2010 IEEE International Conference on Robotics and Automation
Anchorage Convention District
May 3-8, 2010, Anchorage, Alaska, USA

Learning of probabilistic grasping strategies using Programming by Demonstration

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Abstract— **The planning of grasping motions is demanding due to the complexity of modern robot systems. In Programming by Demonstration, the observation of a human teacher allows to draw additional information about grasping strategies. Rosell showed, that the motion planning problem can be simplified by globally restricting the set of valid configurations to a learned subspace. In this work, the transformation of a humanoid grasping strategy to an anthropomorphic robot system is described by a probabilistic model, called variation model, in order to account for modeling and transformation errors. The variation model resembles a soft preference for grasping motions similar to the demonstration and therefore induces a non-uniform sampling distribution on the configuration space. The sampling distribution is used in a standard probabilistic motion planner to plan grasping motions efficiently for new objects in new environments.**

I. INTRODUCTION

A typical service robot has to perform complex manipulation strategies in order to assist a human in his natural environment. The ability to grasp objects with high accuracy and high stability is a prerequisite for most manipulation tasks. Different grasping strategies, i.e. an approach motion and contact points on the object, can be pursued in order to reduce unintentional contacts with the object and the environment, that may lead to object displacement or failure of the grasp. The planning of such constrained grasp motions is demanding due to the high complexity of modern robot systems. In research, the problem is often decomposed into the determination of a set of contact points on the object, e.g. forward grasp planning [1], and a subsequent motion planning step. Constrained motion planning in high-dimensional configuration spaces is a challenging problem itself and requires the use of clever heuristics. In Programming by Demonstration (PbD), the observation of a human operator performing a given task is used to extract information about useful grasping strategies. This information can be exploited to automatically generate useful heuristics for motion and grasp planning.

In this work, we are concerned with learning of grasping strategies for an anthropomorphic robot hand using the PbD paradigm. Building on an initial mapping using virtual fingers and local optimization, a probabilistic model based on factor graphs is learned, which explicitly models the optimization and modeling errors. This learned *variation model* represents a time dependent sampling distribution of the robot configuration space, that is used in a probabilistic motion planer to generate valid solutions for grasps of similar objects in new environments. By explicitly modeling the outcome of the transformation process as a stochastic process, an automatic weighting between exploitation of the knowledge demonstrated by the human operator and the fast exploration of the configuration space is achieved.

II. RELATED WORK

The transformation of human grasps to a robotic hand has to account for differences in kinematics and geometry of the human and robot hand. In [2], [3] and [4], the concept of virtual fingers is used to determine groups of human fingers, which apply similar forces on the object. These sets of human fingers describe the minimal set of actuators, which are necessary to execute the grasp, but can also be used to map human fingertip positions to a robot hand. The direct mapping using inverse kinematics presented in [4] doesn't account for workspace limitations of the robot system but for the mapping of the whole approach motion. Workspace and physical limitations of the robot hand can be considered by formulating and solving an optimization problem describing the mapping process. In [5], global optimization is used to map one set of contact points on the object to the robot hand. For the presented system of equations consisting of linear, quadratic and bilinear monomials all solutions can be found using an iterative relaxation technique. In order to reduce the solution space, collision constraints and the grasp have to be incorporated, which is problematic due to the different algebraic structure. Additionally, the investigation of local variations of the set of contact points, which is necessary when dealing with the imprecise transformation from human fingertip positions to the robot system, was not in the scope of the referenced paper. In real applications, a service robot has to face unknown situations, e.g. scenes with different obstacles. The search for a valid grasp requires the calculation of collision-free approach motions, which is a demanding problem itself and requires the development of powerful heuristics. In telerobotics, the direct mapping of the workspaces has been investigated, which allows for the generation of whole grasping motions but requires the presence of a human operator. For the DLR/HIT hand, [6] presents a direct transformation method relying on the human operator to generate a valid grasp by closed loop control. In this context, it is difficult to exploit the capabilities of the robot system, e.g. a larger joint range.

This work has been partially conducted within the german SFB 588 "Humanoid Robots" granted by DFG and within the ECs Integrated Project DEXMART under grant agreement no. 126239 (FP7/2007-2013) .

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Automatic planning of grasping motions is demanding due to the complexity of the configuration space of the robot hand, e.g. the SAH (including the wrist position and orientation) has 19 degrees of freedom. In [7], the search space for motion planning is reduced by using a subset of the principal components of a large set of training data. The training data is obtained by observing a human, who teleoperates the robot hand using a dataglove. In this work, only a single demonstration is necessary to derive an object-depended search space reduction, which doesn't globally restrict the set of valid finger motions.

Learning and evaluation of custom sampling distributions in a probabilistic motion planning process has been investigated by [8] et al. In [8], the sampling distribution is learned using a grid-based frequency distribution of multiple instances of the planning problem in one scene, reducing planning time for future instances in the same scene. In contrast to this approach, the variation model captures all available information about the demonstrated grasping strategy in one Bayesian model, allowing for the generalization to different scenes and objects.

The definition of the variation model using factor graphs is based on the work of Toussaint, who uses inference methods on probabilistic models [9] to solve the motion planning problem. In the next section, the general problem is defined and necessary definitions are developed.

III. DEFINITIONS

In this work, a probabilistic representation of a human grasping strategy is learned based on one set of trajectories of the human wrist and fingertips. The probabilistic grasping strategy represents a probability distribution on the configuration space of the robot system, which is used in a probabilistic motion planner to generate similar grasping motions for an anthropomorphic robot hand. The necessary definitions are given in this section.

