

Control of Sensory Perception for Discrete Event Systems

by
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Control of Sensory Perception for Discrete Event Systems

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Siv.Ing. (NTNU Norway)

August 1997

*A thesis submitted for the degree of Doctor of Philosophy
of The Australian National University*



Department of Engineering
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Foreword

About the author

Geir Edvin Hovland was born in Stavanger, Norway, in 1970. He received his MSc degree in Control Engineering from the Norwegian University of Science and Technology, Trondheim, Norway in 1993. His MSc thesis was titled “Passivity based velocity observer for robot control”. He received his PhD in 1998 from the Engineering Department of the Australian National University, Canberra, Australia. Since 1997 he has been a senior research scientist at ABB Corporate Research in Oslo, Norway and ABB Robotics in Västerås, Sweden. His current interests include identification and control of lightweight and elastic industrial manipulators, force-controlled industrial manipulation and automation of assembly/disassembly. (Contact email: geir_hovland@ieee.org).

Some of the reviewers comments on the thesis

This thesis is concerned with the application and development of discrete event systems modeling to the problem of the control of sensory perception. The subject and approach taken by the candidate is indeed novel and differs substantially in philosophy and intent from previous approaches to this problem. The work is a significant contribution to the general area of robotics and sensory control.

The notion of discrete sensing states and transitions between states is what distinguishes the approach taken in this thesis from the more continuous-time, information-theoretic methods. The thesis contains significant advances in the state of the art in on-line monitoring of sensor-based robot actions. The emphasis is on monitoring of contact changes and estimation of the contact situation after the transitions, during repetitive execution.

Geir Edvin Hovland

AFTER DUE EXAMINATION AND HAVING FULFILLED
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THE SECOND DAY OF OCTOBER 1998



R. D. Smith
Vice-Chancellor

Mayaue Hou
Registrar

Declaration

The work contained in this thesis, unless explicitly stated, is original research whose major portion was done by the author. The work has not been submitted for a degree at any other university or institution. The results presented in the thesis have been published or submitted to journals and conferences as listed below.

Journal Papers:

- [J1] G.E. Hovland and B.J. McCarragher, Control of Sensory Perception in Discrete Event Systems Using Stochastic Dynamic Programming, *ASME Journal of Dynamic Systems, Measurement and Control*, Vol. 121, No. 2, June 1999.
- [J2] G.E. Hovland and B.J. McCarragher, Control of Sensory Perception in a Mobile Navigation Problem, *The International Journal of Robotics Research*, Vol. 18, No. 2, Feb. 1999, pp. 201-212, ISSN: 0278-3649.
- [J3] G.E. Hovland and B.J. McCarragher, Hidden Markov Models as a Process Monitor in Robotic Assembly, *The International Journal of Robotics Research*, Vol. 17, No. 1, Feb. 1998, pp. 153-168, ISSN: 0278-3649.

Conference Papers:

- [C1] G.E. Hovland and B.J. McCarragher, The Control of Sensory Perception for Discrete Event Systems, *Proceedings of the 1998 IEEE International Conference on Systems, Man and Cybernetics (SMC'98)*, San Diego, USA, 11-14 October 1998, pp. 776-781.
- [C2] G.E. Hovland and B.J. McCarragher, Controlling Sensory Perception for Indoor Navigation, *The 1998 IEEE International Conference on Robotics and Automation*, Leuven, Belgium, 17-21 May 1998, pp. 2211-2216.

