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Modelling and Control for Intelligent Industrial Systems

Adaptive Algorithms in Robotics and
Industrial Engineering

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Foreword

There are two main requirements for the development of intelligent industrial systems: (i) learning and adaptation in unknown environments, (ii) compensation of model uncertainties as well as of unknown or stochastic external disturbances. Learning can be performed with the use of gradient-type algorithms (also applied to nonlinear modeling techniques) or with the use of derivative-free stochastic algorithms. The compensation of uncertainties in the model's parameters as well as of external disturbances can be performed through stochastic estimation algorithms (usually applied to filtering and identification problems), and through the design of adaptive and robust control schemes. The book aims at providing a thorough analysis of the aforementioned issues.

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Preface

Incorporating intelligence in industrial systems can help to increase productivity, cut-off production costs, and to improve working conditions and safety in industrial environments. This need has resulted in the rapid development of modeling and control methods for industrial systems and robots, of fault detection and isolation methods for the prevention of critical situations in industrial work-cells and production plants, of optimization methods aiming at a more profitable functioning of industrial installations and robotic devices and of machine intelligence methods aiming at reducing human intervention in industrial systems operation.

To this end, the book defines and analyzes some main directions of research in modeling and control for industrial systems. These are: (i) industrial robots, (ii) mobile robots and autonomous vehicles, (iii) adaptive and robust control of electromechanical systems, (iv) filtering and stochastic estimation for multi-sensor fusion and sensorless control of industrial systems (iv) fault detection and isolation in robotic and industrial systems, (v) optimization in industrial automation and robotic systems design, (vi) machine intelligence for robots autonomy, and (vii) vision-based industrial systems.

In the area of industrial robots one can distinguish between two main problems: (i) robots operating in a free working space, as in the case of robotic welding, painting, or laser and plasma cutting and (ii) robots performing compliance tasks, as in the case of assembling, finishing of metal surfaces and polishing. When the robotic manipulator operates in a free environment then kinematic and dynamic analysis provide the means for designing a control law that will move appropriately the robot's end effector and will enable the completion of the scheduled tasks. In the case of compliance tasks, the objective is not only to control the end effector's position but also to regulate the force developed due to contact with the processed surface. There are established approaches for simultaneous position and force control of robotic manipulators which were initially designed for rigid-link robots and which were subsequently extended to flexible-link robots.

In the area of mobile robots and autonomous vehicles one has to handle nonholonomic constraints and to avoid potential singularities in the design of the control law. Again the kinematic and dynamic model of the mobile robots provide the basis for deriving a control law that will enable tracking of desirable trajectories. Several applications can be noted such as path tracking by autonomous mobile robots and automatic ground vehicles (AGVs), trajectory tracking and dynamic positioning of surface and underwater vessels and flight control of unmanned aerial vehicles (UAVs). Apart from controller's design, path planning and motion planning are among the problems the robotics/industrial systems engineer have to solve. These problems become particularly complicated when the mobile robot operates in an unknown environment with moving obstacles and stochastic uncertainties in the measurements provided by its sensors.

In the area of adaptive control for electromechanical systems it is necessary to design controllers for the non-ideal but more realistic case in which the system dynamics is not completely known and the system's state vector is not completely measurable. Thus, one has finally to consider the problem of joint nonlinear estimation and control for dynamical systems. Most nonlinear control schemes are based on the assumptions that the state vector of the system is completely measurable and that the system's dynamical model is known (or at least there are known bounds of parametric uncertainties and external disturbances). However, in several cases measurement of the complete state vector is infeasible due to technical difficulties or due to high cost. Additionally, knowledge about the structure of the system's dynamical model and the values of its parameters can be only locally valid, therefore model-based control techniques may prove to be inadequate. To handle these cases control schemes can be implemented through the design of adaptive observers, and adaptive controllers where the state vector is reconstructed by processing output measurements with the use of a state observer or filter.

