INTELLIGENT REAL-TIME CONTROL OF A MULTIFINGERED ROBOT GRIPPER BY LEARNING INCREMENTAL ACTIONS

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ABSTRACT Learning control systems are expected to have several advantages over conventional approaches when dealing with complex, high-dimensional processes. One example is the task of controlling grasping operations of a multifingered, multijoined robot gripper, which has been designed and implemented at our robotics lab (the Darmstadt-Hand). The Advanced Gripper Control with Learning Algorithms -AGRICOLA- presented in this paper is able to maintain a stable grasp even if disturbances are applied. Also it works for objects of different sizes for which the grasping has not been learned. Compared to the conventional stiffness approach the performance of the learning system is equal but the design is much easier, since less knowledge about the gripper-hardware has to be taken into account. The main part of the learning control loop is an associative memory storing the grasping behaviour as determined by the choice of an objective function.

KEYWORDS high-dimensional nonlinear process, stable grasp, object manipulation, associative memories, learning control loop

INTRODUCTION

Within the last years industrial robots played a major role in industrial automation and their increasing flexibility showed new ways for automated assembly. In order to improve the manipulation capabilities of todays robots several dextrous hands have been developed as research tools.

In contrast to standard robot effectors like e.g. two-fingered grippers the multifingered robot hands are able to grasp a large variety of differently shaped objects and to make small changes to orientation and position without moving the whole manipulator. Thus a robot equipped with it operates much more flexible and is able to imitate human dextrous manipulation. Nevertheless, the increased flexibility is accompanied by an increased complexity of the control system, since these grippers are highly nonlinear systems with a large number of inputs and outputs. The implementation of conventional control algorithms (e.g. Salisbury and Mason (1985)) requires detailed knowledge about mechanical design and the dynamics of the gripper in order to determine precompensation factors for the decoupling of position- and torque-control loops. On the other hand learning control loops have proven to be applicable for the control of nonlinear unknown or only partially known systems. Therefore a gripper control system has been designed at which grasping operations are controlled exclusively by associative memories and learning control loops (fig. 3).

The paper is organized as follows: After a short description of the implemented gripper hardware we introduce to the neurobiologically motivated Associative Memory System AMS, an enhanced version of the CMAC. Then the learning coordination of the three fingered gripper by applying incremental actions is discussed and some results are given which have been carried out using the Darmstadt-Hand (Paetsch and Kaneko, 1990). The paper concludes with some statements concerning the efficiency of the learning approach and further research topics.

BASICS

Gripper System

The 0-version gripper system used for the experiments was developed and built at the Technical University of Darmstadt (Germany). It is a three fingered tendon driven gripper with three joints per finger, see fig. 7. Each joint has a joint torque sensor as well as a joint position sensor. Therefore joint torque and joint position control loops can be set up. A simplified blockdiagram of a conventional joint torque control for one finger is shown in fig. 1.

The input values are the desired joint torques and the output values are the actual joint torques. The innermost blocks represent the dynamic behavior of the DC-motors. The nonlinear block in each joint control loop describes the effects within the bowden wires which under certain circumstances produces stability problems in the control loops.

Because of the wire guiding within each finger there exist some coupling effects between the control loops. These coupling effects are represented by the factors K_{pij} $(i, j \in [1, \ldots, 3])$. The factor K_{p12} for example means that joint two will move (joint angle θ_{j2}) when a motion in joint one (joint angle θ_{j1}) appears. A second type of coupling is a torque coupling represented by the factor K_{t32} for example, which means that if a certain torque is applied in joint three an additional joint torque, beside the regular torque transmitted by radial forces in the joint bearings, is produced in joint two because of the wire guiding. The respective decoupling blocks are represented by K_{kpij} and K_{ktij} $(i, j \in [1, \ldots, 3])$. Every conventional control has to decouple the joint loops because otherwise the fingers have a very different behaviour in the different directions in cartesian space due to the kinematic coupling effects. This would lead to large problems in stable grasping under disturbance forces because the finger motion due to a disturbance force is sometimes amplified by the kinematic coupling effects so that the fingers can loose the grasped object. Therefore the coupling effects have to be considered.

