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LEARNING OF GRASPS FOR AN ARTIFICIAL HAND BY TIME CLUSTERING AND TAKAGI-SUGENO MODELING

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Rainer Palm[1], Boyko Iliev[2]

[1]Adjunct professor at the AASS, Department of Technology, Orebro University
SE-70182 Orebro, Sweden, also Siemens Co. Research, Frankfurt, Germany
[2]AASS, Department of Technology, Orebro University SE-70182 Orebro, Sweden,
e-mail: rub.palm@t-online.de, boyko.iliev@tech.oru.se

Abstract. *The focus of the paper is the learning of grasp primitives for a five-fingered anthropomorphic robotic hand via programming-by-demonstration and fuzzy modelling. In this approach, a number of basic grasps is demonstrated by a human operator wearing a data glove which continuously captures the hand pose. The resulting fingertip trajectories and joint angles are clustered and modelled in time and space so that the motions of the fingers forming a particular grasp are modelled in a most effective and compact way. Classification and learning are based on fuzzy clustering and Takagi-Sugeno (TS) modelling. The presented method allows to learn, imitate and recognize the motion sequences forming specific grasps.*

Key words: *Grasp recognition, manipulation robots, programming-by-demonstration, TS-modelling, time clustering*

1. INTRODUCTION

One of the most challenging areas in robotics is the dexterous manipulation with multi-fingered hands. Multi-fingered artificial hands, especially five-fingered artificial hands, are used in the fields of prosthetics, humanoid service robots, remote control and teleoperation in hazardous and dangerous environments, and last but not least in the entertainment industry. Anthropomorphic robotic hands have several features that make them attractive for the field of robotics:

- provide better capabilities for handling objects, sized and shaped for human-oriented environments
- can be teleoperated by a human in a natural way
- can be used to learn and implement human manipulation strategies
- satisfy explicit requirements for design of humanoid robots and prosthetic devices (acceptance by humans). Despite all technical difficulties, many current robotic projects

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aim to build human-like robotic hands (Bicchi 2000). A survey article by Biagiotti (Biagiotti et al. 2002) compares the most well-known robotic hands regarding to their level of anthropomorphism and potential dexterity, i.e. how close they are to a human hand in terms of appearance and functionality.

Our interest is to develop methods for control of anthropomorphic robotic (prosthetic) hands where the manipulation strategies are learned from human demonstrations. The idea is to exploit the structural similarity between the artificial and the human hand in order to achieve similar functionality. This will on the one hand allow for more intuitive teaching a control of complex robotic hands. On the other hand, this approach can be applied for the control of prosthetic hands. It is also desired to mimic the motion of the human hand as close as possible. Extensive research in the field of recognition and learning of human grasps showed that a large number of grasping tasks can be decomposed into pick-and-place sequences, which can be classified with a limited number of grasps. Such grasp taxonomies are developed by Cutkosky (Cutkosky 1989) and Iberall (Iberall 1997). Using such a classification, Kang describes a system, which observes, recognizes and maps human grasps to a robot manipulator (Kang et al. 1997). The human demonstration is captured by a stereo vision system and a data glove. Ikeuchi. presents an approach to programming-by-demonstration (PbD), where dynamic grasp sequences are identified with the help of Hidden Markov Models (HMMs) (Ikeuchi et al. 2005). They show that if the information from a data glove is complemented with tactile sensors, the recognition rate is significantly improved. Ekvall and Kragic also address the PbD problem using the arm trajectory and hand pose as additional features for grasp classification (Ekvall et al. 2005). The mapping of human grasps to an artificial hand has been studied for the purpose of teleoperation, see (van der Smagt et al. 1998) and (Woitara et al. 2004). In both articles the objective is to find a mapping between the fingertip positions of the master and the slave hand. Lopes and Santos-Victor propose an approach to learning by imitation where a robot replicates the motions of a demonstrator based on a *Visuo-Motor Map* (Lopes et al. 2005). The mapping is built from motion data captured by a data glove and a vision system.

However, the approaches to learning and reproduction of human grasps are often adapted to the kinematical structure of the robotic hand. Direct mapping is very difficult unless the hand has a strictly anthropomorphic structure. In addition, the recognition and replication of human demonstrations are often treated as separate problems and solved with dedicated techniques.

