Skill Acquisition for the Intelligent Assisting System Using Virtual Reality Simulator

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Abstract

In this paper we propose a new forthcoming research topic of an Intelligent Assisting System – IAS. Using this system we want to approach the identification and analysis of human manipulation skills. Once manipulation skill can be identified and modeled it is fair to say that it can be learned by currently available technologies leading to a Skill Data Base. Using this data base the IAS will be able to perform rather complex manipulations on the motion control level. Through repeated interaction with the operator for unknown environment states, the manipulation skills in the data base can be increased on-line. We propose a model for manipulation skill based on the grip transformation matrix, which describes the dynamic transformation between the object goal trajectory and contact conditions. The dynamic behavior of the grip transform is regarded as the essence of the performed manipulation skill. We describe the experimental system setup of the IAS and some results confirming the calibration method of the sensor glove. Some simple manipulation examples and simulation results show the feasibility of the proposed manipulation skill model.

Keywords: Intelligent Manipulation, Dextrous Manipulation, Grip Transform, Virtual Reality, Skilled Manipulation, Skill Analysis, Human Skill Transfer.

1 Introduction

Researchers in the fields of computer science, electrical and mechanical engineering have been concerned with the development of intelligent control, robotic and automation systems for a long time. Recently with the availability of fast and powerful computers, capabilities of these systems have improved rapidly, but some difficult conceptual obstacles make it rather complicated to build even more intelligent and sophisticated machines capable of performing in uncertain environments like humans do.

Recognizing such limits makes research in a different direction necessary, i.e. we should try to develop human-friendly and easy-to-use systems, which are understandable and operable without knowing much about computers and programming. The system itself has to anticipate much more what the operator wants to do, has to know about goals and must have a high degree of automation and self-contingency with abilities to handle even unknown situations.

It is going to be more and more important not to have machines just working automatically, nor humans operating machines because of unknown environment situations and the need to react to such changing situations, but to have extended interaction between a human operator and the executing robot or control system. The human operator acts as another system component and is integrated in control loops and processes. To realize such a human-friendly system, the research fields of *Telerobotics*, *Supervisory Control* and *Human Interfaces* can be regarded as key technologies.

In this paper we propose a new forthcoming research topic of an Intelligent Assisting System – IAS (see Fig. 1). Using this system we want to approach the identification and analysis of human manipulation skills, i.e. the ability of altering the environment in a desired, goal-oriented and controlled way. Humans can effectively manipulate a great variety of objects, without thinking about it consciously, and handle objects despite of environment uncertainties in an amazingly adaptive and robust way. If this manipulation skill can be modelled and learned by computers, there will be a dramatic impact on the abilities of future robots and automatic manipulation systems interacting with the environment. Certainly the most interesting topic to be understood using the IAS will be the human manipulative skill.

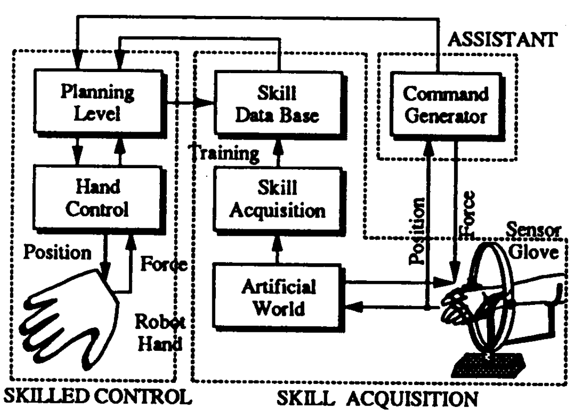


Figure 1: System Structure of the IAS.

Once manipulation skill can be identified and modeled it is fair to say that it can be learned by currently available technologies leading to a *Skill Data Base*. Using this data base the IAS will be able to perform rather complex manipulations on the motion control level and the operator can do the task by only giving the goal in a preferably abstract form. The actual manipulation is then automatically performed by the IAS, which consults the operator only in unknown situations, i.e. environment states which are unknown in the skill data base. Through repeated interaction with the operator the manipulation skills in the data base can be increased on-line and the abilities of the IAS therewith increase.

Section 2 describes the system structure of the proposed IAS. Single topics, characteristics and functional blocks of the IAS are discussed in subsections: functional description (2.1), virtual world simulator (2.2), sensor glove (2.3) and calibration (2.4). Section 3 gives a theoretical model for manipulative skill based on the grip transform first proposed by Salisbury [6] and the concept of internal grasp forces further developed by Kerr and Roth [3]. We will show in an example that the dynamic behavior of this transformation matrix can be interpreted as the essence of the performed manipulation skill. Finally some experimental and simulation results are shown in section 4 followed by conclusions in section 5.

2 Structure of the Intelligent Assisting System – IAS

2.1 Functional Description

This section describes the system structure and functions of the Intelligent Assisting System. Figure 1 shows the overall structure of the IAS. There are three signal flow paths:

- Flow 1: Skill acquisition
- Flow 2: Skilled control, skill transfer
- Flow 3: Assistant.

