Topological Synergies for Grasp Transfer

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***Abstract*— In this contribution, we propose a novel approach towards representing physically stable grasps which enables us to transfer grasps between different hand kinematics. We use a low dimensional topologically inspired coordinate representation which we call *topological synergies*, and which is motivated by the topological notion of winding numbers. We address the transfer problem as a stochastic optimization task and carry out motion planning in our topologically inspired coordinates using the Approximate Inference Control (AICO) framework. This perspective allows us to compute not only the final grasp itself, but also a trajectory in configuration space leading to it. We evaluate our approach using the simulation framework PhysX. The presented experiments, which develop further recent attempts to use topologically inspired coordinates in robotics, demonstrate that our approach makes it possible to transfer a large percentage of grasps between a simulated human hand and a 3-finger Schunk hand.**

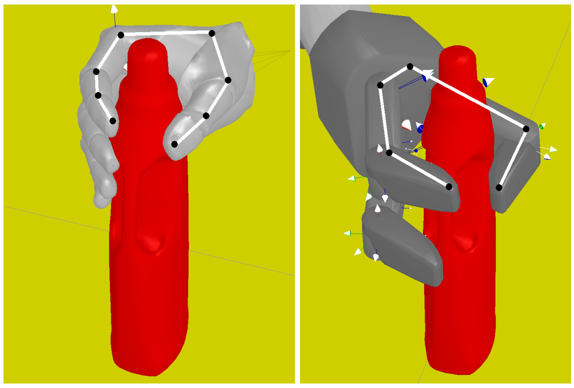

Fig. 1. Demonstrated stable human grasp (left) and transfered grasp (right) applying our topological approach

I. INTRODUCTION

Humans are able to easily imitate another human grasping and manipulating an object. Furthermore, even if one or two of our fingers are incapacitated due to a bandage or injury, we are still able to carry out most tasks as before. While much research in the last few decades has concentrated on robot grasping, the question of how to efficiently represent a stable grasp and how to transfer such grasps between differing hand kinematics remains an open area of research [3]. The work [1] suggested that humans use the concept of *virtual fingers* in order to control hand movements during grasp execution which supports the hypothesis that there might be a non-trivial low-dimensional representation that is used by humans to control, observe and reproduce grasps. In a similar vein, the framework of *postural synergies* [16], [15] and *force synergies* [17], where a linear subspace is used for representing grasp postures and forces respectively, tries to find such a low-dimensional representation.

A classical and popular approach towards finding good grasps is to proceed via a *force closure analysis* which takes into account the contact positions and normals between the hand's surface and the object being grasped. While this approach is theoretically sound, it can be problematic in practice since the robot's sensor input might be noisy, making object pose and normal estimation difficult. Furthermore, even if perfect knowledge of the object is assumed, computing stable grasps often still relies on a computationally expensive brute force search. Simulation software packages such as GraspIT [11], for example, can attempt to find force-closed grasps by sampling hand positions on a sphere surrounding the object, approaching the object until contact occurs and then closing the hand as much as possible, but using such a 'blind' method requires a lot of tests that might take too long to carry out on a real robot.

In this workshop paper, we argue that some of the problems surrounding this type of analysis are caused by the *representation of the state space*. If one works, for example, with the joint space coordinates directly, there exists no obvious way of transferring a grasp to a new kinematic hand structure with different joint lenghts or a different number of joints. In this work, we hence begin to explore an alternative – topologically motivated – coordinate representation which can be transferred between different hand kinematics and which describes not just the hand's state space but also the *interaction* between the hand and object. Our work falls into a class of recent methods in robotics and computer graphics inspired by concepts from topology such as [8], [19], [12].

In summary, this work makes the following contributions:

a) We evaluate a novel low-dimensional *topologically motivated* grasp representation for the purpose of grasp transfer which describes how much a hand is wrapped around an object.
b) We use this representation with a planning framework based on Approximate Inference Control (AICO) [18] in order to transfer grasps between different hands.
c) We demonstrate the success of our motion synthesis method in simulation by transferring a set of grasps from a human hand to the Schunk robot hand.
d) We evaluate the transferred grasps' stability using a realistic physics simulation carried out using the PhysX simulation software.