In the area of robust control for electromechanical systems one has to consider controllers capable of maintaining the desirable performance of the industrial or robotic system despite unmodeled dynamics and external disturbances. The design of such controllers can take place either in the time domain, as in the case of sliding mode control or H -infinity control, or in the frequency domain as in the case of robust control based on Kharitonov's theory. In the latter case one can provide the industrial system with the desirable robustness using a low-order controller and only feedback of the system's output. Whilst sliding-mode and H -infinity robust control can be particularly useful for robotic and motion transmission systems, Kharitonov's theory can provide reliable and easy to implement robust controllers for the electric power transmission and distribution system.

In the area of filtering and stochastic estimation one can see several applications to autonomous robots and to the development of control systems over communication networks. The need for robots capable of operating autonomously in unknown environments imposes the use of nonlinear estimation for reconstructing missing

information and for providing the robots control loop with robustness to uncertain of ambiguous information. Additionally, the development of control systems over communication networks requires the application of nonlinear filtering for fusing distributed sensor measurements so as to obtain a global and fault-free estimate of the state of large-scale and spatially distributed systems. Filtering and estimation methods for industrial systems comprise nonlinear state observers, Kalman filtering approaches for nonlinear systems and its variants (Extended Kalman Filter, Sigma-Point Kalman Filters, etc.), and nonparametric estimators such as Particle Filters. Of primary importance is sensor-fusion based control for industrial systems, with particular applications to industrial robotic manipulators, as well as to mobile robots and autonomous vehicles (land vehicles, surface and underwater vessels or unmanned aerial vehicles). Moreover, the need for distributed filtering and estimation for industrial systems becomes apparent for networked control systems as well as for the autonomous navigation of unmanned vehicles.

In the area of fault detection and isolation one can note several examples of faults taking place in robotic and industrial systems. Robotic systems components, such as sensors, actuators, joints and motors, undergo changes with time due to prolonged functioning or a harsh operating environment and their performance may degrade to an unacceptable level. Moreover, in electric power systems, there is need for early diagnosis of cascading events, which finally lead to the collapse of the electricity network. The need for a systematic method that will permit preventive maintenance through the diagnosis of incipient faults is obvious. At the same time it is desirable to reduce the false alarms rate so as to avoid unnecessary and costly interruptions of industrial processes and robotic tasks. In the design of fault diagnosis tools the industrial systems engineer comes against two problems: (i) development of accurate models of the system in the fault-free condition, through system identification methods and filtering/ stochastic estimation methods (ii) optimal selection of the fault threshold so as to detect slight changes of the system's condition and at the same time to avoid false alarms. Additionally one can consider the problems of fault diagnosis in the frequency domain and fault diagnosis with parity equations and pattern recognition methods.

In the area of optimization for industrial and robotic systems one can find several applications of nonlinear programming-based optimization as well as of evolutionary optimization. There has been extensive research on nonlinear programming methods, such as gradient methods, while their convergence to optimum has been established through stochastic approximations theory. Robotics is a promising application field for nonlinear programming-based optimization, e.g. for problems of motion planning and adaptation to unknown environments, target tracking and collective behavior of multi-robot systems. On the other-hand evolutionary algorithms are very efficient for performing global optimization in cases that real-time constraints are not restrictive, e.g. in several production planning and resource management problems. Industrial and robotic systems engineers have to be well acquainted with optimization methods, so as to design industrial systems that will excel in perfor-

mance metrics and at the same time will operate at minimum cost.

In the area of machine intelligence for robots autonomy one can note several applications both in control and in fault diagnosis tasks. Machine intelligence methods are particularly useful when analytical models of the robotic system are hard to obtain due to inherent complexity or due to infinite dimensionality of the robot's model. In such cases it is preferable to develop a model-free controller of the robotic system, exploiting machine learning tools (e.g. neural and wavelet networks, fuzzy models or automata models) instead of pursuing the design of a model-based controller through analytical techniques. Additionally, to perform fault diagnosis in robotic and industrial systems with event-driven dynamics it is recommended again to apply machine intelligence tools such as automata, while to handle the uncertainty associated with such systems probabilistic or possibilistic state machines can be used as fault diagnosers.