One can see that the gripper is a comparatively complex, nonlinear process therefore being a good canidate for applying a learning control scheme

Learning Elements

The Associative Memory System AMS discussed below is a suitable system for storing a nonlinear input-output relationship and for a fast recall of the stored information. AMS is conceptually based on CMAC (Cerebellar Model Articulation Controller), which was originally proposed by Albus (1975) as a model for information processing in the human cerebellar cortex.

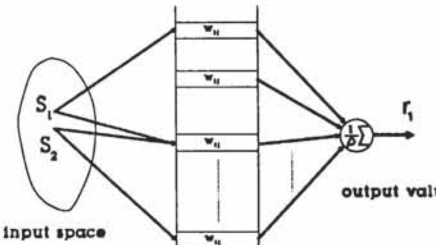

Figure 2: The basic mapping mechanism of AMS

AMS can be represented mathematically by the overall mapping (see fig. 2)

$$f: \qquad \underline{s} \longrightarrow \underline{r} \tag{1}$$

where $\underline{s}$ is an n-dimensional input vector (stimulus) and $\underline{r}$ is an m–dimensional output vector (response). An encoding procedure selects a constant number of cells (memory locations) ρ out of p ($\rho \ll p$) memory cells depending on the contents of the input information $\underline{s}$. The output value is determined by the mean value of the ρ selected memory locations (active weights). During the learning phase (training), the generated output $\hat{\underline{r}}$ is compared with a desired output $\underline{r}$. The correction value $(\underline{r} - \hat{\underline{r}})$ can then be determined and added to each active weight.