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- [C3] G.E. Hovland and B.J. McCarragher, Sensitivity Analysis of a Sensory Perception Controller, *Proceedings of Control 97*, Sydney, 20-22 October 1997.
- [C4] H. Bruyninckx, G.E. Hovland and B.J. McCarragher, Robust Sensing for Force-Controlled Assembly, *Workshop Text for the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS'97)*, Grenoble, 8-13 September 1997.
- [C5] G.E. Hovland and B.J. McCarragher, Combining Force and Position Measurements for the Monitoring of Robotic Assembly, *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS'97)*, Grenoble, 8-13 September 1997.
- [C6] G.E. Hovland and B.J. McCarragher, Dynamic Sensor Selection for Robotic Systems, *Proceedings of the 1997 IEEE International Conference on Robotics and Automation*, Albuquerque, 20-25 April 1997, pp. 272-277.
- [C7] G.E. Hovland and B.J. McCarragher, Control of Sensory Perception Using Stochastic Dynamic Programming, *Proceedings of the 1st Australian Data Fusion Symposium*, Adelaide, 21-23 November 1996, pp. 196-201.
- [C8] G.E. Hovland and B.J. McCarragher, Frequency-Domain Force Measurements for Discrete Event Contact Recognition, *Proceedings of the 1996 IEEE International Conference on Robotics and Automation*, Minneapolis, 22-28 April 1996, pp. 1166-1171.
- [C9] G.E. Hovland and B.J. McCarragher, State Transition Recognition in Robotic Assembly Using Hidden Markov Models, *Proceedings of the 1995 National Conference of the Australian Robot Association*, Melbourne, 5-7 July 1995, pp.75-86.
- [C10] G.E. Hovland and B.J. McCarragher, A Hidden Markov Approach to the Monitoring of Robotic Assembly, *Proceedings of the 6th Irish DSP and Control Colloquium*, Queen's University Belfast, Belfast, 19-20 June 1995 (F. Gaston and G. Dodds eds).

In addition to the above papers, the following papers whose contents do not directly relate to the material in the thesis were published as joint work with other members of the Automated Systems Laboratory Group in the Department of Engineering, ANU.

- [E1] B.J. McCarragher, G. Hovland, P. Sikka, P. Aigner and D. Austin, Hybrid Dynamic Modelling and Control of Constrained Manipulation Systems, *IEEE Robotics and Automation Magazine*, June 1997 Special Issue on Discrete Event Systems.

- [E2] G.E. Hovland, P. Sikka and B.J. McCarragher, Skill Acquisition from Human Demonstration Using a Hidden Markov Model, *Proceedings of the 1996 IEEE International Conference on Robotics and Automation*, Minneapolis, 22-28 April 1996, pp. 2706-2711.

Canberra, August 1997.

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G.E.H
August 1997

Abstract

The problem of controlling sensory perception for use in discrete event feedback control systems is addressed in this thesis. The sensory perception controller (SPC) is formulated as a sequential Markov decision problem. The SPC has two main objectives; 1) to collect perceptual information to identify discrete events with high levels of confidence and 2) to keep the sensing costs low. Several event recognition techniques are available where each of the event recognisers produces confidence levels of recognised events. For a discrete event control system running in normal operation, the confidence levels are typically large and only a few event recognisers are needed. Then, as the event recognition becomes harder, the confidence levels will decrease and additional event recognisers are utilised by the SPC. The final product is an intelligent architecture with the ability to actively control the use of sensory input and perception to achieve high performance discrete event recognition.

The discrete event control framework is chosen for several reasons. First, the theory of discrete event systems is applicable to a wide range of systems. In particular, manufacturing, robotics, communication networks, transportation systems and logistic systems all fall within the class of discrete event systems. Second, the dynamics of the sensing signals used by the event recognisers are often strong and contain a large amount of information at the occurrence of discrete events. Third, because of the discrete nature of events, feedback information is not required continuously. Hence, valuable processing time is available between events. Fourth, the discrete events are a natural common representational format for the sensors. A common sensor format aids the decision process when dealing with different sensor types. Fifth, the sensing aspect of discrete event systems has often been neglected in the literature. In this thesis we present a unique approach to on-line discrete event identification.

The thesis contains both theoretical results and demonstrated real-world applications. The main theoretical contributions of the thesis are 1) the development of a sensory

perception controller for the dynamic real-time selection of event recognisers. The proposed solution solves the Markov decision process using stochastic dynamic programming (SDP). SDP guarantees cost-efficiency of the real-time SPC by solving a sequential constrained optimisation problem. 2) A sensitivity analysis method for the sensory perception controller has been developed by exploring the relationship between Markov decision theory and linear programming. The sensitivity analysis aids in the robust tuning of the SPC by finding low sensitivity areas for the controller parameters.