The demonstrated trajectories of the wrist and fingertips of the human operator are described by a discrete path τ_{h} in the human configuration space $\mathbb{C}_{\text{h}}$. Time is discretized due to the limited frequency of sensor data (20Hz) and the use of discrete steps in the motion planning algorithm. The input is given by the demonstrated trajectory τ_{h} of an example solution in the human configuration space:

$$\tau_{\text{h}}\colon \{1, ..., T\} \rightarrow \mathbb{C}_{\text{h}} = \mathbb{R}^3 \times SO(3) \times \mathbb{R}^{15} \qquad (1)$$

The human configuration space $\mathbb{C}_h$ consists of the position and orientation of the human wrist and 20 finger joint values, one abduction-adduction and three flexion-extension joints for each finger. The hand model resembles the kinematic model of the human hand. The trajectory is stored relative to the object o with the position and orientation described by the Gaussian distribution $N_o(\mu_o, \Sigma_o)$ on $\mathbb{R}^3 \times SO(3)$ with mean μ_o and covariance Σ_o. Orientations are represented in scaled-axis notation, see [10]. The robot configuration space $\mathbb{C}_{\text{r}}$ is defined as $\mathbb{R}^3 \times SO(3) \times \mathbb{R}^m$, where m is the number of degrees of freedom of the robot hand. The grasp quality is described by the measure $\phi_o : \mathbb{C}_{\text{r}} \rightarrow [0, 1]$. In this work, $\phi_o(\vec{k})$ is computed in two steps. First, in a given configuration $\vec{k}$ the hand is closed with uniform speed until all fingers have contact or the joint limits are reached. Second, the force-closure quality measure is calculated, i.e. the radius of the largest ball lying completely in the grasp wrench space (centered at the origin). Constraints, that have to be valid on all points of the trajectory, are described by the function $\psi_o : \mathbb{C}_{\text{r}} \rightarrow \{0, 1\}$. In this work, ψ_o will assign 0 to collision-free configurations, 1 otherwise.

IV. APPROACH

In this section, we outline our general approach of learning grasping strategies using Programming by Demonstration. The PbD process is summarized in fig. 1. A human operator demonstrates the grasping strategy on real objects in a sensory environment [4] being observed by multiple sensor systems including a 6D motion tracking device for the wrist position and orientation and two datagloves measuring 22 degrees of freedom of the human hands. The sensor data is filtered, segmented and mapped to symbolic operators. For each grasp operator, the example-trajectory τ_{h} is obtained by storing the wrist and fingertip trajectories relative to the grasped object. The localization error $N_o(\mu_o, \Sigma_o)$ is obtained by stereo-camera object localization with IVT [11].

In this work, the focus is on mapping an observed, humanoid grasping strategy to an anthropomorphic robot system with different kinematics and geometry. Instead of a direct mapping of trajectories, a probabilistic model is learned, which embodies a generalized version of the strategy and can be used to grasp a similar object in an environment with additional obstacles. The complete process is shown in fig. 2. The direct transformation of the grasping strategy to the robot hand has to take the kinematic and geometric differences into account. In the first step, the different number of fingers l of the robot hand and the human hand have to be considered. For example, the robot hand SAH, which is used in the experiments, has a thumb and only three oppositional fingers. Virtual fingers, see section II, are calculated in the last point on τ_{h} to assign one demonstrated finger trajectory to each robot finger. Due to its special role, the thumb is directly mapped to a single virtual finger. For the oppositional fingers, the set of $l - 1$ virtual fingers with minimal grasp cohesive index is computed. From each virtual finger, a real finger is chosen leading to the discrete path τ_{v}, which is the starting point for the transformation of the strategy to the robot hand.

In the second step, the grasping strategy has to be transformed into the workspace of the robot hand taking geometric, e.g. finger width, finger length, and kinematic, e.g. joints, differences into account. Let $F_i(\vec{k})$ be the 3d position of the ith finger in the configuration $\vec{k}$. $H_i(\vec{k})$ is the homogenous matrix describing the position and

