Advances in Robotic Systems

Part 1 of 2

CONTROL AND DYNAMIC SYSTEMS

ADVANCES IN THEORY
AND APPLICATIONS

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CONTROL AND DYNAMIC SYSTEMS

Advances in Theory and Applications

Volume 39

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PREFACE

Research and development in robotic systems has been an area of interest for decades. However, because of increasingly powerful advances in technology, the activity in robotic systems has increased significantly over the past decade. Major centers of research and development in robotic systems were established on the international scene, and these became focal points for the brilliant research efforts of many academicians and industrial professionals. As a result, this is a particularly appropriate time to treat the issue of robotic systems in this international series. Thus this volume and Volume 40 in this series are devoted to the timely theme of "Advances in Robotic Systems Dynamics and Control."

The first contribution to this volume, "Applications of Neural Networks to Robotics," by Sukhan Lee and George A. Bekey, is an excellent example of the impact of powerful advances in technology on advances in robotic systems. Specifically, while neural network theory has been pursued for decades, it is only now, with the tremendous advances in integrated electronics, that it is possible to reduce neural network techniques to practice and in particular, to do so in the case of robotic systems. The control of robot manipulators involves three fundamental problems: task planning, trajectory planning, and motion control. To date, most of the useful work in robotics has been in the areas of trajectory planning and motion control. It is these areas to which neural network techniques are presented in this first contribution.

The next contribution, "A Unified Approach to Kinematic Modeling, Identification, and Compensation for Robot Calibration," by Hanqi Zhuang and Zvi S. Roth, is a rather comprehensive treatment of the robot calibration problem, which is the process of enhancing the accuracy of a robot manipulator through modification of the robot control software. Three distinct actions are required in this process of robot calibration, namely, measurement, identification, and modification. The need for robot calibration arises in many applications, and its importance is further manifested by the growing number of publications in this area in recent years. In addition to critically examining the status of this area of major importance to robotic systems, this contribution presents a unified approach to all phases of model-based calibration of robotic manipulators. As such, this is an important element of these two volumes.

The systems aspects of robotics, in general, and of robot control, in particular, are manifested through a number of technical facts. These are their degrees of freedom, the system dynamics descriptions and sensors involved in task performance, modern robotics computer control implementations, coordination in multiple robotic elements systems, and the development of planning and task decomposition programs. The next contribution, "Nonlinear Control Algorithms in Robotic Systems," by T.J. Tarn, S. Ganguly, and A.K. Bejczy, focuses on robot control algorithms and their real-time implementation. It presents a rather comprehensive treatment of the issues involved in addition to powerful techniques for this problem.

The next contribution, "Kinematic and Dynamic Task Space Motion Planning for Robot Control," by Z. Li, T.J. Tarn, and A.K. Bejczy, presents techniques for an integrated treatment of robotic motion planning and control, which traditionally have been treated as separate issues. A rather comprehensive analysis of the literature on robot motion planning is presented. The techniques presented in this contribution provide a framework within which intelligent robot motion planners can be designed; as such, this contribution is an essential element of these two volumes on advances in robotic systems dynamics and control.

The next contribution, "Discrete Kinematic Modeling Techniques in Cartesian Space for Robotic System," by Witold Jacak, presents rather powerful techniques for kinematic modeling in robotic systems. The techniques for modeling robotic kinematics presented in this contribution have the essential features of convenience in computer simulation of robotic motion, facility in analysis of obstacle avoidance, and functional simplicity (i.e., computational complexity is kept to a minimum). Because of the fundamental importance of the issues treated in this contribution, it is an essential element of these two volumes.

Dexterous, multifingered grippers have been the subject of considerable research in robotic systems. The kinematic and force control problems engendered by these devices have been analyzed in depth in the literature. In the next contribution, "Force Distribution Algorithms for Multifingered Grippers," by Jung-Ha Kim, Vijay R. Kumar, and Kenneth J. Waldron, highly effective techniques are presented for computing finger forces for multifingered grippers through the means of decomposition of the finger forces field into equilibrating forces and interacting forces. The techniques presented are optimal for two- and three-fingered grippers and suboptimal for more complicated grippers.

Because of their simplicity, PD (or PID) controllers are widely used with various robot arm control methods. Other methods utilized include approximate linearization techniques, the computed torque method, hierarchical control techniques, the feedforward compensation method, and adaptive control techniques. In the next contribution, "Frequency Analysis for a Discrete-Time Robot System," by Yilong Chen, it is shown that lag-lead compensation techniques are substantially more effective than PID controllers with respect to static accuracy, better stability, reduced sensitivity to system model uncertainty, and less sensitivity to noise. In other words, they are more robust.