Two real-world applications are presented. First, several event recognition techniques have been developed for a robotic assembly task. Robotic assembly fits particularly well in the discrete event framework, where discrete events correspond to changes in contact states between the workpiece and the environment. Force measurements in particular contain a significant amount of information when the contact state changes. Second, the sensory perception control theory and the sensitivity analysis have been demonstrated for a mobile navigation problem. The cost-efficient use of sensory perception reduces the need for mobile robots to carry heavy computational resources.

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Nomenclature

Acronyms

| | |
|-----|----------------------------------|
| DEC | : Discrete Event Controller |
| DES | : Discrete Event System |
| DF | : Distance Functions |
| HMM | : Hidden Markov Model |
| LP | : Linear Programming |
| MLP | : Multilayer Perceptron |
| QR | : Qualitative Reasoning |
| SDP | : Stochastic Dynamic Programming |
| SPC | : Sensory Perception Controller |

Symbols

| | |
|----------------------------|---|
| \mathbf{A} | : LP constraint matrix in standard form |
| $a_k \in \mathcal{A}$ | : Markov action space |
| $a_n(z, s_i)$ | : Optimal action function |
| \mathbf{b} | : LP constraint vector in standard form |
| \mathbf{c} | : LP cost vector |
| C | : Confidence level |
| e_i | : Discrete event |
| $e^*(n)$ | : Recognised event by the SPC after the n th action |
| (F_x, F_y, M_z) | : Planar force/torque measurements |
| $(\Delta F_x, \Delta F_y)$ | : Change of planar force measurements |
| K | : SDP state reward constant |
| k_i | : Individual monitor costs |
| l_i | : Individual monitor rewards |
| \mathbf{N} | : Submatrix of \mathbf{A} corresponding to non-basic LP variables |
| N_m | : Number of available process monitors |
| $P_{n,ij}(z, a)$ | : SDP state transition probability |

| | |
|-----------------------|--|
| (P_x, P_y, θ) | : Planar position measurements |
| $R_n(z, s_i, a_k)$ | : Markov reward function |
| $r(s_i, a_1)$ | : Markov state rewards |
| $s_i \in \mathcal{S}$ | : Markov state space |
| $V_n(z, s_i)$ | : Optimal value function |
| \mathbf{x} | : LP state vector in standard form |
| \mathbf{x}^* | : Optimal basic feasible LP solution |
| \mathbf{x}_B | : LP basic variable vector |
| \mathbf{x}_N | : LP non-basic variable vector |
| z | : Permutation of process monitors |
| z^* | : Optimal permutation of process monitors |
| α | : Discount factor |
| γ_i | : State describing DES |
| γ^* | : Final recognised DES state |
| κ | : Total accumulated SDP cost |
| $\lambda(s_i, a_k)$ | : LP state variables |
| μ | : Confidence level discretisation function |
| $\sigma(n)$ | : State of SPC after the n th action |
| τ | : Map from discrete events to DES state |
| ϕ | : Edges of geometric model |
| Φ | : Sensitivity analysis parameter |
| ψ | : Surfaces of geometric model |

Chapter 1

Introduction

1.1 Motivation

Perceptual capabilities are often the main bottleneck for successful operation of discrete event autonomous systems. As the degree of system uncertainty and ambiguity increases, one sensor alone may not provide sufficient information. Research in the area of multi-sensor fusion has increased the robustness of systems operating in uncertain environments. However, these solutions often require high computational power by utilising all the sensors continuously. As the tasks become more complex and more numerous, the number of relevant features of the environment quickly exceeds the sensing and processing resources that are feasible to supply to real-world control systems. Hence, there is an increasing need for controlling sensory perception. An intelligent sensory perception system is able to perform time-constrained on-line analysis of autonomous systems. Typically, in normal operation only a few sensors are needed. Then, as the quality of the sensing decreases, more sensors are utilised. The design of a sensory perception controller is an important contribution to the development of discrete event autonomous systems operating in uncertain and unpredictable environments.