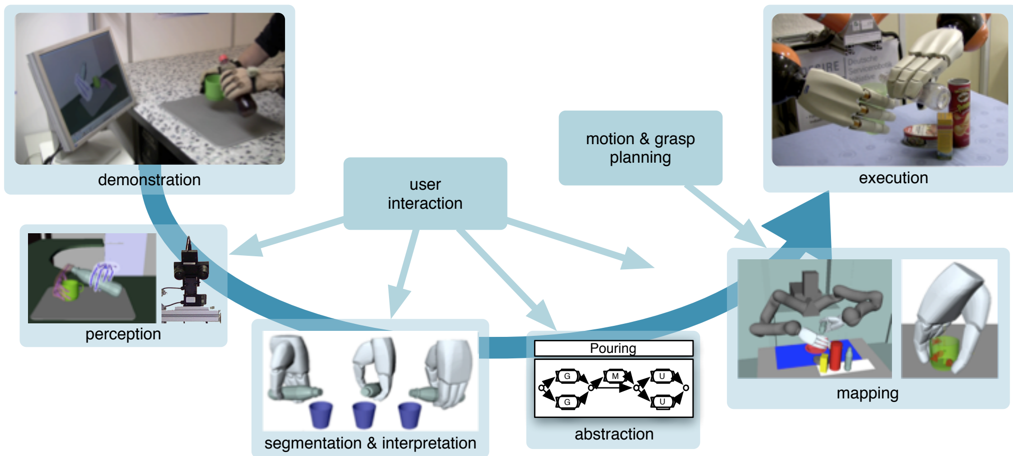

Fig. 1. Programming by demonstration: Learning of grasping strategies

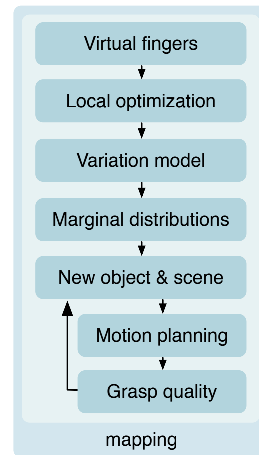

Fig. 2. Mapping of grasping strategies: overview

orientation of the hand in the configuration $\vec{k}$ and ${}^{\mathrm{r}}T_{\mathrm{h}}$ is the homogenous matrix describing the transformation from the human hand base frame to the robot hand base frame. $J_i(\vec{k})$ represents the ith joint value of the configuration $\vec{k}$.

The following distance functions $d_i : \mathbb{C} \times \{1, ..., T\} \rightarrow \mathbb{R}_{>0}$ are defined as:

$$\begin{aligned}
d_j(\vec{k}, t) &= \|F_j(\tau_v(t)) - F_j(\vec{k})\| \;\forall j = 1, 2, 3, 4 \\
d_5(\vec{k}, t) &= \|\, H(\vec{k})^{-1} \cdot {}^{\mathrm{r}}T_{\mathrm{h}} \cdot H(\tau_v(t))\| \\
d_6(\vec{k}, t) &= \begin{cases} 0, & \vec{k} \text{ is collision-free} \\ 1, & \text{otherwise} \end{cases} \\
d_7(\vec{k}, t) &= \begin{cases} 0, & t \leq 1 \\ \max\limits_{i=1,..,m} |J_i(\vec{k}) - J_i(\tau_{\mathrm{r}}(t-1))|, & t > 1 \end{cases}
\end{aligned}$$

d_1, d_2, d_3 and d_4 calculate the distance of the fingertip of the thumb, point finger, middle finger and ring finger of the robot and human hand. d_5 calculates the distance of the human to the robot wrist (sum of positional error, in mm, and rotational error, in degree). d_6 measures, if a given configuration is collision free. d_7 calculates the distance between two subsequent configurations. Each distance function will be multiplied by a weight $w_i \in \mathbb{R}_{>0}$. The weights do not depend on the problem instance and have been experimentally determined to be $(w_1, w_2, w_3, w_4, w_5, w_6, w_7) = (3, 1, 1, 1, 0.1, 10000, 10)$ for the SAH. The weight w_1 of the thumb distance o the demonstrated trajectory equals the summed weight of the oppositional fingers (w_2, w_3 and w_4). More uniform values lead to a larger thumb offset, which is disadvantageous since the thumb of the SAH is less flexible than the human one and therefore large errors can't be compensated in the motion planning step. The weight of the wrist w_5 reflects, that keeping close to the human hand pose is less important than the distance of the finger tips. w_5 can be increased, if the shape and size of the robot hand matches the human hand. The weight for collisions w_6 has been set to a large number instead of ∞ to allow for the traversal of forbidden areas in the search space. Smoothness is maintained by w_7, that weights the distance of the joint angles of subsequent time steps and therefore depends on the temporal discretization.

Finally, an optimization problem based on the path τ_{v}, the weights w_i and the distance functions d_i is formulated:

$$\forall t = 1, ..., T : \tau_{\mathrm{r}}(t) = \arg\min_{\vec{k} \in \mathbb{C}_r} \sum_{i=1}^{7} w_i d_i(\vec{k}, t) \qquad (2)$$

Due to the high dimension of the configuration space, smoothness is only considered between two subsequent time steps and the optimization problem is formulated point-wise.

The problem is solved approximately using the Rosenbrock method [12], which is a fast, robust, 0-order optimization technique, and robust[1] inverse kinematics f_i^{-1} for each finger i [13], which solves the problem of linked joints by interpolation of reference values. In the Rosenbrock optimization process, for each configuration $\vec{k}$, inverse kinematics are used to place the finger tips near the current point on the demonstrated trajectory, which effectively reduces the problem size. The joint values of the ith Finger are calculated using

$$f_i^{-1}(H(\vec{k})^{-1} \cdot {}^{\mathrm{r}}T_{\mathrm{h}} \cdot F_i(\tau_v(t)))$$

The result is a locally optimal discrete path τ_{r}, where each point is modeled as an estimator of the demonstrated fingertip positions. Based on this assumption, the euclidean mean squared error of the optimized fingertip positions is used to obtain the (degenerated) covariance matrices $\Sigma_r(t)$.

In general, the learned robot trajectory τ_{r} depends on the object and the scene in the demonstration environment. In order to adapt the grasping strategy to different objects

[1] Points, that are not in the workspace of the finger are shortened, and joint angles, that are not in the allowed range, are cut off.

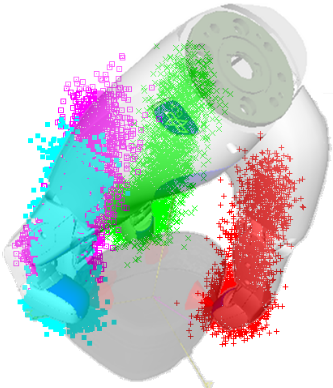

Fig. 3. Variation model: product of marginal distributions for the ham can grasping strategy, $\Sigma_m = 0$

and scenes, the allowed range of variations of the strategy is explicitly described in a probabilistic model. By following a Bayesian approach, the employed parametric model can be regarded as an efficient way to describe the lack of information about the real structure of the grasping motion. The parametric structure of the model allows to abstract from a single demonstration using a global modeling error and to infer information about single random variables in the model, which will be used in the evaluation of the model in section VI. In contrast, the frequenist approach requires a high number of demonstrations in order to calculate a frequency distribution of valid grasping motions.