The goal of automation is to produce goods at as low a cost as possible. In practice, costs may be divided into two groups: fixed and variable. Variable costs depend upon details of the manufacturing process and include, in the cases where robots are used, that part of the cost of driving a robot, which varies with robot motion, and some maintenance costs. Fixed costs include taxes, heating costs, building maintenance, and, in the case of a robot, robot operating costs. If one assumes that the fixed costs dominate, then cost per item produced will be proportional to the time taken to produce the item. In other words, minimum production cost is closely related to minimum production time. The next contribution, "Minimum Cost Trajectory Planning for Industrial Robots," by Kang G. Shin and Neil D. McKay, presents an in-depth treatment of this significant issue of minimum cost utilization of robots in industrial production and techniques for accomplishing this.

An essential issue in many robotic systems is the detection of shapes of objects with which a robotic system is to interact. The next contribution, "Tactile Sensing Techniques in Robotic Systems," by Takeshi Tsujimura and Tetsuro Yabuta, presents techniques for dealing with this major issue through the utilization of force/torque sensors and probes. Computer vision is one of the means examined frequently in the literature with respect to this issue of environment recognition, but it is not without significant computational limitations. As a result, this contribution is significant in that it presents techniques for an important alternative where there are, indeed, few alternatives.

In robotic systems many types of sensors may be used to gather information on the surrounding environment. Different sensors possess distinct characteristics, which are designed based on differing physical principles, operate in a wide range of the electromagnetic spectrum, and are geared toward a variety of applications. A single sensor operating alone provides a limited sensing range and can be inherently unreliable due to possible operational errors. However, a synergistic operation of many sensors provides a rich body of information on the sensed environment from a wide range of the electromagnetic spectrum. In the next contribution, "Sensor Data Fusion in Robotic Systems," by J.K. Aggarwal and Y.F. Wang, an in-depth treatment is presented of techniques and systems for data fusion, once again a major issue in many robotics applications.

This volume is a particularly appropriate one as the first of a companion set of two volumes on advances in robotic systems dynamics and control. The authors are all to be commended for their superb contributions, which will provide a significant reference source for workers on the international scene for years to come.

CONTENTS

APPLICATIONS OF NEURAL NETWORKS TO ROBOTICS

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I. Introduction

The field of robotics concerns the design and application of articulated mechanical systems to manipulate and transfer objects, to perform mechanical tasks with versatility approaching that of human arms and to provide mobility. A variety of autonomous and semi-autonomous systems are termed "robots" if they involve processing of sensory inputs from the environment and some mechanical interaction with it.

In view of the fact that robot manipulators (or legs) are open-chain kinematic mechanisms, their control is difficult. There is clearly coupling between motions of individual segments. Furthermore, the parameters of a manipulator depend upon its configuration and the governing equations are highly nonlinear. The control of robots is particularly difficult since the desired trajectory of the end-point of the arms (or legs) is normally specified in Cartesian space, while motions are actually obtained from actuators located at the joints. The transformation from Cartesian to joint coordinates is a computationally intensive problem,

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the accurate solution of which depends both on the algorithms used and on precise knowledge of robot parameters. Living organisms with articulated extremities perform the transformation from goal space to actuator (muscle) coordinates whenever they move. While some aspects of this transformation appear to be pre-programmed in the genes (thus enabling animals to move almost immediately after birth), other aspects appear to be learned from experience. This aspect of motion control in biological systems has provided a model for the application of connectionist approaches to robot control, since neural networks can, in principle, be trained to approximate relations between variables regardless of their analytical dependency [35]. Hence, it is appealing to attempt to solve various aspects of the robot control problem without accurate knowledge of the governing equations or parameters, by using neural networks trained by a sufficiently large number of examples.

The control of a robot manipulator involves three fundamental problems: task planning, trajectory planning and motion control. In the task planning phase, high level planners manage and coordinate information concerning the job to be performed. Trajectory planning involves finding the sequence of points through which the manipulator end-point must pass, given initial and goal coordinates, intermediate (or via) points and appropriate constraints.

Such constraints may include limits on velocity and acceleration or the need to avoid obstacles. Given such a trajectory, the motion control problem consists of finding the joint torques which will cause the arm to follow it while satisfying the constraints. Artificial neural networks find applications in all three of the problem areas indicated above. However, since most of the useful work to date has been done in trajectory planning and motion control, we shall discuss these two areas first. There are two approaches to the trajectory planning problem, which are referred to as *joint space planning* and *Cartesian space planning* respectively. Since trajectory constraints are generally specified in Cartesian space, planning a trajectory in joint space requires that the location of the end points and via points be transformed to their corresponding joint space coordinates. A smooth trajectory can then be obtained (say by fitting a polynomial to these points) [7]. Alternatively, the path planning can be done in Cartesian coordinates and then each path point converted into its corresponding joint space values for control. Clearly, the key to Cartesian space trajectory planning is the transformation of information from Cartesian to joint coordinates, known as a robot arm inverse kinematic problem, which we consider next.