The approach presented in this paper deals with learning, recognition and imitation of human grasps with the help of Takagi-Sugeno fuzzy modelling. Two types of models are built: models of the fingertip trajectories, joint angle trajectories and inverse coordinate transformations between fingertip coordinates and joint angles. The new idea of this approach is to incorporate the discrete time variable of a grasping sequence in the modeling process (*time clustering*) and interpret the time as a model input (Palm et al. 2006). One advantage of the approach is that it gives the hand motion a human-like appearance which is important for prosthetics. These models can be used to replay, scale and recognize demonstrated grasps in a most flexible way. We do not address the grasp stability problem since no tactile information is available from the demonstrations. Even if we had some, it will not be of great help since human tactile sensing is far more superior than what a robotic hand can achieve. Thus, the grasp stability problem is best addressed using force control (Tegin et al. 2007).

This paper is organized as follows: Section 2.1 deals with the five-fingered artificial hand, which is our experimental platform. In Section 2.2 the imitation of operator motions using a sensor glove and the subsequent recording of sequences of grasps is described. In Section 2.3 a simulation model of the hand for the generation of the grasp models is presented. Section 3 discusses the learning and classification of grasps using fuzzy clustering and TS-modeling. Section 4 presents experiments and simulations of selected grasps. Section 5 draws some conclusions and establishes directions for future work.

2. EXPERIMENTAL PLATFORM FOR HUMAN-LIKE DEXTEROUS MANIPULATION

2.1. Artificial five-fingered hand

The long-term goal of the project "Dexterous Manipulation" at the Center for Applied Autonomous Sensor Systems (AASS) is to develop an artificial hand which is capable of performing human-like manipulation. More specifically, the aim is to build an artificial five-fingered hand and develop a control methodology for grasping and manipulation in unstructured environments. The results should be applicable for the control of both robotic and prosthetic hands.

The prototype of the hand and its simulation is shown in Figures 1 and 2, respectively. The main requirement was to reproduce the human hand's size and kinematics as close as possible.

Fig. 1 The AASS dexterous hand

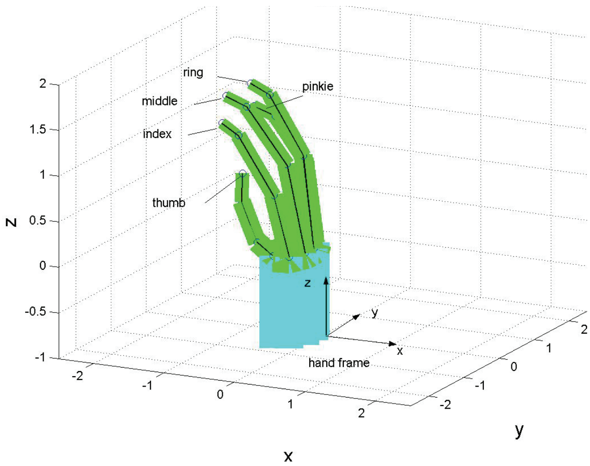


Fig. 2 Simulation of the hand

Therefore, the dimensions of the hand are approximately the same as those of an adult male person. All fingers can perform flexion/extension and abduction/adduction motions. The motion of the thumb is defined in a slightly different way due to its special kinematical structure.

2.2. Learning and imitation of grasps: general principles

Although the human hand is able to deal with a great variety of manipulation tasks, researchers have found a small number of commonly observed grasping strategies, see (Cutkosky 1989). These have served as a reference for the design of robotic hands as the well as research in grasping and manipulation (Bicchi 2000, Biagiotti et al. 2002). In this paper we use the grasp taxonomy by Iberall (Iberall 1997) which describes 21 typical grasp configurations of the human hand. The classification of postures of the human hand into a set of grasps is motivated by the simplification of the complexity of human hand motions and actions.

