In [17] and [12-14], additional learning control methodologies are discussed.

In summary, a combination of strategies to deal with anticipated and unanticipated changes seems to be appropriate. Fast reaction to potentially catastrophic changes is essential. As more information concerning the location and exact nature of the change comes in then the initial control action is refined to not only ensure stability but also reestablish certain level of performance to the system. A reliable way to detect and identify changes is essential to the well being of the system and its being able to perform as expected. *Actuators therefore specifically designed to assist in the identification of the new plant model and conditions may be appropriate in autonomous systems.*

Learning Control

Learning is an important dimension or attribute of Intelligent Control [4]. Highly autonomous behavior is a very desirable characteristic of advanced control systems, so they perform well under changing conditions in the plant and the environment (even in the control goals), without external intervention. This requires the ability to adapt to changes affecting, in a significant manner, the operating region of the system. Adaptive behavior of this type typically is not offered by conventional control systems. Additional decision making abilities should be added to meet the increased control requirements. The controller's capacity to learn from past experience is an integral part of such highly autonomous controllers. The goal of introducing learning methods in control is to broaden the region of operability of conventional control systems. Therefore the ability to learn is one of the fundamental attributes of autonomous intelligent behavior [1][4]. An introduction to learning in control can be found in [12]; contributions to learning control include our work in neural networks and also [13-14, 17].

Hybrid Systems

Hybrid control systems contain two distinct types of systems, continuous-state and discrete-state, that interact with each other. Their study is essential in designing sequential supervisory controllers for continuous-state systems, and it is central in designing intelligent control systems with high degree of autonomy. Our group has made a number of contributions in this area [15-29].

In the following, a brief outline of our recent results in hybrid control systems is presented indicating at the same time the publication where these results have appeared. Three areas of research contributions are identified and discussed separately. These areas are: Interface and Controller Design in Hybrid Systems; Inductive Learning in Hybrid Control Systems; Hybrid Control System Optimization.

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Interface and Controller Design in Hybrid Systems

In [15], a discrete event model of a continuous time plant described by differential equations is presented. It represents a refinement of our earlier hybrid models. Transition stability, a novel stability concept appropriate for hybrid systems and related to concepts of structural stability in power systems was introduced in [24]. In [19], an overview of our approach was presented. Supremal controllable sublanguages are important in the logical approach to control of discrete event and hybrid systems. In hybrid systems the discrete event models are nondeterministic and in [25] formulas for such languages were derived. In [20], the model developed in our approach [15] is used to study problems in digital control due to quantization of the signals.

Inductive Learning in Hybrid Control Systems

Research in this area has focused on three areas. These areas are 1) learning logically stable hybrid system interfaces, 2) concept learning of stabilizing controllers, and 3) inductive learning of optimal logical discrete event system controllers. Progress in area 1 resulted in the publication of an inductive learning method for identifying logically stable transitions in hybrid control systems in polynomial time [18]. Progress in area 2 extended the learning procedure of [18] to the identification of stabilizing control mappings. In [26], the resulting algorithm was used to autonomously stabilize a detailed simulation model of a communications satellite. In [13], the method was presented as part of a general overview on the use of Boolean concept learning of control mappings. Progress in area 3 concentrated on the development of polynomial time algorithms for the on-line identification of optimal discrete event system controllers. Initial experiments along this line were reported in [13], where an extension of L*-algorithm was used to ``learn" optimal discrete event system controllers.

Hybrid Control System Optimization

This research work developed polynomial-time algorithms for determining optimal collections of control agents used in the supervision of hybrid systems. Significant progress was achieved with the development of an alternating minimization algorithm whose theoretical computational complexity scaled as "O(n^{3.5}L)" and whose observed computational complexity scaled as "O(n^2 L)" ("n" parameterizes problem size and "L" parameterizes precision of optimal answer). In [27] analytical results on the proposed algorithm's computational complexity were presented. Applications include the design of hierarchical controllers [28] and the design of supervisory controllers [29].

Discrete Event Systems and Petri Nets

Discrete event system theory is important in intelligent control, as it can be used for example to study planning the different control tasks. Discrete event systems have been studied in connection to hybrid systems, see the references to hybrid control below; see also [30-33] for additional contributions. Recently we have developed a very promising approach to design feedback Petri net controllers for discrete event systems described by Petri nets [34].

Petri nets are very powerful and flexible graphical and mathematical modeling tools. As a graphical tools Petri nets can be used as a visual communication aid similar to flow charts, block diagrams and networks and for simulation of discrete event systems. As a mathematical tool it is possible to set up state equations that describe the behavior of the system. In the past their use in control has been somewhat limited, the main reason being

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the lack of appropriate methodologies to control systems described via Petri nets. Recently an approach to feedback control of systems described via Petri nets was developed, that uses the concept of place invariants of the net and it is simple and transparent. It appears that for the first time one will be able to systematically derive feedback controllers for real practical discrete event systems [34].