The modeling error, e.g. differences in the kinematics and geometric of the human and robot hand, is approximated by a Gaussian distribution on $\mathbb{C}_r$ with zero mean and empirically determined covariance Σ_m. Due to the structure of the optimization problem, learning of precision grasps is in general more accurate than learning of power grasps, see mean squared error in table I. For precision grasps, Σ_m is based on the standard deviation of the fingertip positions 8mm (to consider the finger width of the robot hand), 5mm for the wrist position and $2°$ for the wrist orientation, which approximates sensor noise of the tracking device [14]. For power grasps, the exclusion of the finger curveture in the optimization process has to be explicitly considered by enlargement of the finger tip and wrist position standard deviation by 10mm. Based on the learned robot trajectory $\tau_\text{r}(t)$ with optimization error $\Sigma_\text{r}(t)$, the modeling error Σ_m, the object localization error Σ_o and smoothness constraints the variation model M is calculated, see section V.

The variation model represents a preference on a range of variations of the direct mapping of the demonstrated grasping strategy. In a new scene with different obstacles, this generalization is necessary to generate a collision free grasping motion fulfilling the goal criteria. For example, in fig. 3 the demonstrated strategy was to grasp the ham can straight from above while keeping the fingers close to the object. The paths of the individual fingers will have to be adapted if a slightly different can is grasped or additional objects in the scene block the motions of the direct transformation. The complexity of the configuration space of the robot $\mathbb{C}_r$ ($\geq$ 19 dofs) requires a powerful heuristic to search for a valid grasping motion. In state of the art motion planners, a powerful way to represent prior knowledge is to use non-uniform sampling distributions to focus search on relevant parts of the configuration space. In this work, the transformed grasping strategy and the allowed range of variations is explicitly modeled as a time dependent sampling distribution on $\mathbb{C}_r$ based on the learned variation model. Sampling from this distribution in a probabilistic motion planner leads to a concentration on grasping motions similar to the demonstrated grasping strategy, which is a powerful task-dependent heuristic. Different strategies can be considered simultaneously by superimposing the learned sampling distributions. The motion planning process will be described in section VII. Due to the interaction of the Gaussian error models and the collision and smoothness constraints, sampling from the variation model is time consuming. In section VI, an approximation of the sampling distribution, that can be precalculated based on the marginal distributions, will be discussed.

V. VARIATION MODEL

In this section, the variation model is introduced based on factor graphs, which allow for efficient modeling using single influences on random variables. The variation model combines the error models $\Sigma_r(t)$, Σ_m and Σ_o with smoothness constraints in one joint probability distribution on the set of discrete paths of length T in $\mathbb{C}_r$. The structure of the graph is chosen in a way to condition the joint probability distribution on the direct transformation τ_r but allowing for variations. The variations are restricted by incorporating the smoothness constraint, which forces similar values on neighboring trajectory points. The constraints ψ_o are incorporated in the constraint motion planning step.

A. Definition of the variation model based on factor graphs

The variation model is described by the factor graphs in fig. 4, which resemble the joint distribution $P(O)P(X_1, ..., X_T|O)$. An introduction to factor graphs, which also points out the relation to Dynamic Bayesian

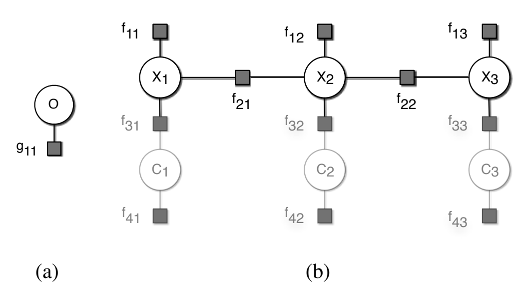

Fig. 4. Variation model: factor graphs for object localization (a) and the demonstrated grasping strategy with smoothness constraints (b), (T=3)

Networks, can be found in [15]. In this work, factor graphs have been chosen because the marginal distributions of the variables X_i can be efficiently calculated and a complex joint probability distribution can be defined based on a set of probability distributions on a subset of the random variables.

The nodes $X_t \in \mathbb{C}_r$ describe the robot configuration at time t. The position and orientation of the object is represented by O. The factors f_{it} and g_{11} describe influences on the random variables. The factor f_{1t} models the dependency of X_t on the learned direct mapping $\tau_r(t)$ and describes the expected deviation of the real value x_t from $\tau_r(t)$. A smooth transition between neighboring points X_t and X_{t+1} is enforced by the factor f_{2t}, which forces x_{t+1} to be near x_t. The factor g_{11} describes the dependency of O on the object localization. The smoothness covariance S_t depends on the discretization of τ_r, e.g. $S_t = 10^2 \cdot I_3$. In order to efficiently calculate the marginals $P(X_t)$, the factors are modeled as Gaussian:

$$\begin{aligned} f_{1t}(x_t) &= N_{x_t}(\tau_r(t), \Sigma_r(t) + \Sigma_m) \\ f_{2t}(x_t, x_{t+1}) &= N_{x_{t+1}}(x_t, S_t) \\ g_{11}(o) &= N_o(\mu_o, \Sigma_o) \end{aligned}$$

In general, additional constraints have to be considered in the transformation of the human grasp to the robot system, e.g. collision avoidance or safety constraints. Constraints, that can be approximated by a linear model, e.g. using Taylor expansion, can be incorporated in the factor graph, which will be explained in the next subsection.