The development of IAS is done in three steps corresponding to these flows.

Flow 1: Skill Acquisition

A sensor glove is attached to the hand of the human operator and the operator can interact with objects in a virtual reality. Finger joint positions of the glove are fed into the virtual world simulator, which calculates interacting forces.

The operator gets a feedback of the generated forces, and can so feel physically present in the virtual world (telepresence with simulated slave manipulator and task environment). Analyzing the available data of joint torques and positions, essential parameters for the model of the performed manipulation skill can be derived. These extracted parameters necessary to describe the manipulation task are then stored in a data base.

Flow 2: Skill Transfer

In this step the acquired skill of flow 1 now available in the skill data base is used to manipulate objects in an intelligent way with a robotic hand. A robot hand with position and force sensors can then perform complex tasks by applying the acquired manipulation skill to the task environment. Since only the most essential parameters are stored in the data base, the robot hand not necessarily needs to have the same structure as the sensor glove used for acquiring the skill.

Flow 3: Assisting Manipulation

In this mode the IAS performs as an assistant to the human operator. The *assistant* function block (see Fig. 1) identifies and anticipates the action the human operator wants to perform, and if the necessary skill has been stored in the skill data base before, it is applied. In case of an unknown goal the human wants the system to perform, the assistant switches automatically in learning mode and closely watches the human performing the unknown skill. Therewith new manipulation skills can be learned on-line and the knowledge of the IAS increases along by watching the human performing manipulations.

2.2 Virtual World Simulator

The experimental system for skill acquisition as described above, has three main functional blocks (see Fig. 2):

- Control of sensor glove hardware at motion control level
- Calculation of forces acting on objects and the hand in the virtual world (solid state model)
- Graphics animation block for easy-to-understand graphical man-machine interface to the system operator

The position sensor signals of the sensor glove give information about the joint angles of the operator's hand, which are fed to both to the graphics animation block and the solid state model. Using a solid state model of hand and objects in the virtual world, new object positions due to force interactions are calculated and then fed also to the graphics animation module. Calculating the joint torques for a feedback to the sensor glove realizes a force-display. The operator has so both, a force feedback as well as a graphical animation for good telepresence. Figure 3 shows two example pictures of the animated hand and an object of the virtual world.

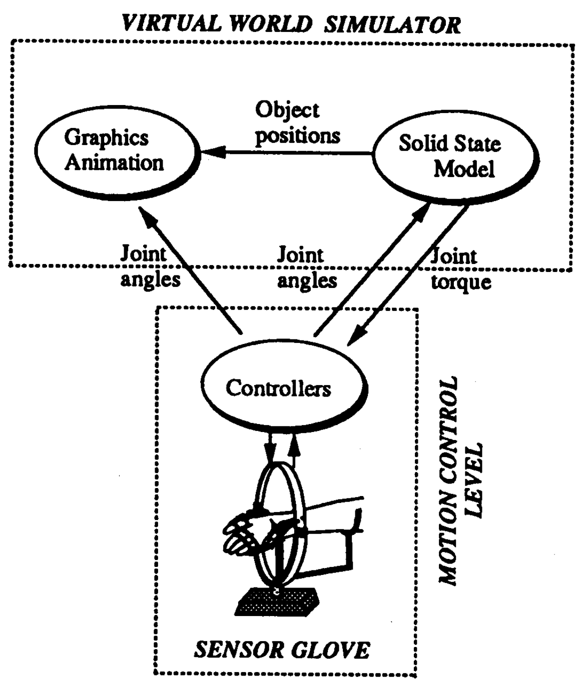


Figure 2: Virtual World Simulator Structure.

2.3 Sensor Glove Hardware

The IAS hardware consists of a sensor glove with 10 degrees of freedom attached to the hand of the human operator. Figure 4 shows a schematic of the sensor glove hardware structure and the joint angles of the human hand which can be measured. There are 3 degrees-of-freedom for the wrist, 3 for the index finger, 2

(a)

(b)

Figure 3: Graphics Animation Example.

for the thumb and 2 for the rest of the fingers. Interaction with the virtual world simulator allows the calculation and feedback of appropriate forces to the force controlled actuators of the sensor glove and therewith the operator can feel physically present in the virtual world. The controlling computer system observes manipulation tasks performed by the operator. Complete data of the manipulation process, i.e. position and force data of manipulated objects and hand joint positions and torques are accumulated. Figure 5 shows the sensor glove hardware.