The control of sensory perception fits particularly well in the discrete event framework. The traditional approach to the control of sensory perception in feedback control systems requires heavy continuous computations during execution. The continuous computations often outweigh the actual sensing costs and the practical value of such solutions is limited. In the discrete event formalism, the control of sensory perception is only needed at the occurrence of the events. Hence, valuable processing time is available between the occurrence of events for other components of the discrete event

control architecture.

A wide range of different sensor types have been used in autonomous control systems. The sensory perception models and sensor selection strategies often depend on the specifics of the sensor types used in each application. Hence, transferring these methods to other systems with different sensor types is often difficult. For example, active vision research has focussed on planning using vision sensors, such as cameras, range finders and illuminators. A host of other sensors such as tactile sensors, three-dimensional range sensors, force-torque sensors and acoustic sensors are currently being used in, for example, robotics and manufacturing applications. Tarabanis, Allen and Tsai (1995) surveyed the area of vision-based systems and write: *Further work needs to be done to properly integrate these sensors and their unique constraints into the overall planning system.*

One advantage of the discrete event framework is the common representational format provided for different sensor types. The natural common format is the discrete events occurring during execution. The general sensory perception control theory presented in this thesis is applicable to a wide range of sensor types in different discrete event control systems. In particular, the discrete event framework has proven successful in manufacturing problems, robotic assembly, mobile robot navigation, communication networks, transportation systems and logistic systems.

The control of discrete event systems has received a significant amount of attention in recent years, see for example Baccelli, et.al. (1992), Cassandras (1993), Cassandras, Lafortune and Olsder (1995), Rubinstein and Shapiro (1993). Traditionally, perfect sensing of discrete events has been assumed. In other work, for example Kumar and Garg (1995), Özveren and Willsky (1990), the requirement of perfect event recognition is reduced to a sub-set of all possible discrete events. State ambiguities are allowed to develop, but these must be resolvable after a bounded interval of events. For most practical systems the assumption of perfect event sensing is unrealistic. To increase applicability of discrete event theory, there is a need for dealing with the sensing aspects of discrete events. Discrete event identification is one of the main difficulties with interfacing continuous-time systems with discrete event controllers.

In this thesis we present a new and unique approach to discrete event identification. A sensory perception controller actively selects different event monitors to identify discrete events as they occur with high levels of confidence and low sensing costs. The method improves the applicability of discrete event theory by increasing the event recognition rates compared to single sensor systems. The total sensing costs are low compared to

multi-sensor fusion techniques where all the sensors are used for every event occurrence. Hence, the proposed method is well suited to event identification in real-time feedback control systems operating in uncertain environments.

1.2 Contributions

The thesis contributes in the following areas:

- i. The sensory perception controller (SPC) is formulated as a sequential Markov decision problem in a discrete event feedback control system. The Markov formulation allows for fast-real time solutions and provides a facility for sensitivity analysis. The discrete event formalism offers advantages in providing a common representational format for different sensor types, highlighting sensing at the occurrence of discrete events where the signal dynamics are often strong and reducing the sensing costs by avoiding continuous control of sensory perception.
- ii. A fast real-time SPC algorithm has been developed solving the Markov decision process using stochastic dynamic programming (SDP). SDP is used to determine the optimal sequence of sensing strategies. The SDP algorithm provides a cost-efficient solution to the sensory perception control problem. A low-cost SPC is required to improve the performance compared to existing multi-sensor fusion algorithms.
- iii. A thorough sensitivity analysis of the controller has been developed. The sensitivity analysis aids in the robust tuning of the SPC by finding low sensitivity areas for the model parameters. The sensitivity analysis is performed by exploring the relationship between discounted Markov decision problems and linear programming. Linear programming allows for a thorough sensitivity analysis without having to solve the problem from scratch for each new model parameter.
- iv. The last decade has seen little effort in applying Markov decision theory to practical systems. In this thesis the sensory perception controller has been successfully implemented in two applications; robotic assembly and mobile navigation. The cost of sensing is reduced compared to multi-sensor systems where all the sensors are used all the time. The experiments also demonstrate that the sensory perception controller achieves higher event recognition rates than any individual sensor. Moreover, the experiments show how the sensing system is able to recover from undetected discrete events.