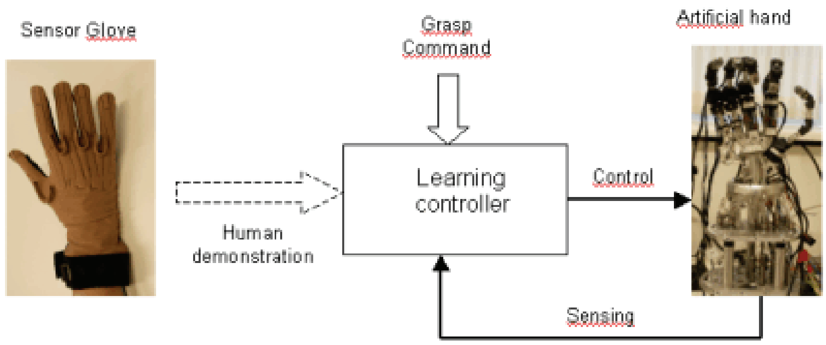


Fig. 3 Learning grasps from human demonstrations

The idea of our approach to human-like dexterous manipulation is illustrated in Figure 3. In the initial phase, a human operator performs demonstrations of grasps (from Iberall 1997) manipulating various objects. During these demonstrations, a sensor glove (see Asada et al. 2000) captures the respective hand configurations and motion patterns and stores them in a computer. Next, models of all demonstrated grasps are created to form the basis of the learning controller. These models are used for the development of grasp primitives. The controller must be able to perform manipulation tasks with different complexity by blending or switching between basic primitives.

To evaluate the performance of the learning controller, the learned grasps are first imitated and then compared with the hand motions from recorded demonstrations. If this imitation stage is successful, we need to include tactile and visual feedback depending on the type of task. Since the focus of this article is on the imitation part, in our simulations we assume that hand's position and orientation with respect to the grasped object are similar to those from the demonstration. To compensate for the uncertainty, the grasp motions continue until all fingers establish contact with the object. In a real experiment, force control must be activated at this stage to ensure a stable grasp.

2.3. Simulation of grasping processes with the artificial hand

In order to study grasping processes and to develop the regarding models a kinematical and dynamical simulation of the artificial hand has been done. The hand consists of 5 fingers each of which equipped with 3 links and 3 joints (see Fig. 2). The kinematical relations can be studied by the example of a single finger (see Fig. 4). The transformation matrices include rotations and translations between coordinate frames. Translations and rotations are calculated by so-called homogeneous transformations with the help of which a point $P_{C4} = (x_4, y_4, z_4, 1)^T$ in local homogeneous fingertip coordinates can be transformed into the base frame C_0 by $P_{C0} = T_1 \cdot T_2 \cdot T_3 \cdot T_3 \cdot P_{C4}$ where a transformation matrix T_i defines the transformation between the coordinate systems C_i and C_{i-1}.

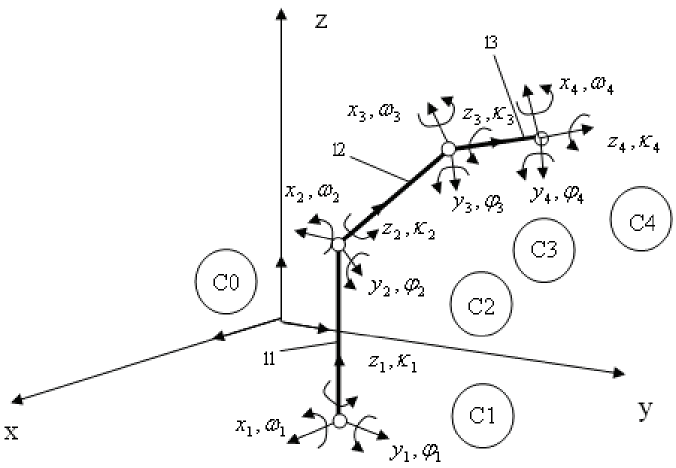


Fig. 4 Configuration of a single finger

With this hand model an analytical simulation of grasps becomes possible independently of recorded data from human operators. Special grasp primitives mentioned by (Iberall 1997) are 'Nippers pinch' (or precision grasp) and 'Extension grasp'. The nippers pinch was simulated as "grasping a stick" and the extension grasp as "touching a plane".

The current development aims at the simulation of a group of grasp primitives and their transfer to the real artificial hand. Figure 5 shows four different grasp primitives on the basis of which a dexterous manipulation can be built.