In the area of vision-based industrial systems one can note robotic visual servoing as an application where machine vision provides the necessary information for the functioning of the associated control loop. Visual servoing-based robotic systems are rapidly expanding due to the increase in computer processing power and low prices of cameras, image grabbers, CPUs and computer memory. In order to satisfy strict accuracy constraints imposed by demanding manufacturing specifications, visual servoing systems must be fault tolerant. This means that in the presence of temporary or permanent failures of the robotic system components, the system must continue to provide valid control outputs which will allow the robot to complete its assigned tasks. Nowadays, visual servoing-based robotic manipulators have been used in several industrial automation tasks, e.g. in the automotive industry, in warehouse management, or in vision-based navigation of autonomous vehicles. Moreover, visual servoing over networks of cameras can provide the robot's control loop with robust state estimation in case that visual measurements are occluded by noise sources, as it usually happens in harsh industrial environments (e.g. in robot welding and cutting applications).

It is noted that several existing publications in the areas of robotic and industrial systems focus exclusively on control problems. In some cases, issues which are significant for the successful operation of industrial systems, such as modelling and state estimation, sensorless control, or optimization, fault diagnosis, machine intelligence for robots autonomy, and vision-based industrial systems operation are omitted. Thus engineers and researchers have to address to different sources to obtain this information and this fragmentation of knowledge leads to an incomplete presentation of this research field. Unlike many books that treat separately each one of the previous topics, this book follows an interdisciplinary approach in the design of intelligent industrial systems and uses in a complementary way results and methods from the above research fields. The book is organized in 16 chapters:

In Chapter 1, a study of industrial robotic systems is provided, for the case of contact-free operation. This part of the book includes the dynamic and kinematic analysis of rigid-link robotic manipulators, and advances to more specialized topics, such as dynamic and kinematic analysis of flexible-link robots, and control of rigid-link and flexible-link robots in contact-free operation.

In Chapter 2, an analysis of industrial robot control is given, for the case of compliance tasks. First, rigid-link robotic models are considered and the impedance control and hybrid position-force control methods are analyzed. Next, force control methods are generalized in the case of flexible-link robots performing compliance tasks.

In Chapter 3, an analysis of the kinematic model of autonomous land vehicles is given and nonlinear control for this type of vehicles is analyzed. Moreover, the kinematic and dynamic model of surface vessels is studied and nonlinear control for the dynamic ship positioning problem is also analyzed.

In Chapter 4, a method for the design of stable adaptive control schemes for a class of industrial systems is first studied. The considered adaptive controllers can be based either on feedback of the complete state vector or on feedback of the system's output. In the latter case the objective is to succeed simultaneous estimation of the system's state vector and identification of the unknown system dynamics. Lyapunov analysis provides necessary and sufficient conditions in the controller's design that assure the stability of the control loop. Examples of adaptive control applications to industrial systems are presented.

In Chapter 5, robust control approaches for industrial systems are studied. Such methods are based on sliding-mode control theory where the controller's design is performed in the time domain and Kharitonov's stability theory where the controller's design is performed in the frequency domain. Applications to the problem of robust electric power system stabilization are given.

In Chapter 6, filtering and stochastic estimation methods are proposed for the control of linear and nonlinear dynamical systems. Starting from the theory of linear state observers the chapter proceeds to the standard Kalman filter and its generalization to the nonlinear case which is the Extended Kalman Filter. Additionally, Sigma-Point Kalman Filters are proposed as an improved nonlinear state estimation approach. Finally, to circumvent the restrictive assumption of Gaussian noise used in Kalman Filtering and its variants, the Particle Filter is proposed. Applications of filtering and estimation methods to industrial systems control when using a reduced number of sensors are presented.

In Chapter 7, sensor fusion with the use of filtering methods is studied and state estimation of nonlinear systems based on the fusion of measurements from distributed sources is proposed for the implementation of stochastic control loops for industrial systems. The Extended Kalman and Particle Filtering are first proposed

for estimating, through multi-sensor fusion, the state vector of an industrial robotic manipulator and the state vector of a mobile robot. Moreover, sensor fusion with the use of Kalman and Particle Filtering is proposed for the reconstruction from output measurements the state vector of a ship which performs dynamic positioning.