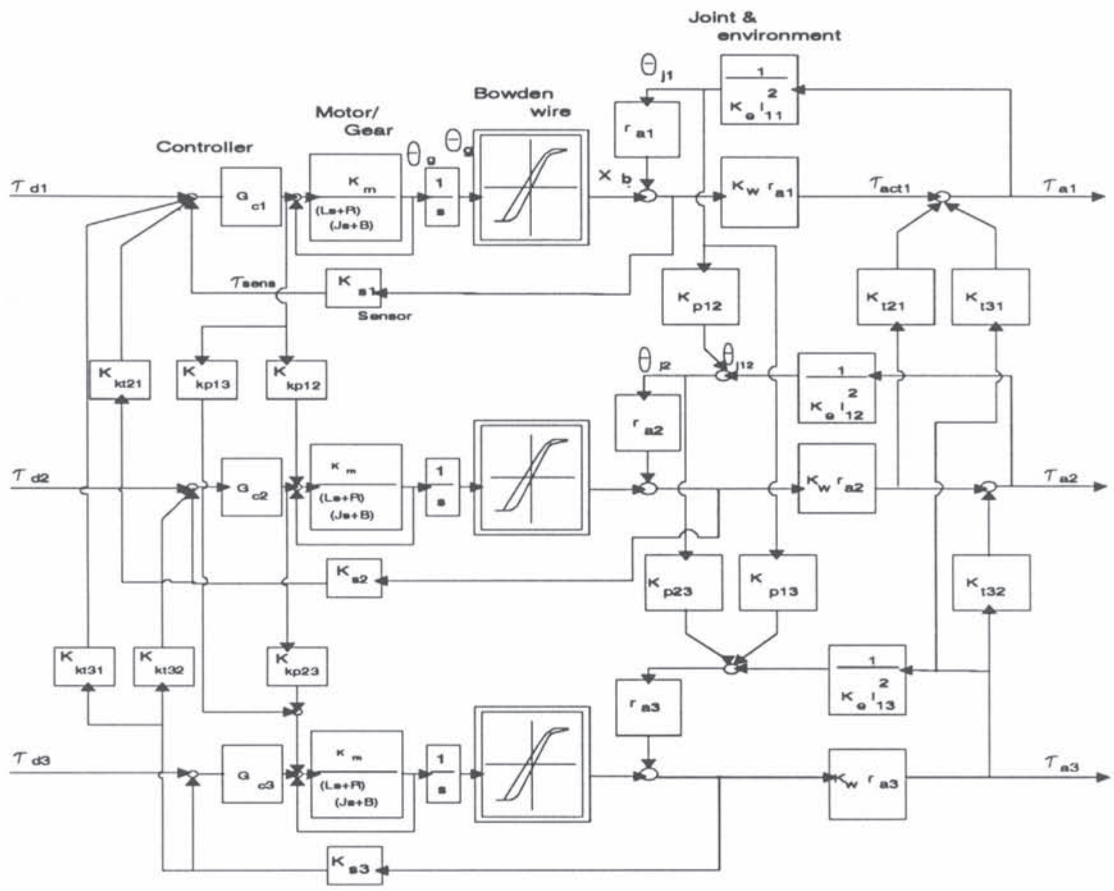

Figure 1: Simplified blockdiagram of the joint torque control for one finger

One of the characteristics of the encoding mechanism is that similar input vectors are mapped to similar sets of activated memory cells. This yields the AMS most fundamental feature of generalization, i.e. similar inputs generate similar outputs. The response for untrained stimulus vectors in the neighborhood of trained points is calculated by an automatic multidimensional interpolation over the output values of the trained points, for details see e.g. Tolle and Ersue (1992).

AGRICOLA
Advanced Gripper Control with Learning Algorithms

In general a grasping operation can be characterized by the four phases approach, contact, grasping and handling.

During approach, the geometrical data of the target are used for preshaping the gripper i.e. for opening the hand wide enough not to collide with the target. This involves the determination of joint angles so that the finger tips can be located at prespecified points of a cartesian space:

$$\underline{q} = \underline{f}^{-1}(\underline{p}) \qquad (2)$$

where $\underline{q}$ represents vectors of joint angles and $\underline{p}$ the cartesian positions of the finger tips, respectively. Also $\underline{f}^{-1}$ represents a mapping from position to joint coordinates, the so called inverse kinematics function.

We trained an AMS-block off-line using $\underline{p}$ as stimulus ($\underline{s}$) and $\underline{q}$ as response ($\underline{r}$) vector. The

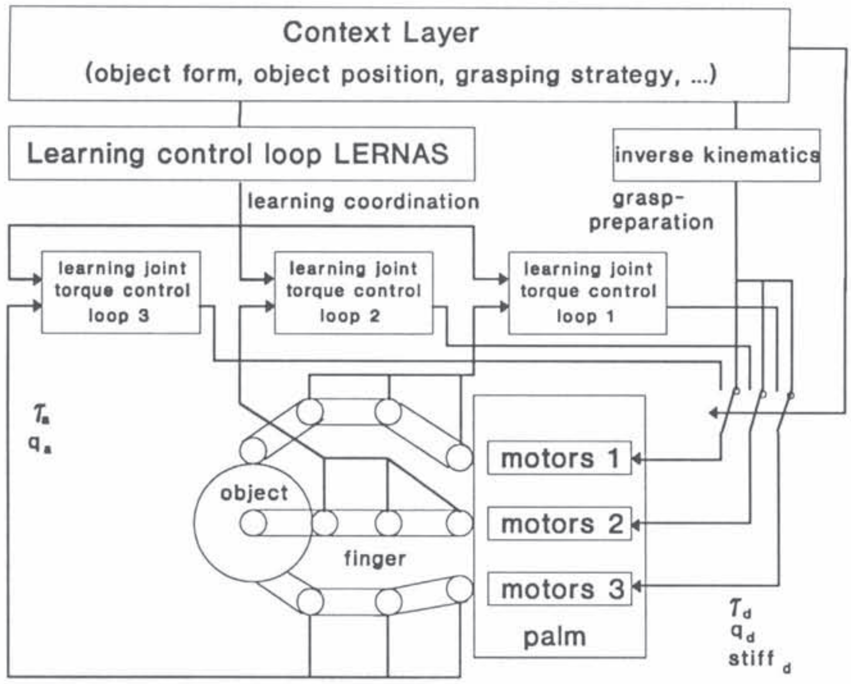

Figure 3: AGRICOLA - Advanced Gripper Control with Learning Algorithms

joint vectors $\underline{q}$ were selected by a random number generator. Based on the forward kinematics relationship

$$\underline{p} = \underline{f}(\underline{q}) \tag{3}$$

which can be simulated easily, one can compute for each given $\underline{q}$ the corresponding $\underline{p}$ values. As a result of storing $\underline{q}$ and $\underline{p}$ in AMS, the associative memory learns the correct inverse kinematics after sufficient training. By a recall, the AMS-block can subsequently be used to provide the joint angles for a given finger tip position within the workspace.

After the approach phase the hand is closed until all fingers detect a contact with the object. We implemented the detection by a continuous supervision of the joint forces.