- v. The applications required the development and implementation of several process monitoring techniques. The appendices present new and unique techniques for discrete event recognition based on force/torque and position measurements. Hidden Markov Models (HMMs) have proven to be a powerful tool for discrete event recognition. The method 1) allows for dynamic force/torque measurements, 2) accounts for sensor noise and friction and 3) exploits the fact that the amount of force information is large at the occurrence of the events.

A monitor using position measurements has been developed. The position based monitor is sensitive to geometrical model uncertainties, but still adds useful information to the sensory perception controller. The main advantage of the method is its computational efficiency.

A multilayer perceptron (MLP) network using both force/torque and position measurements for event recognition has been implemented. One advantage of this method compared to the other solutions presented is the fact that it models both dynamic and static behaviour. The MLP is able to achieve relatively large successful event recognition rates compared to other methods.

1.3 Organisation of the Thesis

The thesis contains both theoretical results and two demonstrated real-world applications. It is comprised of the following chapters.

Chapter 2 formulates the problem of sensory perception control. The discrete event framework is used and the sensory perception controller is formulated as an active element of a feedback control structure. The chapter contains a literature survey of research relevant to the sensory perception problem and concludes with a formulation of the SPC as a sequential Markov decision process.

Chapter 3 presents the stochastic dynamic programming solution to the Markov decision process. The solution provides a fast algorithm for use in real-time feedback control systems. Several different data fusion methods are incorporated and a sensory perception control example is given. The chapter ends with a discussion of some advantages and limitations of the proposed method.

Chapter 4 examines the sensitivity analysis of the controller developed in Chapter 3. Due to the iterative nature of dynamic programming, a direct sensitivity approach

is difficult. The sensitivity analysis is performed by exploring the relationship between discounted Markov decision problems and linear programming.

Chapter 5 demonstrates the control of sensory perception for a planar robotic assembly task. The assembly task is modelled as a constrained motion system and the discrete events correspond to changes in the motion constraints. The control of sensory perception is demonstrated using four different event recognition techniques.

Chapter 6 demonstrates the control of sensory perception in mobile navigation. The navigation problem is modelled as a discrete event system, where the discrete events correspond to changes in the mobile unit motion constraints. The sensory perception problem is demonstrated for a planar model containing three rooms, fixed walls and open or closed doors.

Chapter 7 brings the conclusions of the thesis. Open problems and areas for further research are discussed.

The appendices present several process monitors which allow us to demonstrate the control of sensory perception for robotic assembly and mobile navigation in Chapter 5 and 6.

Appendix A presents a process monitor based on Hidden Markov Models (HMMs). Each discrete event is modelled by a HMM which represents a stochastic, knowledge-based system. The HMMs are trained off-line on planar force/torque measurements. In real-time operation all HMMs corresponding to possible events are evaluated. The event with the highest model score is chosen and the associated confidence level is also calculated from the HMM model scores.

Appendix B presents a process monitor based on position measurements and distance functions. The monitor is based on a geometrical model of the world and calculates the nearest distances between all relevant surfaces and edges. The monitor recognises the world states and calculates confidence levels based on the distance functions.

Appendix C describes a multilayer perceptron process monitor. The network is trained off-line on force/torque and position measurements. Each network output corresponds to a discrete event. In real-time operation the measured forces/torques and positions are used as the network inputs. The event with the highest corresponding network output is chosen and the associated confidence level is calculated from the network outputs.

Appendix D describes a process monitor based on qualitative reasoning. The control of sensory perception requires each monitor to produce confidence level outputs of the recognised discrete events. The monitor based on qualitative reasoning was developed by McCarragher and Asada (1993). The original contribution in this appendix is the incorporation of confidence levels to the process monitor.