References

Autonomous Intelligent Control

[1]. P.J.Antsaklis and K.M.Passino, Eds, An Introduction to Intelligent and Autonomous Control, 448 pages, Kluwer Academic Publishers, 1993.

[2]. P. J. Antsaklis and K. M. Passino, "Introduction to Intelligent Control Systems with High Degree of Autonomy", Introduction to Intelligent and Autonomous Control, P.J.Antsaklis and K.M.Passino, Eds., Chapter 1, pp. 1-26, Kluwer,1993.

[3]. P. J. Antsaklis, M. D. Lemmon and J. A. Stiver, "Learning to be Autonomous: Intelligent Supervisory Control", in Intelligent Control: Theory and Practice, Gupta M.M., Sinha N.K., eds., IEEE Press, Piscataway, NJ, 1995.

[4]. "Defining Intelligent Control", Report of the Task Force on Intelligent Control, P.J Antsaklis, Chair. In IEEE Control Systems Magazine, pp. 4-5 & 58-66, June 1994. Also in Proceedings of the 1994 International Symposium on Intelligent Control, pp. (i)-(xvii), Columbus, OH, August 16-18, 1994.

Neural Networks

[5]. P. J. Antsaklis, "Neural Networks for the Intelligent Control of High Autonomy Systems", chapter 1 in Mathematical Approaches to Neural Networks, J.G. Taylor, Ed., pp 1-23, Elsevier, 1993.

[6]. I. K. Konstantopoulos and P. J. Antsaklis, "Integration of Controls and Diagnostics Using Neural Networks", Proc of the 1994 American Control Conference, pp. 1717-1721, Baltimore, MD, June 29-July 1, 1994.

[7]. Z. Hou and P. J. Antsaklis, "Identification and Control of a Powertrain System Using Neural Networks", Proc of the Symposium on Implicit and Nonlinear Systems, Univ of Texas at Arlington, Ft. Worth, TX, Dec. 14-15, 1992.

[8]. M. A. Sartori and P.J. Antsaklis, "Implementations of Learning Control Systems Using Neural Networks", IEEE Control Systems, in Special Issue on 'Neural Networks in Control Systems', Vol.12, No.3, pp.49-57, April 1992.

[9]. M. A. Sartori and P.J. Antsaklis, "Failure Behavior Identification for a Space Antenna via Neural Networks", Proc of American Control Conference, pp.567-568, Chicago, IL, June 24-26, 1992.

[10]. P.J. Antsaklis, "Neural Networks in Control Systems", Guest Editor's Introduction, IEEE Control Systems Magazine, Vol.10, No.3, pp.3-5, April 1990; Special Issue on 'Neural Networks in Control Systems' of the IEEE Control Systems Magazine, Vol.10, No.3, pp.3-87, April 1990. Also Guest Editor's Introduction, IEEE Control Systems Magazine, Vol.12, No.3, pp.8-10, April 1992; Special Issue on 'Neural Networks in Control Systems' of the IEEE Control Systems Magazine, Vol.12, No.3, pp.8-57, April 1992.

[11]. J. O. Moody and P. J. Antsaklis, "The Dependence Identification Neural Network Construction Algorithm", 1994 International Conference on Neural Networks, Vol VII, pp 4799-4804, Olrando, FL, June 26-July 2, 1994. Also in IEEE Transactions on Neural Networks. To appear.

Learning Control

[12]. P. J. Antsaklis, "Guest Editor's Introduction: Intelligent Learning Control", IEEE Control Systems, Special Issue on Intelligent Learning Control, June 1995.

[13]. M.D. Lemmon, P. J. Antsaklis, Xiaojunun Yang and C. Lucisano, "Control System Synthesis through Inductive Learning of Boolean Concepts", IEEE Control Systems, Special Issue on Intelligent Learning Control, June 1995.

[14]. M. D. Peek and P. J. Antsaklis, "Parameter Learning for Performance Adaptation", IEEE Control Systems Magazine, pp.3-11, December 1990.

P. J. Antsaklis, "Intelligent Control for High Autonomy in Unmanned Underwater Vehicles," P r oceedings of t he N SF/ISR W orkshop o n ' Undersea R obotics a nd I ntelligent C ontrol ' , pp. 25-32, Lisboa, Portugal, March 2-3, 1995.

Hybrid Systems

[15]. J.A. Stiver, P.J. Antsaklis and M.D. Lemmon , "A Logical DES Approach to the Design of Hybrid Control Systems", Technical Report of the ISIS (Interdisciplinary Studies of Intelligent Systems) Group, No. ISIS-94-011, Univ of Notre Dame, November 1994.

[16]. P. J. Antsaklis, J. A. Stiver and M. D. Lemmon, "Hybrid System Modeling and Autonomous Control Systems", Hybrid Systems, R L Grossman, A Nerode, A P Ravn, H Rischel Eds, pp 366-392, Lecture Notes in Computer Science, LNCS 736, Springer-Verlag, 1993.