During the grasping phase the fingers have to exert coordinated forces to the object in order to ensure a stable grasp. Stability with respect to the grasping operation is defined as keeping the object at rest with respect to the hand coordinate system and to move the object back to its original position after it has been shifted due to external forces. The coordination mechanism is based on the learning control loop LERNAS (Ersue, 1984), which imitates human problem solving behaviour. A blockdiagram of this implemented approach is shown in fig. 4.

It consists mainly of two AMS-blocks. Theoretically other implementations of associative memories are also applicable, but as is shown in Mischo, Hormel and Tolle (1991) AMS has some major advantages with respect to convergence and computational complexity. Comparable to the conventional stiffness control approach one associative memory AMS maps joint position errors $\Delta\underline{q}$ to desired joint torques $\underline{\tau}_d$. The optimal control strategy is determined by planning control actions using a nonlinear, unstructured, predictive process model and evaluating the predicted reactions according to a certain performance criterion. The predictive model – giving an estimate of the joint positions $\underline{q}_a$ at time $(k+1)T_0$ (T_0 sampling time) in dependence of the desired joint torque values $\underline{\tau}_d$ and joint positions $\underline{q}_a$ at time kT_0 – is generated on-line by observing the input and output values of the

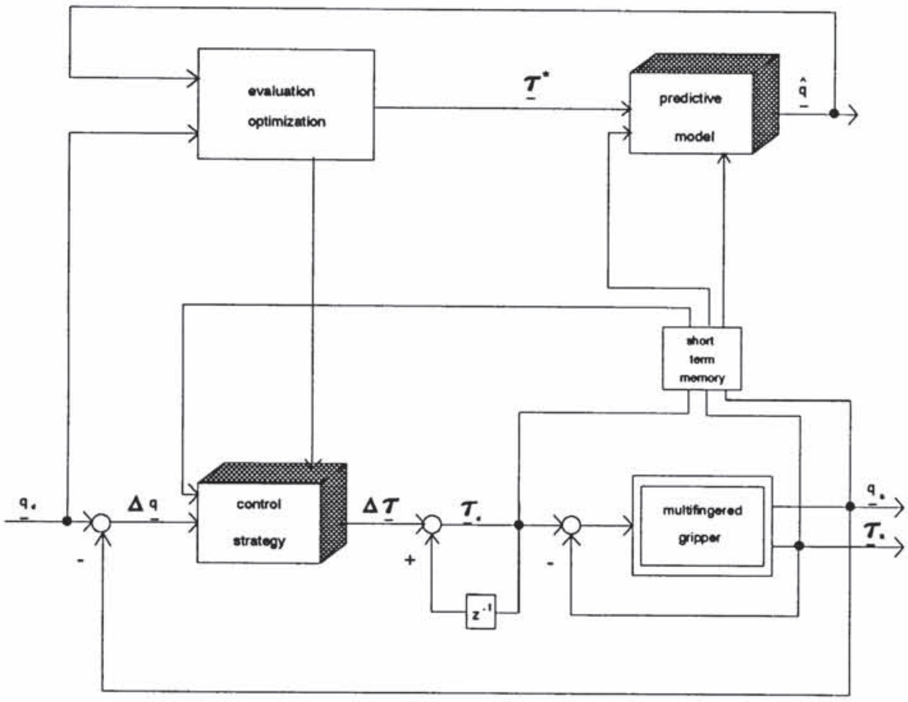

Figure 4: Learning finger coordination (shaded boxes denote AMS-units)

gripper and storing this relationship in another AMS-block.

The continuous updating of the model memory and the on-line optimization ensures that the system is able to follow slow time dependent variations in the process parameters. External forces as they occur during accelerations of the robot arm may be considered as fast changes in the environment. The learning controller can deal with this time variant behaviour by the implemented learning of incremental actions which are added to the currently effective values. In a conventional control loop a linear mapping from situations to incremental actions would lead to stability problems (integrating behaviour). However, the implemented mechanism which is comparable to human control strategies is nonlinear and stable! It should be pointed out that the controller-AMS could also learn absolute joint torques, but the incremental method improves the performance substantially.

In fig. 5 the desired joint torques $\underline{\tau}_d$ of one finger during the grasping phase are shown. The constant values after every manually applied disturbance prove the stability of the grasping operation.