B. Constraints in the factor graph

The gray parts of the factor graph in fig. 4 show, how the constraint function ψ_o can be incorporated in the factor graph. The value of the constraint function at time t is represented by C_t. The factor f_{3t} describes the deterministic evaluation of the constraint function on X_t. At each time step, a specific range of constraint values, given by the mean r_t and covariance matrix R_t, can be enforced by including a prior f_{4t} on C_t. The additional factors are defined as

$$\begin{aligned} f_{3t}(x_t, c_t) &= \delta(c_t - \varphi(x_t)) \\ f_{4t}(c_t) &= N_{c_t}(\psi_o(\tau_r(t)), R_t) \end{aligned}$$

using $N_x(a, 10^{-10})$ to approximate the Kronecker $\delta(x-a)$.

Arbitrary constraints are considered in the motion planning process and not in the factor graph, since the evaluation of a factor graph with a non-linear constraint ψ_o is time consuming and approximative, see section VI.

VI. EVALUATION OF THE VARIATION MODEL

The learned grasping strategy, i.e. the variation model, describes a joint probability distribution $P(O)P(X_1, ..., X_T, C_1, ..., C_T|O)$. In order to calculate the non-uniform sampling distribution on the robot configuration space $\mathbb{C}_r$, which will later be used in the motion planner to guide the search process, samples have to be drawn from the conditional joint marginal distribution $P(X_1, ..., X_T|O)$ respectively the conditional marginal distribution $P(X_t|O)$. In this section, the evaluation of the variation model using belief propagation to calculate the marginal distributions will be discussed.

A. Sampling from the variation model

The probabilistic motion planner, see section VII, requires a sampling distribution, that is defined on the configuration space $\mathbb{C}_r$. In order to guide the search using the learned grasping strategy, configurations are drawn from the marginals $P(X_t|O)$ since the distribution $P(X_1, ..., X_t|O)$ is defined on trajectories on $\mathbb{C}_r$. $P(X_1, ..., X_T|O)$ is implicitly approximated by the product of the marginal distributions $\prod_{t=1}^{T} P(X_t|O)$, which has two important consequences:

1) The marginal distributions are Gaussian, which leads to a high sampling rate
2) Each null set of the product distribution is a null set of the joint distribution, therefore no relevant sub spaces of the search space are cut off in the probabilistic motion planning process

In a cycle-free factor graph, marginal distributions can be calculated using belief propagation, which is a standard inference algorithm [15] based on message passing between connected nodes. For factor graphs with non-linear constraints, see the gray parts in fig. 4, the non-linear factors have to be linearized to calculate the Gaussian transformation. In general, the linearization point will depend on the current estimation of the marginal distribution $P(X_t|O)$, leading to an implicit loop in the factor graph. Loops can be considered in belief propagation by iteratively calculating messages based on the values of the previous iteration step, see loopy belief propagation [16].

B. Calculation of the marginal distributions

In this work, the marginals $P(X_t|O)$ are calculated using belief propagation and the constraints ψ_o are considered in the probabilistic motion planning process. In general, there are two ways of calculating messages. A message $\mu_{n\to f}$ from node n to factor f is computed as

$$\mu_{n\to f}(x) = \prod_{s\in\text{neighbors}(n)\setminus\{f\}} \mu_{s\to n}(x) \ .$$

A message $\mu_{f\to n}$ from factor f to node n is calculated as

$$\mu_{f\to n}(x) = \int_{X\setminus x} f(X) \prod_{s\in\text{neighbors}(f)\setminus\{s\}} \mu_{s\to n}(x) \ .$$

Since Gaussian distributions are closed under product, division and marginalization, messages representing a Gaussian distribution, so called *Gaussian messages*, will be obtained, if the factors are itself Gaussian.

The belief $N_{x_t}(b_{x_t}, B_{x_t})$ of the marginal distribution $P(X_t)$ is calculated by multiplying all incoming messages:

$$\begin{aligned} N_{x_t}(b_{x_t}, B_{x_t}) = \ &\mu_{f_{1t}\to x_t}(x_t) \cdot \mu_{f_{2t}\to x_t}(x_t) \cdot \\ &\mu_{f_{2t+1}\to x_t}(x_t) \cdot \mu_{f_{3t}\to x_t}(x_t) \end{aligned} \quad (3)$$

Equation 3 can be reordered to calculate each message on the right hand side based on the current belief, see [9], exploiting the fact that Gaussians are closed under product and division. In loopy belief propagation, the resulting recursive formula are used to update the beliefs iteratively by calculating new beliefs or messages based on the values of the previous step.

The beliefs of the marginal distributions are used to calculate the joint product distribution, which approximates the true joint distribution. In the next section, a non-uniform sampling distribution will be derived based on the joint product distribution. The sampling distribution represents the learned grasping strategy, that has been generalized from the direct transformation by using the modeling, transformation and object localization error to generate allowed variations while satisfying the smoothness constraint.

VII. HIGH-DIMENSIONAL MOTION PLANNING

In the presence of obstacles, planning of grasping motions is a demanding problem due to the dimensionality of the configuration space. Powerful heuristics are needed to plan motions in real environments. The learned grasping strategy can be regarded as a learned heuristic for the probabilistic motion planning process, which guides the search for grasping motions to motions similar to the human demonstration. In this section, a sampling process is presented, that weights the exploitation of the user demonstrated knowledge and the exploration of the configuration space by drawing a sample configuration y according to a non-uniform sampling distribution $P(Y)$. Multiple demonstrations of the same grasping strategy are combined by superimposition of the learned distributions.