In Chapter 8, distributed filtering and estimation methods for industrial systems are studied. Such methods are particularly useful in case that measurements about the industrial system are collected and processed by different monitoring stations. The overall concept is that at each monitoring station a filter tracks the state of the system by fusing measurements which are provided by various sensors, while by fusing the state estimates from the distributed local filters an aggregate state estimate for the industrial system is obtained. In particular, the chapter proposes first the Extended Information Filter (EIF) and the Unscented Information Filter (UIF) as possible approaches for fusing the state estimates provided by the local monitoring stations, under the assumption of Gaussian noises. The EIF and UIF estimated state vector can, in turn, be used by nonlinear controllers which can make the system's state vector track desirable setpoints. Moreover, the Distributed Particle Filter (DPF) is proposed for fusing the state estimates provided by the local monitoring stations (local filters). The motivation for using DPF is that it is well-suited to accommodate non-Gaussian measurements. The DPF estimated state vector is again used by nonlinear controller to make system converge to desirable setpoints. The performance of the Extended Information Filter, of the Unscented Information Filter and of the Distributed Particle Filter is evaluated through simulation experiments in the case of a 2-UAV (unmanned aerial vehicles) model which is monitored and remotely navigated by two local stations.

In Chapter 9, fault detection and isolation theory for efficient condition monitoring of industrial systems is analyzed. Two main issues in statistical methods for fault diagnosis are residuals generation and fault threshold selection. For residuals generation, an accurate model of the system in the fault-free condition is needed. Such models can be obtained through nonlinear identification techniques or through nonlinear state estimation and filtering methods. On the other hand the fault threshold should enable both diagnosis of incipient faults and minimization of the false alarms rate.

In Chapter 10, applications of statistical methods for fault diagnosis are presented. In the first case the problem of early diagnosis of cascading events in the electric power grid is considered. Residuals are generated with the use of a nonlinear model of the distributed electric power system and the fault threshold is determined with the use of the generalized likelihood ratio, assuming that the residuals follow a Gaussian distribution. In the second case, the problem of fault detection and isolation in electric motors is analyzed. It is proposed to use nonlinear filters for the generation of residuals and to derive a fault threshold from the generalized likelihood ratio without prior knowledge of the residuals statistical distribution.

In Chapter 11, it is shown that optimization through nonlinear programming techniques, such as gradient algorithms, can be an efficient approach for solving various problems in the design of intelligent robots, e.g. motion planning for multi-robot systems. A distributed gradient algorithm is proposed for coordinated navigation of an ensemble of mobile robots towards a goal state, and for assuring avoidance of collisions between the robots as well as avoidance of collisions with obstacles. The stability of the multi-robot system is proved with Lyapunov's theory and particularly with LaSalle's theorem. Motion planning with the use of distributed gradient is compared to motion planning based on particle swarm optimization.

In Chapter 12, the two-fold optimization problem of distributed motion planning and distributed filtering for multi-robot systems is studied. Tracking of a target by a multi-robot system is pursued assuming that the target's state vector is not directly measurable and has to be estimated by distributed filtering based on the target's cartesian coordinates and bearing measurements obtained by the individual mobile robots. The robots have to converge in a synchronized manner towards the target, while avoiding collisions between them and avoiding collisions with obstacles in their motion plane. To solve the overall problem, the following steps are followed: (i) distributed filtering, so as to obtain an accurate estimation of the target's state vector. This estimate provides the desirable state vector to be tracked by each one of the mobile robots, (ii) motion planning and control that enables convergence of the vehicles to the goal position and also maintains the cohesion of the vehicles swarm. The efficiency of the proposed distributed filtering and distributed motion planning scheme is tested through simulation experiments.

In Chapter 13, it is shown that evolutionary algorithms are powerful optimization methods which complement the nonlinear programming optimization techniques. In this chapter, a genetic algorithm with a new crossover operator is developed to solve the warehouse replenishment problem. The automated warehouse management is a multi-objective optimization problem since it requires to fulfill goals and performance indexes that are usually conflicting with each other. The decisions taken must ensure optimized usage of resources, cost reduction and better customer service. The proposed genetic algorithm produces Pareto-optimal permutations of the stored products.