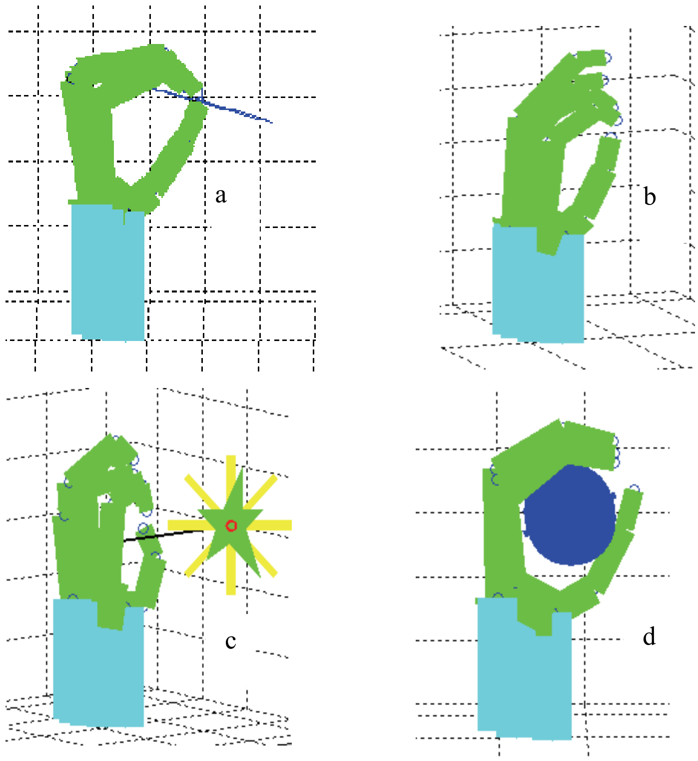


Fig. 5 Four different grasp primitives, a) Touching a plane, b) Penholder grip, c) Precision grasp, d) Cylindrical grasp

3. Learning of Grasp Primitives by Fuzzy Clustering and Takagi-Sugeno Modelling

In this section we describe a new approach to learning by imitation of human grasping using a so-called *time clustering*. The learning is based on fuzzy modelling while the imitation is realized with a biologically inspired scheme corresponding to internal model control (Kawato 1999).

3.1. Modelling of fingertip trajectories by time clustering

Following the ideas described in Section 2.1 we performed experiments in which we collected data sequences of 15 different grasps (see Fig. 6) for which we used a data glove (*CyberGlove)* with 18 sensors. A common problem encountered in the research on programming-by-demonstration is the need for segmentation of the data sequences prior to grasp recognition (Ikeuchi et al. 2005). To avoid it, we recorded only one grasp at a time. Each record started with the pre-grasp posture and ended up with the final grasp posture of the hand. We repeated each demonstration several times to collect enough instances of every particular grasp. From those data, models for each individual grasp primitive have been developed.

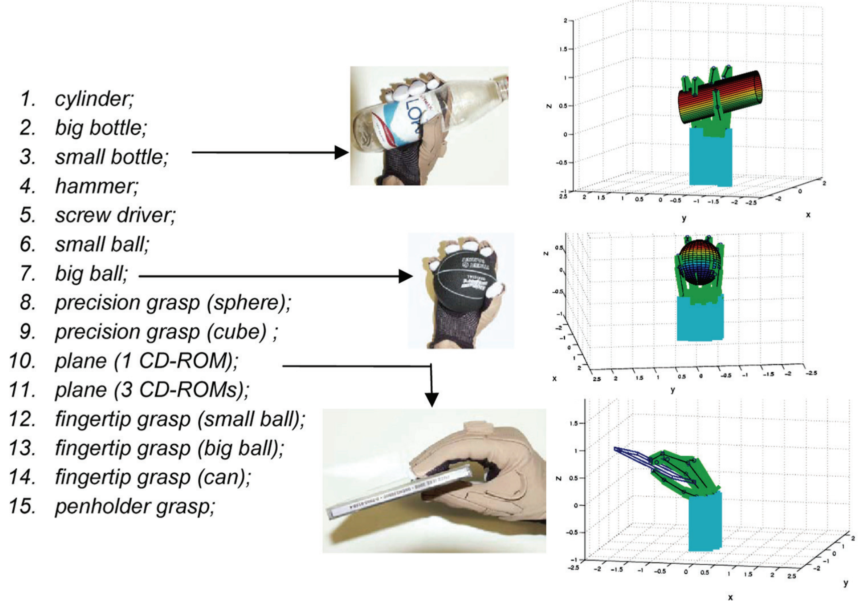


Fig. 6 Grasp primitives

In order to make of model of a complete grasp one should agree upon some features of the grasp like

– Fingertip positions at selected time points

– Joint angles.