In this work, a Rapidly-exploring random tree (RRT) [17] is used to search the high-dimensional configuration space $\mathbb{C}_r$, which is composed of the position and orientation of the wrist of the robot hand and the m finger joint angles. In contrast to uniform sampling of the configuration space of the robot, sampling from $P(Y)$ concentrates search on n learned grasping strategies, which are described by the factor graphs $P(O_i)P(X_{i1},...,X_{iT_i}|O_i)$, $i = 1,...,n$. Let $P(S)$ be a discrete probability distribution on the set $S = \{0,..,n\}$. In this work, the item 0 represents the uniform strategy and 1 to n represent the learned strategies. In the uniform strategy, the length T_0 is 1, $P(O_0)$ and $P(X_{01}|O_0)$ are uniform. $P(S)$ assigns the probability $\beta \in (0,1]$ to the uniform strategy. In the experiments, all learned variation models of one strategy were assigned the same probability. The sampling distribution is implicitly defined by the following scheme:

1) Draw strategy $s \sim P(S)$
2) Draw object position and orientation $o_s \sim P(O_s)$
3) Draw time point $k \sim U(1,...,T_s)$
4) Calculate kth marginal distribution of factor graph s
5) Draw configuration y according to the kth marginal distribution, $y \sim P(X_{sk}|o_s)$

Fig. 5. Ham can: demonstration of the grasping strategy

Fig. 6. Objects (left to right): chips, ham can, jam jar, small cup, salt box

The kth marginal distribution is static for factor graphs without additional constraints, leading to high sampling rates. β weights exploitation of the learned knowledge and random exploration of the search space, i.e. in $\beta \cdot 100\%$ of all cases, a uniformly drawn configuration is used, in $(1-\beta)\cdot 100\%$ of all cases, a configuration will be drawn based on the learned probability distributions. Due to the high dimensionality of the problem, uniform sampling ($\beta = 1$) produced no valid paths in clustered environments. Probabilistic completeness is maintained, if $\beta > 0$.

The sampling distribution is used to extend the RRT, guiding search towards solutions similar to the direct transformation τ_r but allowing for variations in compliance with the smoothness constraint. If the RRT was extended by a sample with $k = T_s$, i.e. the last step of a grasping strategy, the quality measure ϕ_o will be evaluated. If the resulting quality is $\geq \epsilon$, a valid solution has been found.

VIII. EXPERIMENTS

We conducted two series of experiments: grasping objects on a table with and without multiple obstacles. A human operator demonstrated grasping strategies for five different objects, see fig. 5. The objects are shown in fig. 6. Based on the demonstrated discrete paths, virtual fingers were calculated to map the five human fingers to the four fingers of the SAH. The variation models were learned and the marginal distributions calculated using belief propagation and the object localization error $\Sigma_o = 3^2 \cdot I_3$. The motion planer was integrated into the simulator GraspIt! [18].

In the first experiment, we evaluated the approach on grasp planning without additional obstacles and tested the generalization of a learned grasping strategy to different objects. In the second experiment, the generalization to scenes with additional obstacles was investigated. The quality measure $\phi_o(\vec{k})$ is computed by placing the robot hand at $\vec{k}$, closing all fingers using the autograsp function of GraspIt! and calculating the Epsilon quality measure (L1 norm, unit ball TWS). The default friction coefficients

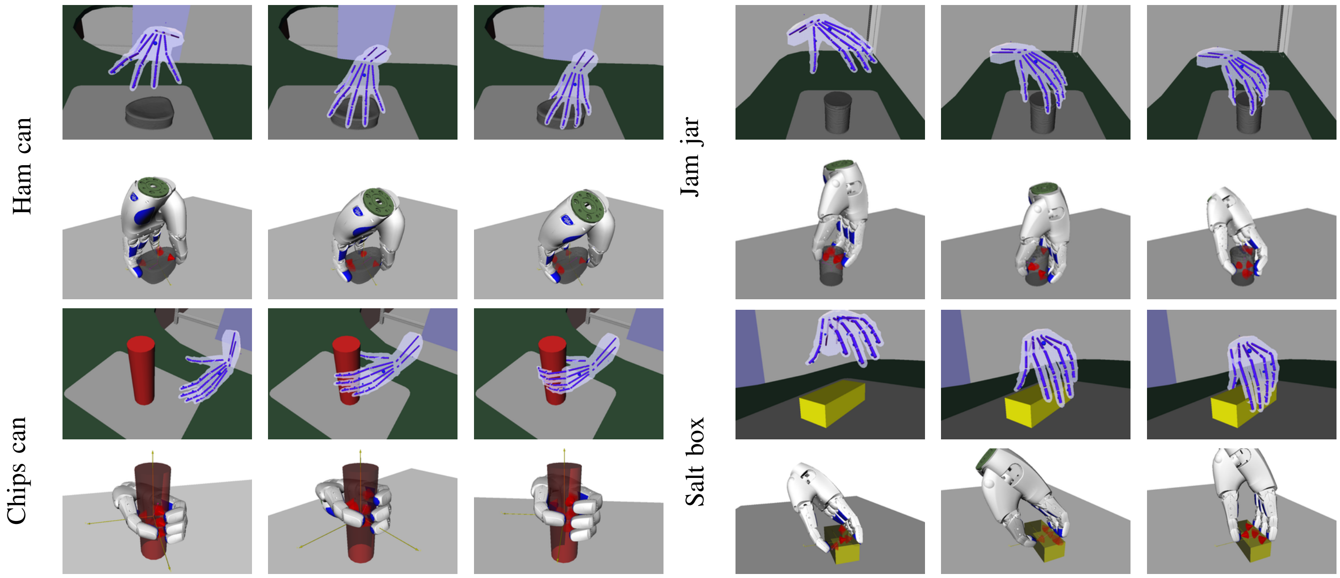

Fig. 7. Experiment 1: human demonstration (top row) and grasp examples (bottom row), planned using the variation model