In Chapter 14, it is shown that machine learning methods are of particular interest in the design of intelligent industrial systems since they can provide efficient control despite model uncertainties and imprecisions. The chapter proposes neural networks with Gauss-Hermite polynomial basis functions for the control of flexible-link manipulators. This neural model employs basis functions which are localized both in space and frequency thus allowing better approximation of the multi-frequency characteristics of vibrating structures. Gauss-Hermite basis functions have also some interesting properties: (i) they remain almost unchanged by the Fourier transform, which means that the weights of the associated neural network demonstrate the energy which is distributed to the various eigenmodes of the

vibrating structure, (ii) unlike wavelet basis functions the Gauss-Hermite basis functions have a clear physical meaning since they represent the solutions of differential equations of stochastic oscillators and each neuron can be regarded as the frequency filter of the respective vibration eigenfrequency.

In Chapter 15, it is shown that machine learning methods can be of particular interest for fault diagnosis of systems that exhibit event-driven dynamics. For this type of systems fault diagnosis based on automata and finite state machine models has to be performed. In this chapter an application of fuzzy automata for fault diagnosis is given. The output of the monitored system is partitioned into linear segments which in turn are assigned to pattern classes (templates) with the use of membership functions. A sequence of templates is generated and becomes input to fuzzy automata which have transitions that correspond to the templates of the properly functioning system. If the automata reach their final states, i.e. the input sequence is accepted by the automata with a membership degree that exceeds a certain threshold, then normal operation is deduced, otherwise, a failure is diagnosed. Fault diagnosis of a DC motor is used as a case study.

In Chapter 16, applications of vision-based robotic systems are analyzed. Visual servoing over a network of synchronized cameras is an example where the significance of machine vision and distributed filtering and control for industrial robotic systems can be seen. A robotic manipulator is considered and a cameras network consisting of multiple vision nodes is assumed to provide the visual information to be used in the control loop. A derivative-free implementation of the Extended Information Filter is used to produce the aggregate state vector of the robot by processing local state estimates coming from the distributed vision nodes. The performance of the considered vision-based control scheme is evaluated through simulation experiments.

From the educational viewpoint, this book is addressed to undergraduate and post-graduate students as an upper-level course supplement. The book's content can be complementary to automatic control and robotics courses, giving emphasis to industrial systems design through the integration of control, estimation, fault diagnosis, optimization and machine intelligence methods. The book can be a useful resource for instructors since it provides teaching material for advanced topics in robotics and industrial engineering.

The book can be also a primary source of a course entitled "Modelling and Control of Intelligent Industrial Systems" which can be part of the academic programme of Electrical, Mechanical, Industrial Engineering and Computer Science Departments. It is also a suitable supplementary source for various other automatic control and robotics courses (such as Control Systems Design, Advanced Topics in Automatic Control, Dynamical Systems Identification, Stochastic Estimation and Multi-Sensor Fusion, Adaptive and Robust Control, Robotics: Dynamics, Kinematics and Basic Control Algorithms, Probabilistic Methods in Robotics, Fault Detection and Isolation of Industrial Systems, Industrial automation and Industrial Systems Optimiza-

tion).

From the applied research and engineering point of view the book will be a useful companion to engineers and researchers since it analyzes a wide spectrum of problems in the area of industrial systems, such as: modelling and control of industrial robots, modelling, and control of mobile robots and autonomous vehicles, modelling and robust/adaptive control of electromechanical systems, estimation and sensor fusion based on measurements obtained from distributed sensors, fault detection/isolation, optimization for industrial production and machine intelligence for adaptive behaviour. As a textbook giving a thorough analysis of the aforementioned issues it is expected to enhance bibliography on industrial systems.

Through the aforementioned 16 chapters, the book is anticipated to provide a sufficient coverage of the topic of modeling and control for intelligent industrial systems and to motivate the continuation of research effort towards the development of adaptive algorithms for robotics and industrial engineering. By proposing an interdisciplinary approach in intelligent industrial systems design, the book can be a useful reference not only for the the robotics and control community, but also for researchers and engineers in the fields of mechatronics, signal processing, and computational intelligence.

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