2.4 Sensor Glove Calibration

Generally the structure of a sensor glove cannot be made completely identical with the kinematic model of the robot hand model to which the glove inputs its sensory signals. As shown in Fig. 4 it is obvious that the two position

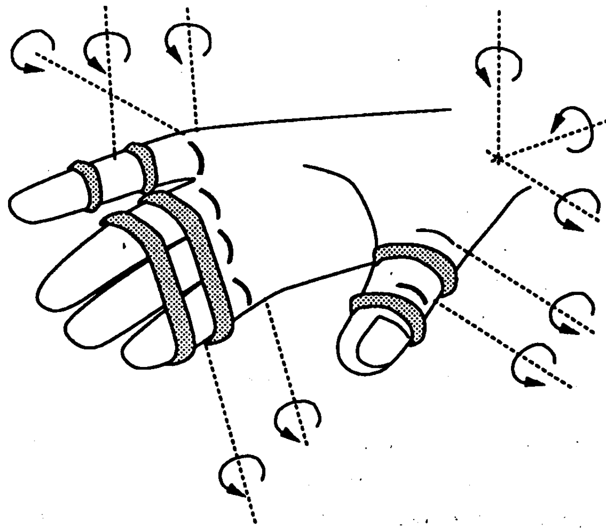


Figure 4: Schematic of Sensor Glove Structure.

sensor angles ψ_1, ψ_2 for the index finger coming from the glove have no simple relationship to the three angles $\theta_1, \theta_2, \theta_3$ used in the kinematic model of the human hand (see Fig. 6).

The mapping between the vectors Ψ and Θ is a complex nonlinear mapping, which can be described as

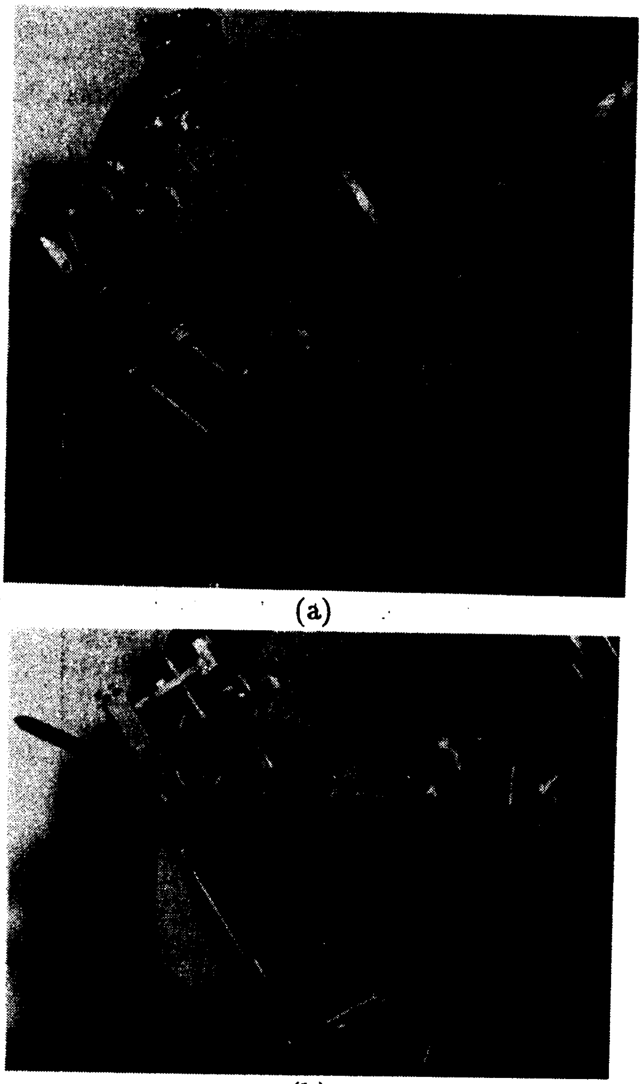
$$\Theta = f(\Psi) \tag{1}$$

where

$$\Psi = \begin{bmatrix} \psi_1 & \psi_2 & \ldots & \psi_m \end{bmatrix}^T$$
$$\Theta = \begin{bmatrix} \theta_1 & \theta_2 & \ldots & \theta_n \end{bmatrix}^T$$

The problem now is to find this nonlinear mapping function $f(\Psi)$, which is a rather difficult task in the case of any particular sensor glove structure. If several people want to use the sensor glove, a different mapping function $f(\Psi)$ must be found for every person, because of different hand sizes. We therefore propose to learn the mapping by an artificial neural network (ANN). The good ability of ANNs to learn and approximate static nonlinear mapping functions is well known and understood. The advantage of using an ANN for the mapping also is, that for a different person operating the sensor glove a different set of weight matrices for the ANNs can be used.

First we must generate a set of training patterns for the artificial neural network. This is



(a)

(b)

Figure 5: Photos of the Sensor Glove Hardware.

done by detecting the x/y-coordinates of the finger-tip position in a plane, where the finger model has three degrees of freedom moving in the same plane in space. As one can see this is also a redundant problem. We now measure x/y-coordinates of the finger-tip corresponding to sensor readings ψ_1, ψ_2 of the two position sensors of the sensor glove. The first angle θ_1 of the finger model can be estimated roughly and an inverse kinematic model is used to solve for the two remaining angles θ_2 and θ_3. This solution puts the finger-tip of the finger model on the same x/y-position as measured before. Because the estimation for θ_1 is very approximate, we adjust the angles θ_i in a way that the overall finger has a "natural" look.