The latter is even more important if one wants to recognize a grasp from others only by using the kinematical data of the hand. Although these features are included or can be recovered from the data sequence (Asada et al. 2000), their handling and generalization with respect to other grasps can hardly be managed. Therefore, there is a need for a model of the recorded grasp sequences that reflects the *behaviour of the hand in time*. Such a model is generated by Takagi-Sugeno fuzzy modelling and fuzzy clustering (Palm et al. 2003). The basic idea is to consider the 3 fingertip coordinates as model outputs as well as the time instants as model inputs (see Fig. 7).

The incorporation of the time in the modelling process has the following advantages

- The dynamic motion behaviour can be stored with only few parameters.
- Hand motions get a human-like appearance
- Recorded motions can be replayed faster/slower by choosing longer/shorter time intervals between each motion step.
- A "close hand" operation can be transformed directly into a "open hand" operation by playing the time parameter backwards.

The TS fuzzy model is constructed from captured data as follows. Let the trajectory of a fingertip be described by the nonlinear function

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

where $\mathbf{x} \in R^3$, $\mathbf{f} \in R^3$, $t \in R^+$. Equation (1) can be linearized at selected time points t_i ασ

$$\mathbf{x}(t) = \mathbf{x}(t_i) + \left.\frac{\Delta \mathbf{f}(t)}{\Delta t}\right|_{t_i} \cdot (t - t_i) \tag{2}$$

which is a linear equation in τ.

$$\mathbf{x}(t) = \mathbf{A}_i \cdot t + \mathbf{d}_i \tag{3}$$

where

$$\mathbf{A}_i = \left.\frac{\Delta \mathbf{f}(t)}{\Delta t}\right|_{t_i} \in R^3 \text{ and } \mathbf{d}_i = \mathbf{x}(t_i) - \left.\frac{\Delta \mathbf{f}(t)}{\Delta t}\right|_{t_i} \cdot t_i \in R^3$$

Using (3) as a local linear model one can express (1) in terms of an interpolation between several local linear models by applying Takagi-Sugeno fuzzy modelling (Takagi, Sugeno 1985)

$$\mathbf{x}(t) = \sum_{i=1}^{c} w_i(t)(\mathbf{A}_i \cdot t + \mathbf{d}_i) \tag{4}$$

where $w_i(t) \in [0, 1]$ is the degree of membership of the time point τ to a cluster with the cluster center t_i, c is number of clusters, and $\sum_{i=1}^{c} w_i t) = 1$.

Let τ be the time and $\mathbf{x} = (x, y, z)^T$ the fingertip coordinates. Then the principle clustering and modelling steps are:

- Choose an appropriate number χ of local linear models (data clusters)
- Find χ cluster centers (t_i, x_i, y_i, z_i), ι = 1... χ in the product space of the data quadruples (t, x, y, z) by Fuzzy-c-elliptotype clustering
- Find the corresponding fuzzy regions in the space of input data τ by projection of the clusters in the product space into Gustafson-Kessel clusters (GK) onto the input space (Gustafson, Kessel 1979)
- Calculate χ local linear (affine) models (4) using the GK clusters from step 2.

The degree of membership $w_i(t)$ of an input data point τ in an input cluster C_i is determined by

$$w_i(t) = \frac{1}{\sum_{j=1}^{c} \left(\frac{(t - t_i)^T M_{i\,proj} (t - t_i)}{(t - t_j)^T M_{i\,proj} (t - t_j)} \right)^{\frac{1}{m_{proj} - 1}}} \tag{5}$$

The projected cluster centers t_i and the induced matrices $M_{i\,proj}$ define the input clusters C_i, $i = 1...c$. The parameter $m_{proj} > 1$ determines the fuzziness of an individual cluster.

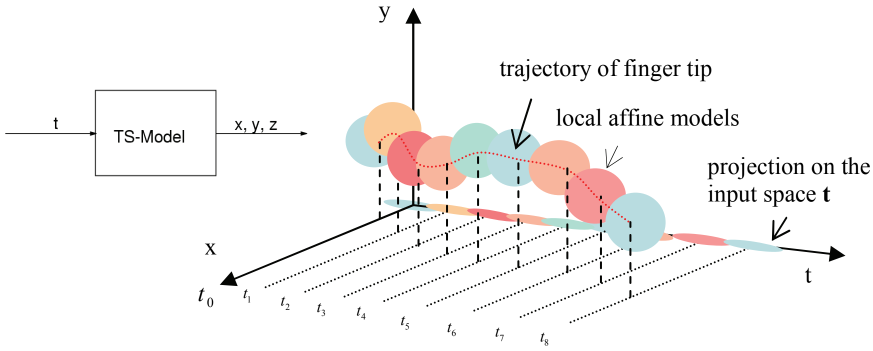


Fig. 7 Principle of Time Clustering

3.2. Modeling of inverse kinematics

In a similar way the inverse kinematics of each finger for a particular grasp is modelled. Let