TABLE I
SUMMARY OF THE FIRST AND SECOND EXPERIMENT (LAST FOUR ROWS)

Object	Quality	ETA (s)	Nodes	MSE (mm)	ETA_0 (s)
Ham	0.25	1.3	774	6.5^2	0%
Jam	0.24	0.65	817	8.7^2	2.1
Chips	0.17	1.5	469	13.4^2	3.2 (4%)
Salt	0.12	1.29	972	13.8^2	8.3 (53%)
Small cup	0.19	1.8	636	7.6^2	9.0 (65%)
Bottle	0.07	3.0	530	–	0%
Big cup	0.12	2.0	813	–	1.5 (45%)
Ham	0.25	6.1	502	–	0%
3 Chips	0.08	6.9	207	–	0%
Chips	0.08	5.6	179	–	0%
Jam	0.13	3.2	290	–	2.3 (78%)

of GraspIt! were reduced by 0.4 to approximate the real finger friction. For motion planning, a standard RRT with the CONNECT heuristic and the learned non-uniform sampling distribution $P(Y)$ has been used to plan 100 grasping motions for each object in each experiment. In each trial, a set of 100 start nodes has been created by sampling from $N(b_1, B_1)$. The parameter β was set to 0.05. In order to compare the planning result to a standard approach, a simple RRT planner, which uses $N(b_T, B_T)$ to create target configurations with a probability of 0.1, has been implemented in GraspIt!. The averaged results of all experiments are summarized in table I. The value *Quality* describes the best quality of all trials. *ETA* characterizes the motion planning result, i.e. the planning time until a valid goal configuration $\vec{k}$ (with $\phi_o(\vec{k}) \geq 0.05 =: \epsilon$) is encountered. Additionally, the table shows the average number of nodes and the mean squared error of the direct transformation τ_r. The result of the standard RRT is described by ETA_0 with percentage of success in brackets.

A. Grasps without additional obstacles

In the first series of experiments, the objects were placed on a table without additional obstacles. The calculation of the virtual fingers for the five grasping strategies yielded that the combination of the middle and ring finger is optimal for the ham can and the combination of the pinky and ring finger is optimal for the other strategies. The generalization of the learned grasping strategy to similar objects was tested on a big cup using the grasping strategy for the small cup and on a small bottle using the strategy for the chips can. Four experiments are shown in fig. 7. The learned grasps were successfully executed on the real robot system, see fig. 8.

B. Grasps with multiple obstacles

In the second series of experiments, generalization to situations, where a direct mapping of grasps would fail, was evaluated on four scenes with additional obstacles. The ham can was approached on an arc, the chips can and the jam jar on a straight line. The first two investigated scenes, see fig. 9, contained narrow passages, leading to a demanding planning problem due to the high-dimensionality of the configuration space (19 dofs). The variance described by the variation model was necessary to move the fingers on a collision free path between the object and the obstacles. The last two scenes required an adaptation of the fingertip locations on the object. The chips can lay flat on a table, so the fingers couldn't wrap the object anymore and a precision grasp had to be established. The jam jar had been placed in a hole and a grasp a few cm above the demonstrated grasping position had to be found. By using the learned distributions, all problems were solved in ≤ 7 seconds. The standard RRT yielded no solution except for the jam jar.

IX. CONCLUSION

In this work, a novel approach to learning of grasping strategies using Programming by Demonstration has been

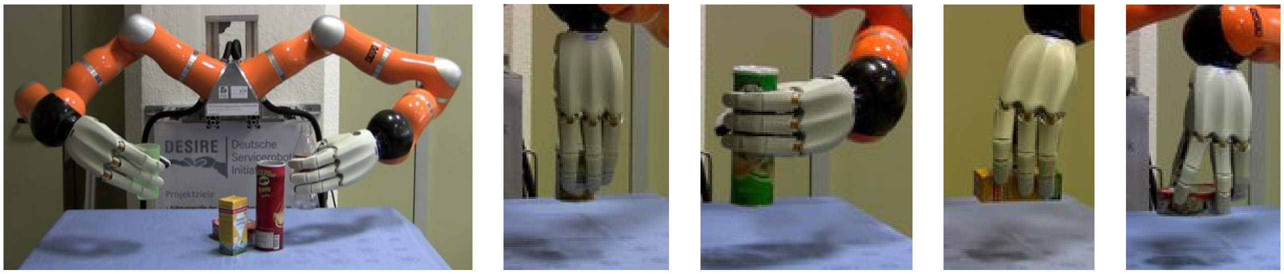

Fig. 8. Execution on the real robot system (left to right): big cup and small bottle, jam jar, chips can, salt box, ham can