Repeating this procedure for 20 x/y-points in

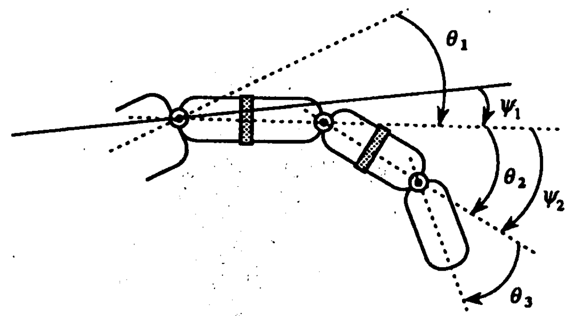


Figure 6: Position of Angle Sensors.

the workspace of the finger, we get 20 training patterns for each finger. Table 1 shows the training patterns for the index finger. Figure 7 shows the structure of the ANN used, with 3 layers, 2 inputs, 10 nodes in the hidden layer, 3 outputs. After training the ANN performs the nonlinear mapping between Ψ and Θ as shown in Fig. 8, where $IN_i \equiv \psi_i$ for $i = 1,2$ and $OUT_j \equiv \theta_j$ for $j = 1,2,3$.

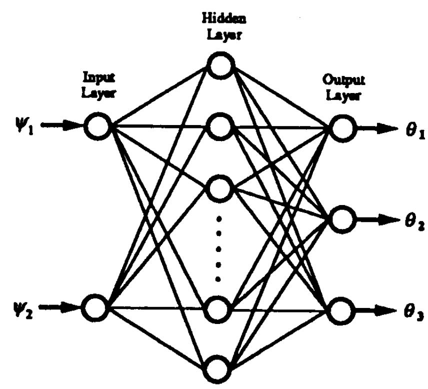


Figure 7: Artificial Neural Network Structure.

3 Manipulation Skill Model

In this section we propose a model for extracting necessary parameters out of the huge amount of gathered data to sufficiently model the performed manipulation skill. Based on the grip transformation matrix, this model describes the dynamic transformation between the goal trajectory of the generalized force vector acting on the object and the contact wrenches which realize such forces. We regard the dynamic behavior of the grip transform as the essence of

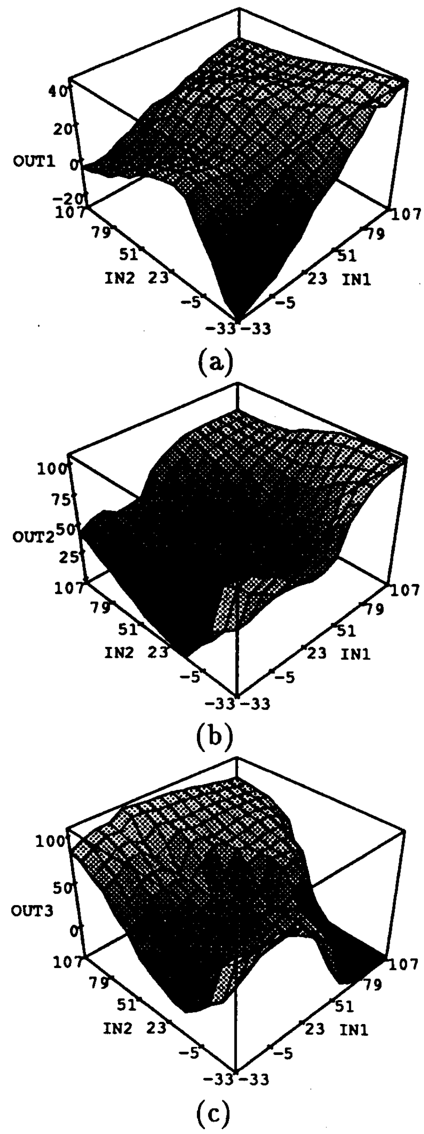


Figure 8: ANN Outputs After Learning.

the performed manipulation skill. Humans do not think in terms of such mathematical models when manipulating things, but rather of the desired goal state of the environment. This makes it very difficult for humans to actually explain or describe their exact methods of manipulation.