$$\mathbf{x}(t) = \mathbf{f}(\mathbf{q}); \qquad \mathbf{q}(t) = \mathbf{f}^{-1}(\mathbf{x}) \tag{6}$$

be the nonlinear direct and inverse transformation for a single finger where the inverse transformation is not necessarily unique for the existing finger kinematics. From (6) one can easily obtain the differential transformations

$$\dot{\mathbf{x}}(t) = \mathbf{J}(\mathbf{q})\dot{\mathbf{q}}; \qquad \dot{\mathbf{q}}(t) = \mathbf{J}^{+}(\mathbf{x})\dot{\mathbf{x}} \tag{7}$$

where $\mathbf{J}(\mathbf{q}) = \partial\mathbf{q} / \partial\mathbf{x}$ is the Jacobian and $\mathbf{J}^{+}(\mathbf{x})$ is the pseudo inverse Jacobian. Since $\mathbf{x}(t)$ or $\dot{\mathbf{x}}(t)$, respectively, are already known from (4), the inverse kinematics in (7) remains to be computed. In order to avoid the time-consuming calculation of the inverse Jacobian at every time instant the inverse differential kinematics is approximated by a TS model

$$\dot{\mathbf{q}}(t) = \sum_{i=1}^{c} w_i(\mathbf{q})\mathbf{J}_i^{+}(\mathbf{x}_i)\dot{\mathbf{x}} \tag{8}$$

where $w_i(\mathbf{q}) \in [0, 1]$ is the degree of membership of the angle vector $\mathbf{q}$ to a cluster with the cluster center $\mathbf{q}_i$, $\mathbf{J}_i^{+}(\mathbf{x}_i)$ are the pseudo-inverse Jacobians in the cluster centers $\mathbf{x}_i$. Due to the errors $\Delta\mathbf{x} = \mathbf{x}(t) - \mathbf{x}_m(t)$ between the desired position $\mathbf{x}(t)$ and the real position $\mathbf{x}_m(t)$ a correction of the angles is done using the analytical forward kinematics $\mathbf{x}_m = \mathbf{f}(\mathbf{q}(t))$ of the finger (see Fig. 8) which changes (8) into

$$\dot{\mathbf{q}}(t) = \sum_{i=1}^{c} w_i(\mathbf{x})\mathbf{J}_i^{+}(\mathbf{x}_i)(\dot{\mathbf{x}} + K \cdot (\mathbf{x}(t) - \mathbf{x}_m(t))) \tag{9}$$

where K is a scalar that has to be determined so that the optimization loop is stable. It has to be emphasized that the correction or optimization loop using the forward kinematics $\mathbf{f}(\mathbf{q}(t))$ is started at every new time instant and stops either until a lower bound $\|\Delta\mathbf{x}\| < \varepsilon$ is reached or a given number of optimization steps is executed. Kawato (1999) used a related technique which suggests that humans use both kinematical and dynamical internal models in movement planning and control. In our implementation, a grasp command activates the respective forward dynamic model of type (6) to generate the desired trajectory in Cartesian space. The desired joint space trajectories are obtained using the inverse kinematical model (8). The grasping motion continues until contact with the object is established.

3.3. Classification of a given grasp

In the previous section we showed that TS-fuzzy models can be successfully used for modeling and imitation of human grasps. Now, we will show that they can also be used for classification of grasps in data from recorded human demonstrations. This task can be divided into two aspects:

- Segmentation of recorded data and identification of sequences corresponding to grasps.
- Classification of the identified grasps according to the grasp primitive models.

If we just observe captured motions of a human arm while executing several grasp actions it is very difficult to identify the exact moment when a grasp sequence starts and ends. Related research shows that this task can be solved efficiently only by fusion of additional information sources such as tactile sensing and vision (see (Ikeuchi et al. 2005) and (Ekvall et al. 2005)). Since *classification* is the scope of this article we assume that the segmentation is already done (Palm et al. 2007). Under this condition, the problem can be solved as follows.