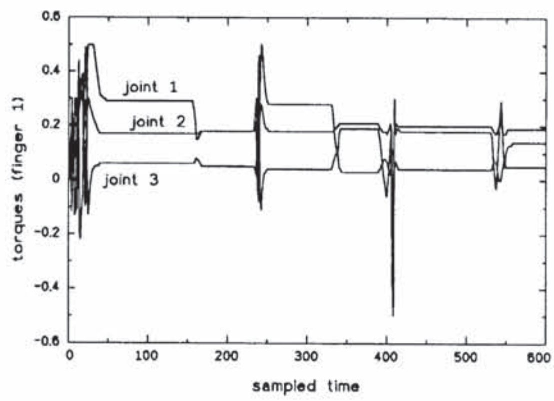

Figure 5: The calculated joint torques of one finger (disturbances are manually applied)

Our learning approach is also suitable to learn the finger coordination for object manipulation. The handling task depends only on the trajectory of desired joint angles. Figure 6 shows the actual joint positions and the desired joint torques during a peg-in-hole manipulation, respectively.

Figure 6: The joint positions and joint torques of one finger during an object manipulation

CONCLUSION

The presented learning gripper control system is able to achieve a stable grasp and to realize object manipulation.

In contrast to a conventional algorithmic control scheme the implementation effort is less. Details about the gripper mechanics, internal parameters for decoupling or precompensation are not necessary. The learning system is able to learn a control behaviour specified by an objective function in contrast to a heuristical set up of the stiffness matrix by trial and error. The learning system stores the process behaviour instead of identification and modelling. The inverse kinematic is learned off-line in contrast to the on-line computation of the algorithmic approach.

The performance of the system can be improved by a VLSI-chip for AMS which is currently under development at our department. Further research activities are concerned with the extension of the system to a learning hand-arm control.

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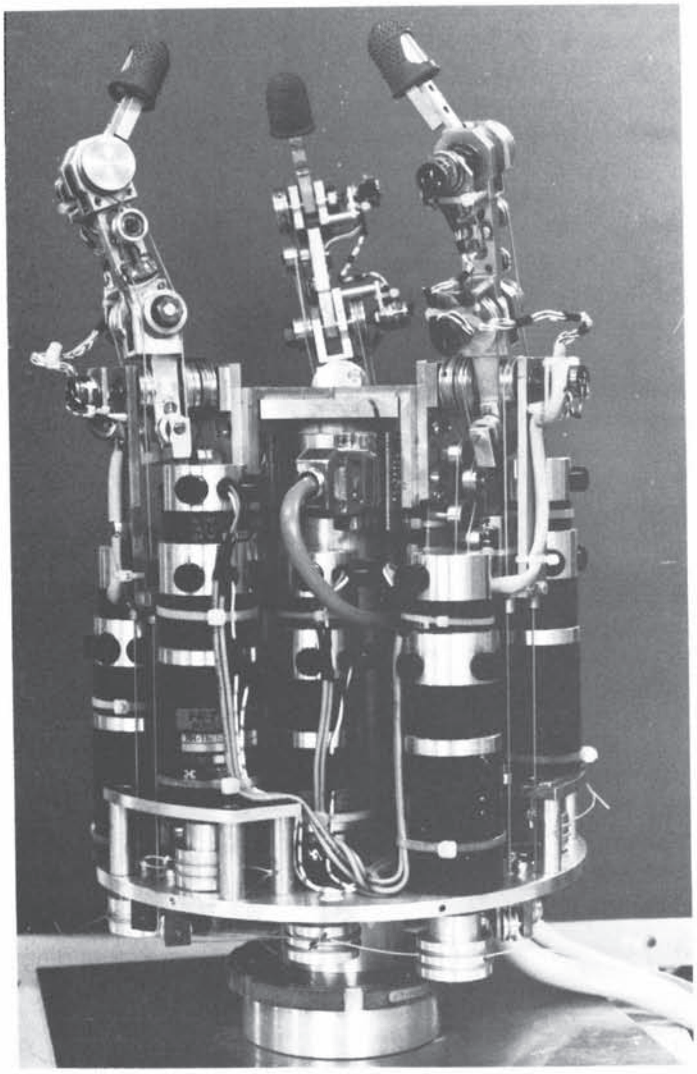

Figure 7: The Darmstadt-Hand