Manipulative skill can be defined as the dynamics of the generalized external force $\mathbf{f}(t)$ acting on the object. To manipulate the object in a goal-oriented way the external force vector $\mathbf{f}(t)$ has to be controlled along a desired trajectory, i.e. magnitude and direction of $\mathbf{f}(t)$ vary with time e.g. when moving the object to a desired goal position. Usually $\mathbf{f}(t)$ is applied by multiple contacts from fingers of a hand, where contact conditions and actuating degrees of freedom are

Table 1: Index-Finger Training Patterns

ψ_1 [°]	ψ_2 [°]	θ_1 [°]	θ_2 [°]	θ_3 [°]
-20.50	-8.20	0.00	0.00	0.00
-12.50	30.10	11.56	25.44	18.57
-15.30	10.00	-0.31	22.10	10.28
-7.50	44.60	11.98	47.04	33.51
-7.50	55.10	13.12	51.45	49.10
4.50	62.45	26.41	53.11	37.54
-23.15	28.90	-1.72	32.36	31.65
2.00	73.40	25.42	82.40	42.37
-32.70	94.80	-8.56	80.07	68.49
35.45	33.80	62.55	17.34	16.57
18.05	2.15	41.56	5.24	2.56
24.70	70.80	55.10	52.84	27.95
-13.55	108.86	21.72	108.86	53.72
-23.45	88.90	3.44	71.88	60.43
2.60	50.30	25.00	44.40	32.00
-17.50	90.55	10.00	79.56	63.24
-32.65	32.20	-17.45	31.14	35.10
-9.30	98.50	20.00	85.06	64.18
32.40	15.60	50.26	25.36	17.73
6.70	61.00	31.56	56.12	45.35

to be coordinated in an appropriate way. Generally this is done by humans without consciously thinking about the way of grasping the object. It is a rather intelligent task to transform the desired trajectory of $\mathbf{f}(t)$ to a trajectory of the grip transform $\mathrm{G}(t)$ as defined later in eq.(7), which includes number of contacts, contact positions, direction of contact wrenches, and number of degrees of freedom for each contact. Therefore we formulate the following proposition:

Proposition 1 *The time-dependent behaviour of the grip transform matrix* $\mathrm{G}(t)$ *is regarded as manipulative skill on its lowest level.*

The following section reviews the concept of force balance of the grasped object for arbitrarily applied grasp wrenches, the idea of internal forces and the definition of the grip transform $\mathrm{G}(t)$. Section 3.2 shows a simple manipulative skill example, illustrating proposition 1.

3.1 Grip Transformation Matrix

If a rigid body is stably grasped by m fingers (see Fig. 9), forces and moments must be balanced to external forces $\mathbf{f}(t)$, where $\mathbf{f}(t) \in \mathbf{R}^6$

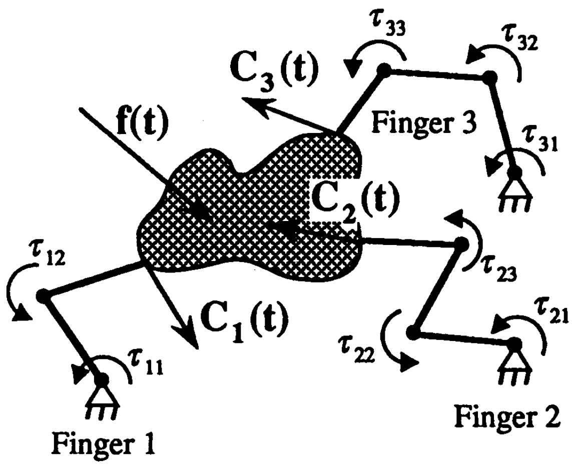


Figure 9: Object in Stable Grasp.

is the generalized force vector. If the $(n(t) \times 1)$ vector $\mathbf{c}(t)$ contains the finger contact wrench intensities, the force balance can be written as

$$-\mathbf{f}(t) = \mathbf{W}(t)\mathbf{c}(t) \tag{2}$$

where $\mathbf{W}$ is a $(6 \times n(t))$ matrix containing the $n(t)$ contact wrenches in its columns, which has first been proposed for the static case by Salisbury [6][7]. The matrix $\mathbf{W}(t)$, the grasping force intensities $\mathbf{c}(t)$ and the external force acting on the body $\mathbf{f}(t)$ must be regarded as time-varying, where not only the magnitude, but also the rank and size of the matrix $\mathbf{W}(t)$ can vary.

Generally the grasped object is overconstrained by the wrenches exerted by the m fingers, i.e. there are some additional degrees of freedom with which the internal grasp forces can be chosen arbitrarily. For a given $\mathbf{f}(t)$ there will be no unique solution for $\mathbf{c}(t)$ of eq.(2). Any solution for $\mathbf{c}(t)$ can be split into two vectors, the particular solution $\mathbf{c_p}(t)$ and the homogenous solution $\mathbf{c_h}(t)$ such that

$$\mathbf{c}(t) = \mathbf{c_p}(t) + \mathbf{c_h}(t) \tag{3}$$

where $\mathbf{c_p}(t)$ is orthogonal to $\mathbf{c_h}(t)$, and $\mathbf{c_h}(t)$ lies in the null space of $\mathbf{W}(t)$. $\mathbf{c_p}(t)$ can be calculated using the right generalized inverse of $\mathbf{W}(t)$:

$$\mathbf{c_p}(t) = -\mathbf{W}^{+}_{\mathbf{R}}(t)\mathbf{f}(t) \tag{4}$$

where $\mathbf{W}^{+}_{\mathbf{R}}(t) = [\mathbf{W}^{\mathbf{T}}(t)\mathbf{W}(t)]^{-1}\mathbf{W}^{\mathbf{T}}(t)$ and $\mathbf{c_h}(t)$ corresponds to the internal grasp forces.