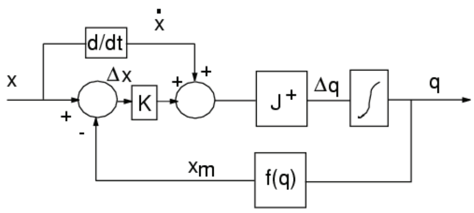


Fig. 8. Inverse kinematics with correction

Let the model of each grasp primitive be built with the same number of clusters $i = 1...c$ so that each time period T_l, $l = 1...L$ determining the duration of the λ-th grasp primitive is divided into $\chi-1$ time interval $\Delta t_i = t_i - t_{i-1}$, $i = 2...c$, for which $\Delta t_i \approx \Delta t_j$, $i, j = 2...c$, $i \neq j$. The '≈'-sign means that the time clustering process leads only to approximated equidistant time intervals. In order to avoid calibration and re-scaling procedures let the grasp actions be executed in an environment comparable with the modeled grasp primitives. Furthermore let

$$\begin{aligned} V_{model\,l} &= [V_{index}, V_{middle}, V_{ring}, V_{pinkie}, V_{thumb}]_l \\ V_{index\,l} &= [\mathbf{x}_1, ..., \mathbf{x}_i, ..., \mathbf{x}_c]_{index\,l} \\ &\vdots \\ V_{thumb\,l} &= [\mathbf{x}_1, ..., \mathbf{x}_i, ..., \mathbf{x}_c]_{thumb\,l} \\ \mathbf{x}_i &= (x_i, y_i, z_i)^T \end{aligned} \tag{10}$$

where the matrix $V_{model\,l}$ includes the output cluster centers $\mathbf{x}_i$ of every finger for the λ-th grasp model. Let us now build a model of the grasp to be classified. From the clustering one obtains the matrix

$$V_{grasp} = [V_{index}, V_{middle}, V_{ring}, V_{pinkie}, V_{thumb}]_{grasp} \tag{11}$$

Then the decision on the grasp is done by applying the Euclidean matrix norm

$$N_l = \left\| V_m - V_{grasp} \right\|_1 \tag{12}$$

Finally, the unknown grasp is classified to the grasp model with the smallest norm $\min(N_l)$, $l = 1...L$, and the recognition of the grasp is finished.

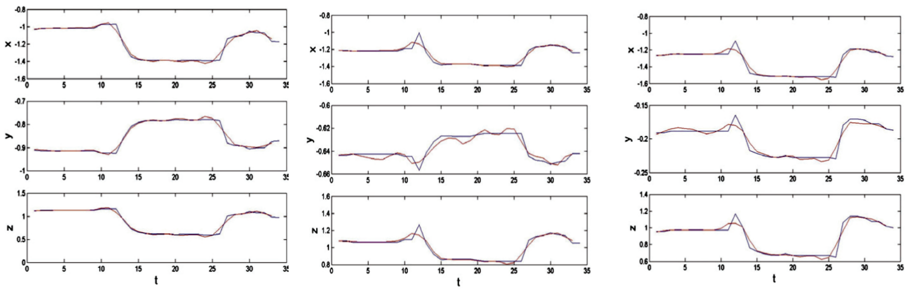
4. Experiments And Simulations

In this section we present the experimental evaluation of the proposed approach for modelling and classification of grasps. We tested 15 different grasps (see Fig 6) and recorded several instances for each one to perform the modelling. Here, one of the tested grasps 'grasp CD-ROM' and its simulation is shown. The motion trajectories are generated according to the scheme in Fig. 8. The grasp is completed when the fingers establish contact with the object.