Chapter 2

Formulation of the Sensory Perception Control Problem

2.1 Discrete Event Formalism

The sensory perception control problem addressed in this thesis is formulated in the discrete event control framework. Ramadge and Wonham (1989) defined a discrete event system (DES) as a *dynamic system that evolves in accordance with the abrupt occurrence, at possibly unknown irregular intervals, of physical events.*

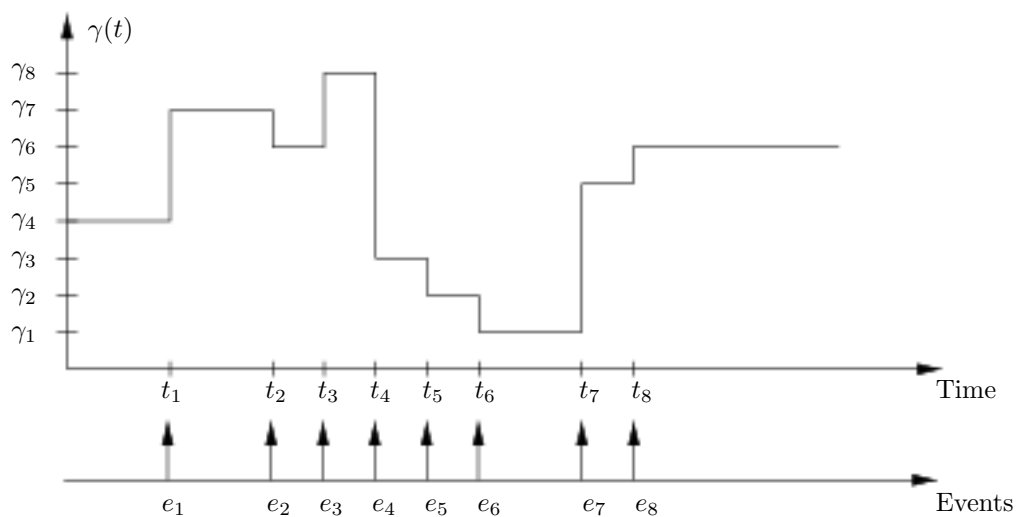


Figure 2.1: Sample path of a discrete event system.

Figure 2.1 shows a sample path of a discrete event system. The DES state variable, denoted $\gamma(t)$, is piece-wise constant and can only change value at the occurrence of a discrete event. The sensory perception controller (SPC) has two main objectives; 1) to collect perceptual information to identify discrete events with high levels of confidence and 2) to keep the sensing costs low. The general sensory perception control problem for discrete event systems is formulated as follows.

Problem Statement: *Given the occurrence of a discrete event, consult event monitors such as to minimise the cost related to the event recognition error plus the costs of obtaining the monitor outputs, ie. find the optimal V*

$$V = \min f(e^* - e) + \sum_{i \in \mathcal{I}} g(k_i) \quad (2.1)$$

The term $\sum g(k_i)$ represents the cost of obtaining the monitor outputs, where k_i are the individual monitor costs. The individual monitor costs are usually fixed and determined off-line. Only the event monitors actually consulted by the SPC are contained in the set \mathcal{I} . The term $f(e^* - e)$ represents the cost related to the event recognition error, where e^* is the recognised event from the SPC. In general, the correct event e is unknown. Hence, the event recognition error $e^* - e$ is also unknown. In this thesis, each individual event monitor produces a confidence level $C \in [0, 1]$ which is used to estimate the event recognition error. A large confidence level indicates a low recognition error. A trade-off has to be made between the event recognition errors and the monitor costs. Low monitor costs often result in large average event recognition errors, while large monitor costs often result in low average event recognition errors.

Figure 2.2 shows the block diagram of the discrete event control structure. The perceptual capabilities of the discrete event system consist of several process monitors. Process monitor i recognises a discrete event $e^i(t_k)$ occurring at time t_k . Due to noisy measurements, model uncertainties or world unpredictability, the recognised event $e^i(t_k)$ may not correspond to the actual physical event $e(t_k)$ that occurred. A very important feature of a process monitor is its ability to indicate the confidence level of the recognised event. A good process monitor produces low confidence levels for events recognised incorrectly and large confidence levels for events recognised correctly.

When a discrete event occurs, the sensory perception controller (SPC) has the option of consulting any of the process monitors. The SPC has two main objectives. First, the SPC must use the recognised events $e^i(t_k)$ and the corresponding confidence levels $C^i(t_k)$ efficiently to correctly recognise the actual discrete events. Even when some of