If the columns of the $(n(t) \times (n(t)-6))$ matrix $\mathrm{N}(t)$ are set to be orthonormal basis vectors $\mathbf{c_{i,h}}(t)$ spanning the $(n(t)-6)$-dimensional null space of $\mathbf{W}(t)$

$$\mathrm{N}(t) = \left[\ \mathbf{c_{1,h}}(t) \quad \dots \quad \mathbf{c_{n(t)-6,h}}(t)\ \right] \tag{5}$$

then $\mathbf{c_h}(t)$ can be written in terms of the $((n(t)-6) \times 1)$ vector $\mathbf{f_{int}}(t)$:

$$\mathbf{c_h}(t) = \mathrm{N}(t)\mathbf{f_{int}}(t) \tag{6}$$

The magnitudes of the internal grasp forces are then the elements of $\mathbf{f_{int}}(t)$. A method for optimizing the internal grasp forces including some friction and joint torque limit constraints has been proposed by Kerr and Roth in [3].

The grip transformation matrix $\mathbf{G}(t)$ in controlling manipulation with a multi-fingered hand or multi-armed robot (which is the same control problem) plays essentially the same role as the well known Jacobian matrix J for classical chain robots. $(\mathbf{G^T}(t))^{-1}$ and $\mathbf{G}^{-1}(t)$ may be found geometrically and $\mathbf{G}(t)$ has to be found by matrix inversion. $(\mathbf{G^T}(t))^{-1}$ if formed by augmenting the $(6 \times n(t))$ matrix $\mathbf{W}(t)$ as defined in eq.(2) with the $(n(t)-6)$ $n(t)$-element basis vectors $\mathbf{c_{i,h}}(t)$ spanning $\mathbf{c_h}(t)$ of eq.(6) (null space basis vectors) corresponding to the internal grasp forces.

$$[\mathbf{G^T}(t)]^{-1} = \begin{bmatrix} \mathbf{W}(t) \\ --- \\ \mathbf{c^T_{1,h}}(t) \\ \vdots \\ \mathbf{c^T_{n(t)-6,h}}(t) \end{bmatrix} = \begin{bmatrix} \mathbf{W}(t) \\ --- \\ \mathrm{N^T}(t) \end{bmatrix} \tag{7}$$

This matrix will be square, and assuming that the $(n(t)-6)$ $\mathbf{c_{i,h}}(t)$ are linearly independent, $[\mathbf{G^T}(t)]^{-1}$ will be invertible.

Let us define

$$\mathcal{F}(t) = \begin{bmatrix} \mathbf{f}(t) \\ \mathbf{f_{int}}(t) \end{bmatrix} \tag{8}$$

to be an $n(t)$-vector with the first 6 elements being the net wrench $\mathbf{f}(t)$ (generalized external force) applied to the object and the last $(n(t)-6)$ elements being the magnitudes of the internal grasp forces $\mathbf{f_{int}}(t)$. Now we can write the relation between external net wrench $\mathcal{F}(t)$ and the $n(t)$ contact wrenches at the fingers as

$$\mathcal{F}(t) = (\mathbf{G^T}(t))^{-1}\mathbf{c}(t) \tag{9}$$
$$\mathbf{c}(t) = \mathbf{G^T}(t)\mathcal{F}(t) \tag{10}$$

Using energy conservation principles the following relation between the linear and angular body velocities $\mathbf{v}(t)$ and the twist intensities $\mathbf{d}(t)$ (motion along the axes of the corresponding contact wrench) can be written as

$$\mathbf{d}(t) = \mathbf{G}^{-1}(t)\mathcal{V}(t) \tag{11}$$
$$\mathcal{V}(t) = \mathbf{G}(t)\mathbf{d}(t) \tag{12}$$

where

$$\mathcal{V}(t) = \begin{bmatrix} \mathbf{v}(t) \\ \mathbf{v}_{\text{int}}(t) \end{bmatrix} \tag{13}$$

and $\mathbf{v}_{\text{int}}(t)$ is the $(n(t) - 6 \times 1)$ vector of (virtual in case of rigid body) velocities deforming the body. Eqs.(9), (10), (11) and (12) are useful for sensing and control methods (see [6] for details).

3.2 Skill Example of Sliding Contact

The following example is to illustrate proposition 1 for a very simple manipulation example. Let us consider the pen shown in Fig. 10, grasped by four fingers, each acting on the pen by three wrenches considering a Coulomb friction model. Now consider the simple task of moving one finger after another starting with finger 1 in Fig. 10 to the left sliding over the surface of the pen without breaking contact during the four corresponding time intervals $t_{i-1} \le t < t_i$. It is obvious that the components of the wrenches are functions of the contact point positions, and therewith functions of time. Repeating these four elementary steps, the pen can be moved to the right without breaking contact, if the internal grasping forces are chosen appropriately.