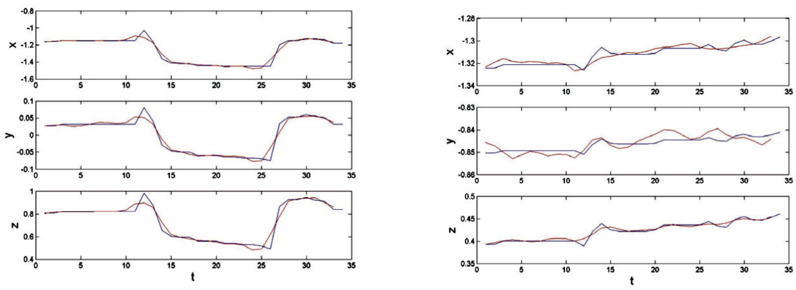
Table 1. Recognition rates

Class	Grasp	Percentage
≥ 75%	4. Hammer	100%
	8. Precision. grasp sphere	87%
	10. Small plane	100%
	11. Big plane	85%
	12. Fingertip small ball	100%
	14. Fingertip can	100%
	15. Penholder grip	85%
< 75%, ≥ 50%	1. Cylinder	71%
	2. Big bottle	57%
	3. Small bottle	57%
	13. Fingertip big ball	71%
< 50%	5. Screwdriver	0%
	6. Small ball	14%
	7. Big ball	28%
	9. Precision grasp cube	42%

For each grasp and finger, 10 fingertip position models with 10 cluster centers have been generated from the collected data. Furthermore, 3 inverse Jacobian models for each grasp primitive and each finger with 3 cluster centers have been built. Since there are 33 time steps for the whole motion, time clustering results in the cluster centers $t_i = 2.04, 5.43, 8.87, 12.30, 15.75, 19.19, 22.65, 26.09, 29.53, 32.94$. They are complemented by the corresponding cluster centers for the x, y, z coordinates of the fingertips. This equidistant spacing can be found for every individual grasp primitive as a result of the time clustering. Figure 9 presents the example of the index, middle, ring, and pinkie finger and the thumb performing the task 'grasp CD-ROM'. All results show a good or even excellent modelling quality.



a. Index finger time b. Middle finger c. Ring finger



d. Ring finger e. Thumb

Fig. 9 Time plots for "CD ROM grasp", original: red, model: blue

The experimental results for the grasp recognition are divided into 3 groups of recognition rates:

1. grasps with a recognition rate ≥ 75 %
2. grasps with a recognition rate < 75 % - ≥ 50 %
3. grasps with a recognition rate < 50 %.

The results confirm the assumption that distinct grasps can be discriminated quite well from each other while the discrimination between similar grasps is difficult. Therefore, merging of similar grasps and building of larger classes can improve the recognition process significantly. Examples of such classes are grasps (4, 5, 15), grasps (10, 11), and grasp (8,9). Table I shows the recognition rates for this method. A comparison of this method with another fuzzy recognition method (Palm et al. 2007) and an approach based on Hidden Markov Models (HMM) shows that the the method presented here is the most effective (Palm et al. 2008).

5. CONCLUSIONS

In this paper a new fuzzy-logic based approach to learning, imitation and classification of grasps for a five-fingered artificial hand is presented. A set of grasping primitives of the human hand are captured using a sensor glove and represented by Takagi-Sugeno fuzzy models. Fuzzy clustering and modelling of time and space data is a applied to the modelling of fingertip trajectories of grasp primitives. In addition, fuzzy clustering is applied to the classification and recognition of joint configurations for the inverse kinematics of each finger.

The presented approach can be used to control anthropomorphic robotic hands as well as prosthetic hands where human-like behaviour is desired. To improve the PbD process the method will be further developed for the recognition and classification of operator movements in a robotic environment using more sensor information about the robot workspace and the objects to be handled.

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UČENJE ZAHVATA VEŠTAČKOM RUKOM VREMENSKIM GRUPISANJEM I TAKAGI-SUGENO MODELIRANJEM

Rainer Palm, Boyko Iliev

U ovom radu fokus je na učenju primitivnog zahvata petoprstnom antropomorfnom robotskom šakom preko programiranja demonstracijom i fazi modeliranjem. U ovom pristupu, demonstrira se veliki broj osnovnih zahvata ljudskim operaterom koji nosi rukavicu podataka koja neprekidno zahvata položaj ruke. Rezultirajuća prstne putanjei i spojeni zglobovi sakupljeni su i modelirani u vremenu i prostoru tako da pokreti prstiju koji formiraju odgovarajući zahvat mogu da se modeliraju na najefektniji i kompaktniji način. Klasifikacija i učenje su zasnovani na fazi i Takagi-Sugeno (TS) modeliranju. Predstavljeni metod omogućava učenje, imitaciju i prepoznavanje pokreta koji slede formirajući specifične zahvate.

Ključne reči: *Zahvat prepoznavanja, programiranje demonstracijom, manipulacioni roboti, robotska šaka; TS-modeliranje, vremensko grupisanje*