[17]. M. D. Lemmon, J. A. Stiver and P. J. Antsaklis, "Event Identification and Intelligent Hybrid Control", Hybrid Systems, R L Grossman, A Nerode, A P Ravn, H Rischel Eds, pp 269-296, Lecture Notes in Computer Science, LNCS 736, Springer-Verlag, 1993.

[18]. M. D. Lemmon and P. J. Antsaklis, "Inductively Inferring Valid Logical Models of Continuous-State Dynamical Systems", Technical Report of the ISIS Group, No. ISIS-93-010, Univ of Notre Dame, December 1993. Journal of Theoretical Computer Science, vol 137, January 1995.

[19]. P. J. Antsaklis, M. D. Lemmon and J. A. Stiver, "Modeling and Design of Hybrid Control Systems", 2nd IEEE Mediterranean Symposium on New Directions in Control and Automation, pp 440-447, Chania, Crete, Greece, June 19-22, 1994.

[20]. J. A. Stiver, P. J. Antsaklis and M. D. Lemmon, "Digital Control from a Hybrid Perspective", Proc of the 33rd IEEE Conference on Decision and Control, pp 4241-4246, Lake Buena Vista, FL, Dec 14-16, 1994.

[21]. Xiaojunun Yang, P. J. Antsaklis and M.D. Lemmon, "On the Supremal Controllable Sublanguage in the Discrete Event Model of Nondeterministic Hybrid Control Systems", Technical Report of the ISIS Group, No. ISIS-94-004, Univ of Notre Dame, March 1994.

[22]. J. A. Stiver and P. J. Antsaklis, "On the Controllability of Hybrid Control Systems", Proc 32nd IEEE Conference on Decision and Control, pp. 294-299, San Antonio, TX, Dec. 15-17, 1993.

[23]. J. A. Stiver and P. J. Antsaklis, "Modeling and Analysis of Hybrid Control Systems", Proc of the 31st Conference on Decision and Control, pp.3748-3751, Tucson, AZ, Dec. 16-18, 1992.

[24]. M. D. Lemmon and P. J. Antsaklis, "On The Stability of Logical Transitions in Hybrid Control Systems", Technical Report of the ISIS Group, No. ISIS-93-009, Univ of Notre Dame, December 1993. Submitted for Journal publication.

[25]. Xiaojun Yang, P. J. Antsaklis and M.D. Lemmon, "On the Supremal Controllable Sublanguage in the Discrete Event Model of Nondeterministic Hybrid Control Systems", Technical Report of the ISIS Group, No. ISIS-94-004, Univ of Notre Dame, March 1994; revised November 1994. Submitted for journal publication.

[26]. C. Lucisano and M.D. Lemmon, "Query-Based Attitude Control of a Low Altitude Communications Satellite", Technical Report of the ISIS Group, No. ISIS-94-012, Univ of Notre Dame, September 1994.

[27]. M.D. Lemmon and P.T. Szymanski, "Interior Point Implementations of Alternating Minimization Training", Technical Report of the ISIS Group, No. ISIS-94-008, Univ of Notre Dame, June 1994.

[28]. P.T. Szymanski and M.D. Lemmon, "Interior Point Methods in the Design of Hierarchical Controllers", Proc of the 9th Intern Symposium on Intelligent Control, pp. 33-38, Columbus, OH, August 1994.

[29]. P.T. Szymanski and M.D. Lemmon, "A Modified Interior Point Method for Supervisory Controller Design", Proc of the 33rd IEEE Conference on Decision and Control, Lake Buena Vista, FL, Dec 14-16, 1994.

Discrete Event Systems

[30]. K. M. Passino and P. J. Antsaklis, "On the Optimal Control of Discrete Event Systems", Proc. of the 28th IEEE Conf. on Decision and Control, pp. 2713-2718, Tampa, FL, Dec. 13-15, 1989.

[31]. K. M. Passino and P. J. Antsaklis, "Event Rates and Aggregation in Hierarchical Discrete Event Systems", Journal of Discrete Event Dynamic Systems, Vol.1, No.3, pp. 271-288, January 1992.

[32]. K. M. Passino and P. J. Antsaklis, "A Metric Space Approach to the Specification of the Heuristic Function for the A^* Algorithm", IEEE Trans. on Systems, Man, and Cybernetics, Vol 24, no 1, pp 159-166, Jan 1994.

[33]. K. M. Passino, A. N. Michel and P. J. Antsaklis, "Lyapunov Stability of a Class of Discrete Event Systems", IEEE Trans. Auto Contr, Vol.39, No.2, pp 269-279, Febr 1994; correction, p 1531, July 1994.

[34]. J. Moody, K. Yamalidou, M. D. Lemmon and P. J. Antsaklis, "Feedback Control of Petri Nets Based on Place Invariants", Proc of the 33rd IEEE Conference on Decision and Control, pp 3104-3109, Lake Buena Vista, FL, Dec 14-16, 1994. Also to appear in Automatica.