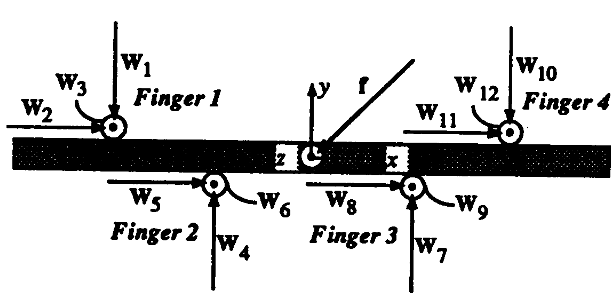


Figure 10: Pen Example Grasped by 4 Fingers.

In the following we write this task with sliding contact motions in terms of the matrix $\mathbf{W}(t)$, which was defined in equation (2) as

$$\mathbf{W}^T(t) = \begin{bmatrix} 0 & -1 & 0 & 0 & 0 & \phi_1(t) \\ 1 & 0 & 0 & 0 & 0 & -r \\ 0 & 0 & 1 & r & \phi_1(t) & 0 \\ 0 & 1 & 0 & 0 & 0 & -\phi_2(t) \\ 1 & 0 & 0 & 0 & 0 & r \\ 0 & 0 & 1 & -r & \phi_2(t) & 0 \\ 0 & 1 & 0 & 0 & 0 & \phi_3(t) \\ 1 & 0 & 0 & 0 & 0 & r \\ 0 & 0 & 1 & -r & -\phi_3(t) & 0 \\ 0 & -1 & 0 & 0 & 0 & -\phi_4(t) \\ 1 & 0 & 0 & 0 & 0 & -r \\ 0 & 0 & 1 & r & -\phi_4(t) & 0 \end{bmatrix} \tag{14}$$

where

$$\phi_i(t) = \begin{cases} l_i & 0 \le t < t_{i-1} \\ l_i + \alpha_i(t - t_{i-1}) & t_{i-1} \le t < t_i \\ l_i + \alpha_i(t_i - t_{i-1}) & t_i \le t \end{cases} \tag{15}$$

for $i = 1, .., 4$ and l_i denotes the initial distance of finger i from the center of mass, r is the radius of the pen and $\alpha_i \ge 0$, determines the sliding speed. The external disturbing force $\mathbf{f}(t)$ is the constant gravitational force:

$$\mathbf{f}(t) = \begin{bmatrix} 0 & -mg & 0 & 0 & 0 & 0 \end{bmatrix}^T \tag{16}$$

The internal grasp forces may be chosen arbitrarily within the limits of frictional constraints. Kerr and Roth [3] have proposed a method for optimal choice of the internal grasp forces. In the above example of sliding contacts, we can write the following friction and contact constraints for the 4 steps of sliding contact motion, where Coulomb friction is linearized with a conservative estimation for the friction coefficient μ. The wrench intensities are denoted by c_i for wrench $\mathbf{w}_i$, $i = 1, .., 12$. For maintaining contacts we need the normal wrench intensities to be

$$c_i \ge f_0 \qquad i = 1, 4, 7, 10 \tag{17}$$

where f_0 is the minimal bias threshold contact force. For sliding contact of finger i, the friction constraints for the three contact wrench intensities c_j, c_{j+1}, c_{j+2} of finger k follow as

$$c_{j+1} + \mu c_j < 0 \qquad k = i \tag{18}$$
$$c_{j+1} + \mu c_j \ge 0 \qquad k \ne i \tag{19}$$
$$c_{j+1} - \mu c_j \le 0 \qquad k \ne i \tag{20}$$
$$c_{j+2} + \mu c_j \ge 0 \qquad k \ne i \tag{21}$$
$$c_{j+2} - \mu c_j \le 0 \qquad k \ne i \tag{22}$$

where $j = 3k - 2$ and $k = 1, .., 4$.

The magnitudes of the internal grasping forces can easily be found using the Simplex algorithm solving the above linear programming problems.

Having determined the dynamic behavior of $G(t)$ and the reference trajectories for the contact wrench intensities $c_i(t)$, it is fairly easy to design a control algorithm for the joint actuators in the joint space (refer e.g. to [?]).

