10. PROBLEMS OF ROBOT CONTROL

At any given moment our brain manages to control 244 different mechanical degrees of freedom that involve more than 600 different body muscles (Nourse 1964, Saziorski 1984). In fact, dozens of different muscles routinely act simultaneously. For example, the muscles in each arm or leg control 30 mechanical degrees of freedom, utilizing rather complicated muscle combinations (Saziorski 1984). This control is accomplished through feedback control based on a variety of different sensors: stress and strain sensors in the muscle, tactile sensors in the skin, joint sensors, and—often essential—the visual system. Underlying these faculties lies the brain's vast, unconscious power of coordination of which we are fortunately unaware. The complexity of this control becomes obvious as soon as one attempts to equip a robot arm with only a small fraction of human dexterity.

Let us consider the simple example of grasping and inserting a screw. First the robot must sense the screw. To do so, the robot must determine the screw's position, and then choose a suitable gripper position. The choice depends on the shape of the screw, its location on the table, and the presence of other objects which might hinder the robot. The screw might, for example, lie in a box with other parts. The gripper position is also affected by the screw's purpose: it makes a big difference if the screw only needs to be moved, or if it should actually be inserted. As soon as such questions are answered, a trajectory to the screw's target location can be determined. The screw's orientation and any possible obstacles must be factored into the trajectory planning. The joint angles and torques required to move the arm as planned are then calculated. The joint angles and torques depend on the geometry and the moments of inertia of the robot arm and, while the movement should be as fast as possible, the corresponding joint angles and torques must not exceed, at any place in the trajectory, the mechanical limits of the robot. If such violations occur, the trajectory planning must be repeated. After the trajectory planning and after the screw has been brought to the appropiate location, the threads must be aligned with a precision in the hundredths of millimeters. This task seems, of course, much easier for people; after a rough placement of the screw, one can make use of counter forces from the threads in guiding the screw into the thread hole. In fact, our robot will need to use a similar strategy of compliant motion since the very precise location information is not achievable by cameras alone.

Presently, there are essentially two approaches for the solution of the problems mentioned. The first, *artificial intelligence*, is based on the development of a number of sophisticated programs, ideally designed to foresee all potential situations. This method has yielded a remarkable number of successes. Its weakness lies in the difficulty of finding the problem solving heuristics that work for all important practical situations.

The second approach attempts to understand the strategy of movement control by biological organisms for the purpose of abstracting *neural algorithms*. Our present state of knowledge of biological motion control, however, is still too fragmented to make possible the construction of robot control on a biological basis which could compete successfully with conventional algorithms. Nonetheless, there are a number of promising approaches based on conceptions of neural networks. Arbib (1981), and Arbib and Amari (1985), give a good overview of the problems to be solved and provide some conceptual presentations of their solutions.

Particularly important is the connection of motor action with sensory perception (*sensory-motor coordination*). It is the perfection of this feature that is so outstanding in higher biological organisms and that makes these organisms so superior to our present technical solutions. This sensory-motor coordination is not rigidly preprogramed, but rather, at least in higher animals, adapts and develops in a maturing phase by concerted actions of sensory and motor experience. If one artificially interrupts these concerted actions, then the development of a sensory controlled dexterity does not take place (Held and Hein 1963).

In Chapters 11 and 12 we show how such sensory motor coordination can emerge during the formation of neural maps. This will be demonstrated by a representative example, the problem of coordinating movements of a robot arm with pictures from a pair of stereo cameras. We will examine two computer simulations in order to focus on two different aspects of the problem.

In Chapters 11 and 12 we explore the *kinematics* of a robot arm. There a neural network will learn the relation between arm configurations as they appear in the camera and corresponding joint angles. That relation must take into account the geometrical features of the arm, the features of the optical projection through the cameras, and the position of the cameras relative to the arm. We will also see how the network model can gradually learn visuomotor control from a sequence of trial movements without any prior information. In Chapter 11 we will consider the task of positioning the end effector of a robot arm. In Chapter 12 we will be concerned with the problem of how an arm and its gripper can be properly oriented relative to an object that the robot is supposed to grasp.

Through kinematics one takes into consideration only the geometry. From this point of view all segments of the arm are massless and, therefore, without inertia. In all cases where effects of inertia do not play a significant role, a purely kinematic description is sufficient. For example, this is the case for joint motors that are sufficiently strong to comply with the movement commands. For fast movements or weaker motors, one must take into account the effects of inertia, *i.e.*, the *dynamics* of the arm. A network algorithm which allows to learn the corresponding control will be the subject of Chapter 13.