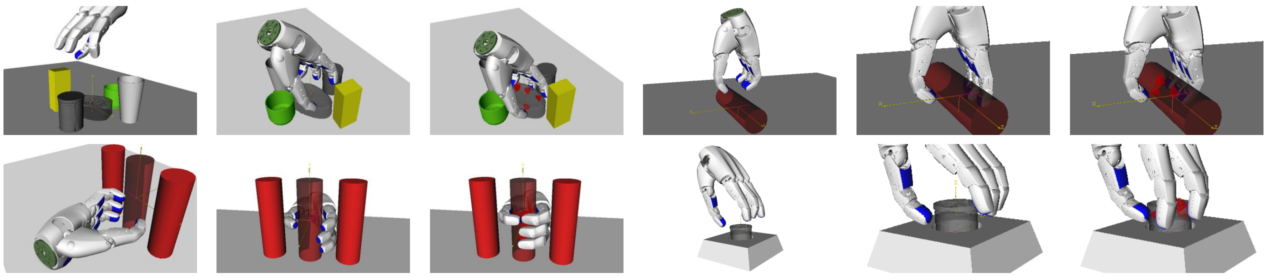

Fig. 9. Grasping in the presence of obstacles: ham can (top left), chips can (bottom left), chips can (top right), jam jar (bottom right)

presented. In order to account for modeling errors, object localization errors and errors in the transformation of the grasping strategy from the human operator to the robot hand, a stochastic counterpart of the grasping strategy, called variation model, is automatically learned. The variation model, which resembles a soft preference for grasping motions similar to the demonstration, is efficiently evaluated by sampling from the product distribution of the marginals, which are calculated using loopy belief propagation. This non-uniform sampling distribution is used in a standard probabilistic motion planner as a heuristic to guide the search process, allowing for the automatic weighting between exploitation of the learned task-dependent knowledge and the exploration of the search space. The incorporation of variations into the strategy representation allows for the flexible application of the learned strategy to different objects and environments. The generality of the approach has been demonstrated on two different experiments on a real anthropomorphic robot system with seven different objects.

X. FUTURE WORK

In the future, multiple demonstrations of grasping strategies will be used to derive an estimation of the modeling covariance error Σ_m, which has been experimentally determined and globally fixed for all experiments.

REFERENCES

[1] Z. Xue, J. Zoellner, and R. Dillmann, "Automatic optimal grasp planning based on found contact points," in *Advanced Intelligent Mechatronics, 2008. AIM 2008. IEEE/ASME International Conference on*, July 2008, pp. 1053–1058.

[2] M. A. Arbib, T. Iberall, and D. Lyons, "Coordinated control programs for movements of the hand," *Experimental brain research*, no. 10, pp. 111–129, 1985.

[3] S. B. Kang, "Robot instruction by human demonstration," Ph.D. dissertation, Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, December 1994.

[4] O. Rogalla, "Abbildung von benutzerdemonstrationen auf variable roboterkonfigurationen," Ph.D. dissertation, Universität Karlsruhe, 2002.

[5] C. Rosales, J. Porta, R. Suarez, and L. Ros, "Finding all valid hand configurations for a given precision grasp," in *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*, May 2008, pp. 1634–1640.

[6] H. Hu, J. Li, Z. Xie, B. Wang, H. Liu, and G. Hirzinger, "A robot arm/hand teleoperation system with telepresence and shared control," in *Advanced Intelligent Mechatronics. Proceedings, 2005 IEEE/ASME International Conference on*, July 2005, pp. 1312–1317.

[7] J. Rosell, R. Suárez, C. Rosales, J. A. García, and A. Pérez, "Motion planning for high dof anthropomorphic hands," in *IEEE International Conference on Robotics and Automation, ICRA 2009*, May 2009, pp. 4025–4030.

[8] M. Zucker, J. Kuffner, and J. Bagnell, "Adaptive workspace biasing for sampling-based planners," in *Robotics and Automation, 2008. ICRA 2008. IEEE International Conference on*, May 2008, pp. 3757–3762.

[9] M. Toussaint, "Bayesian inference for motion control and planning," Technical University Berlin, Technical Report, Tech. Rep., 2008.

[10] E. Kraft, "A quaternion-based unscented kalman filter for orientation tracking," in *Proceedings of the Sixth International Conference on Information Fusion*, vol. 1, 2003, pp. 47–54.

[11] P. Azad, T. Gockel, and R. Dillmann, *Computer Vision – das Praxisbuch*. Elektor-Verlag, 2007.

[12] H. H. Rosenbrock, "An automatic method of finding the greatest or least value of a function," in *Computer Journal 3*, 1960.

[13] L. Jiang, D. Sun, D. Liu, and Y. H. Liu, "Study on inverse kinematics and trajectory tracking control of humanoid robot finger with nonlinearly coupled joints," in *International Conference on Mechatronics and Automation, 2007. ICMA 2007*, August 2007, pp. 3214–3219.

[14] M. Pardowitz, "Inkrementelles und interaktives lernen von handlungswissen für haushaltsroboter," Ph.D. dissertation, Universität Karlsruhe, 2007.

[15] F. Kschischang, S. Member, B. J. Frey, and H. andrea Loeliger, "Factor graphs and the sum-product algorithm," *IEEE Transactions on Information Theory*, vol. 47, pp. 498–519, 2001.

[16] K. P. Murphy, Y. Weiss, and M. I. Jordan, "Loopy belief propagation for approximate inference: An empirical study," in *In Proceedings of Uncertainty in AI*, 1999, pp. 467–475.

[17] J. J. Kuffner, J. Steven, and M. Lavalle, "Rrt-connect: An efficient approach to single-query path planning," in *In Proc. IEEE Int. Conf. on Robotics and Automation*, 2000, pp. 995–1001.

[18] A. T. Miller, "Graspit!: A versatile simulator for robotic grasping," IEEE Robotics and Automation Magazine, Tech. Rep., 2001.