II. Robot Arm Inverse Kinematics

In a robot arm, the joint coordinates θ are related to the Cartesian coordinates $\mathbf{x}$ by the kinematic equation

$$\mathbf{x} = \mathbf{f}(\theta) \tag{1}$$

For a six-degree of freedom arm, both θ and $\mathbf{x}$ are six dimensional vectors. When path planning is done in Cartesian coordinates, the required trajectory is obtained by the planning algorithm and then transformed to joint space by solving eq. (1). Since this solution requires inverting eq. (1), this approach is termed *position-based inverse kinematic control.* In many cases, the trajectory specification includes velocity constraints, in which case the forward kinematic equation is obtained by differentiating eq. (1):

$$\dot{\mathbf{x}} = \mathbf{J}(\theta)\dot{\theta} \tag{2}$$

where the elements of the Jacobian matrix J are the partial derivatives

$$\frac{\partial x_i}{\partial \theta_j} \quad \forall\ i,j$$

Solution of eq. (2) yields the inverse relation

$$\dot{\theta} = \mathbf{J}^{-1}(\theta)\dot{\mathbf{x}} \tag{3}$$

At any joint position θ the planner now computes the velocity $\dot{\mathbf{x}}$ which causes the manipulator end point to move toward the next via point or end point. Thus, trajectory planning based on (3) is referred to as velocity- based inverse kinematic control (or inverse Jacobian control). Clearly, one must assume that the Jacobian is invertible at each point for this method to be feasible. In practice, the Jacobian matrix is well behaved, except near singularity points [7]. Since efficient inversion of the Jacobian is evidently the key to successful application of this method, a number of algorithms have been proposed, e.g. [6, 23].

A manipulator having more degrees of freedom than required by the given task is called a *redundant manipulator*, e.g., a manipulator working in the 6 dimensional Cartesian space with more than 6 joints. The forward kinematics equations, (1) and (2), of a redundant manipulator represent underdetermined set of equations, and the corresponding inverse kinematic solutions yield solution manifolds instead of a unique solution. In this case, the inverse kinematic problem concerns about an optimal solution based on additional constraints or performance indices such as *manipulability*.

It should be noted that success of the inverse kinematic method depends not only on efficient inversion of the Jacobian, but on accurate knowledge of the robot kinematic parameters. In the absence of such knowledge, it may be necessary to use system identification techniques to obtain parameter estimates before trajectory planning can begin. Since neural network approaches do not depend on accurate a-priori knowledge, they are attractive alternatives to the inverse Jacobian method.

One of the earliest connectionist approaches to robot control is due to Albus [1]. His "Cerebellar Model Articulation Controller" (CMAC) uses a three-layer network, the first set of connections being random while the second uses adjustable weights. The network has no advance knowledge of the structure of the system being controlled and thus can be trained to accomplish the robot control task, provided there are sufficient adjustable and random connections. The basic idea of CMAC is to compute control commands by look-up tables rather than by solving control equations analytically. The table is organized in a distributed fashion, so that the function value for any point in the input space is derived by summing the contents over a number of memory locations. While the work of Albus pioneered the application of neural networks to robotics, he did not attempt to model the structural characteristics of networks of neurons as did later investigators.

Kuperstein [22] concerned himself with models of visual motor coordination in robots. While he did not explicitly address the inverse kinematics problem, his work did in fact use neural networks to obtain the transformation needed to convert desired hand coordinates in Cartesian space into the appropriate joint coordinates. The work is based on that of Grossberg and Kuperstein on adaptive sensory-motor control [11]. The system was designed to teach a three-joint robot arm to move to a point in three-dimensional Cartesian space as located by a vision system. No kinematic relationships nor the calibration of joint angles to actuator signals were known *a priori*. The architecture of the system consisted of an input layer fed by a stereo camera, whose outputs are connected to three arrays which convert the visual inputs into distributions in terms of camera orientations and their disparity. These distributions are connected to a target map with adjustable weights. The strategy followed by Kuperstein is the following. First, a random generator activates the target map which orients the robot arm into random positions. These positions are sensed by means of the camera and registered on the input map. The outputs of this map are then correlated with the desired or target locations. At the same time the network receives the visual activation corresponding to the end of the arm and determines an activation pattern which is compared with the actual pattern. Errors are used to adjust weights in the network by means of Hebb's rule [35]. Basically, this is a *circular sensory-motor reaction* [11] in which a spatial representation is formed based on signals used to orient and move in the space.

Ritter, Martinez and Schulten [34, 29] presented a different approach to the above visuomotor coordination problem dealt by Kuperstein. They applied the Kohonen's self-organizing feature mapping algorithm [20] for the construction of topology conserving mappings between the camera