4 Experimental and Simulation Results

4.1 Calibration Result

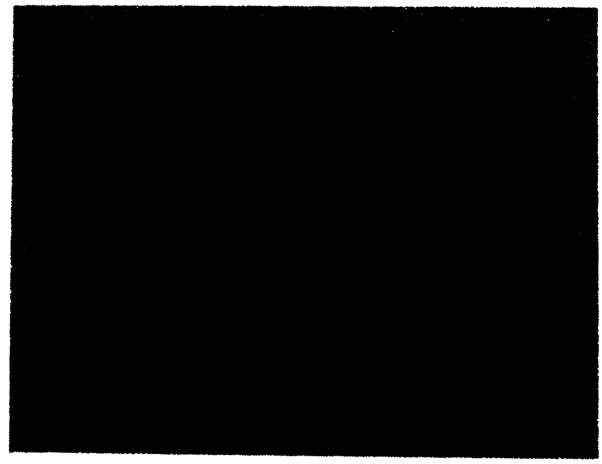
If one tries to form the angle vector $\Theta(\Psi)$ of the index finger of the hand model in the virtual world simulator using some variable gains for linear combinations of the measured angles ψ_i, $i = 1, 2$, calibration cannot be achieved. Even tuning the gain parameters to optimal values will lead to a false hand position as shown is Fig. 11(a), if the human operator's thumb and index finger are in contact. Figure 11(b) shows the same hand position after mapping $\Theta = f(\Psi)$ using as ANN with 10 units in the hidden layer as previously described in section 2.4. It is obvious that the proposed method of learning the nonlinear mapping by an ANN is very effective.

4.2 Simulation of Skill Example

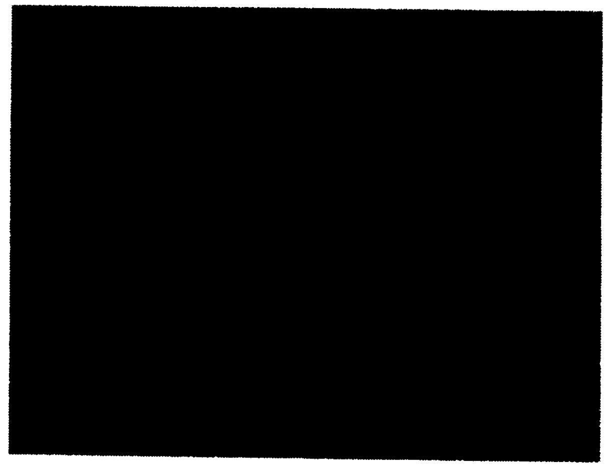
Assuming the example skill described in section 3.2 and the following parameters

- Coulomb friction coefficient: $\mu = 0.25$,
- Pen radius, length, mass: $r = 1\ cm$, $l = 10\ cm$, $mg = 1\ N$,
- Finger initial distances from center of mass and sliding speed parameters: $l_1 = 3\ cm$, $l_2 = 2\ cm$, $l_3 = 2\ cm$, $l_4 = 3\ cm$, $\alpha_i = 1\ cm\ sec^{-1}$,
- Sliding duration times: $t_0 = 0\ sec$, $t_1 = 1\ sec$, $t_2 = 2\ sec$, $t_3 = 3\ sec$, $t_4 = 4\ sec$.

Figure 12 shows the reference trajectories for the wrench intensities, where the following do not vary with time



(a) Calibration by linear combination



(b) Calibration using trained ANN

Figure 11: Calibration Result.

$$\begin{array}{rclrcl} c_1 & = & 0.1\ N & c_2 & = & -0.025\ N \\ c_3 & = & -0.025\ N & c_6 & = & 0.04\ N \\ c_9 & = & -0.04\ N & c_{10} & = & 0.1\ N \\ c_{11} & = & -0.025\ N & c_{12} & = & 0.025\ N \end{array}$$

5 Conclusion

We have proposed an *Intelligent Assisting System — IAS* as a forthcoming research topic. Ongoing research will lead to an understanding of human manipulative skill with the goal to create a manipulation skill data base. Using this data base the IAS is able to perform very complex manipulation tasks on the motion control level forming an intelligent assistant to a human operator. In particular we described the following

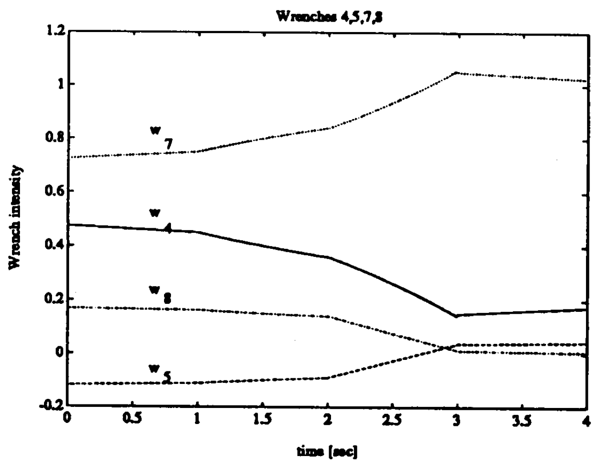


Figure 12: Wrench Intensities for Skill Example.

- Definition of the IAS and its functional modules.
- Development of a 10 degree-of-freedom sensor glove for interaction of the human operator with objects of a virtual world.
- Calibration method for this sensor glove using an artificial neural network to learn and approximate the nonlinear calibration function.
- A model for manipulative skill based on the grip transformation matrix.

Experimental results confirmed the good efficiency of the proposed calibration method using an artificial neural network. A simple example indicated that the proposed model is useful to describe manipulative skill.

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