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This work was funded by the EU FP7 project TOMSY (IST-FP7-270436)

II. RELATED WORK

A posture P_h of a human hand has a state space with more than 20 degrees of freedom [4], [5], [16], while a Schunk robot hand has just 7 degrees of freedom. The question of how to transfer a human hand configuration to a robot hand configuration is hence highly non-trivial and somewhat ill-defined since there exists no natural comparison metric. In a *programming by demonstration* context [7], [10] one would however like to transfer a demonstration from a human subject to the robot in order to teach a robot how to carry out various tasks. Similarly, in the context of teleoperation [13] it is highly desirable to be able to transfer grasps from a human to a robotic hand. Several approaches to the transfer problem have been explored. The work [14] discusses three broad methods for transfer given by a) linear joint mapping - which is applicable if the robot's hand kinematics are very similar to those of the human hand, b) pose mapping - using least squares fitting and c) synergistic fingertip mapping. In more recent work, approaches related to the notion of virtual fingers have been explored in [6], [10], where a subset of the fingers of the human hand are manually mapped to one or more fingers of a robot hand.

One of the key features that the virtual finger, fingertip and synergy approaches share is that they attempt to first reduce the number of dimensions needed to describe a hand pose to a common minimum. Similarly, in the case of postural synergies [17], [2], a lower dimensional linear subspace of the full joint space is extracted using principal component analysis. Recent work [15] investigates cases where a linear dimensionality reduction might be subobtimal for this purpose and explores the use of the nonlinear GP-LVM dimensionality reduction framework. The representation which we develop here falls into this non-linear class of state space representations, but while [15] attempt to *find such a representation by data-analysis*, in this work, we consider *designing* such a representation by drawing inspiration from the tools that topology offers us.

Topology-based representations

Topology, in the rigorous sense, studies topological space such as, but not restricted to, smooth manifolds. Of particular interest to us is the fact that a large class of topological invariants – that is, quantities defined on a topological space which stay invariant under certain continuous deformations of the space – have been developed in this field.

In the context of character animation, [8] have investigated a state space representation utilizing ideas from topology. There, the topological *Gauss linking number*, which describes the linking between two closed curved in $\mathbb{R}^3$ is used as an inspiration to construct a *writhe matrix* to describe how wrapped the limbs of two avatars are. While the writhe matrix itself is not a topological invariant, [8] demonstrate that drawing inspiration from topology can be a very fruitful idea. In the work [19], the writhe matrix is applied in a robotics context for the first time. There, the authors show that the writhe matrix can successfully be used in conjunction with the AICO framework to plan motions. As an example, the authors demonstrate unwrapping a multi-joint robot arm which is initially wrapped around a line segment - a task which is difficult to solve in the high-dimensional joint space directly.

In this paper, we begin to develop a low-dimensional description of the grasp state space which is inspired by another classical topological invariant: The *winding number* of an oriented closed curve $\gamma : [0, 1] \to \mathbb{R}^2$ not containing a point $p \in \mathbb{R}^2$. The winding number for a closed curve is hence integer valued and measures how many times the curve wraps around p. If two plane curves γ_1, γ_2 not containing a point p have a non-zero winding numbers $w(\gamma_1), w(\gamma_2)$, they cannot be continuously deformed into each other without crossing the point p which explains why w is of interest in topology. Let us remark here that, if one is presented with a piecewise linear curve $\gamma : [0, 1] \to \mathbb{R}^2$ not containing the origin, one can easily evaluate w by simply adding up the local angles which the various line segments make with the origin. In the work [12] homology groups and a version of winding numbers of plane-curves were investigated to generate caging grasps on objects with holes. While we are also actively exploring the use of this notion of winding numbers for plane-curves, we will work with a three-dimensional analogue of the winding number that can be calculated for any curve $\gamma : [0, 1] \to \mathbb{R}^3$ which does not traverse some fixed reference point $p \in \mathbb{R}^3$.

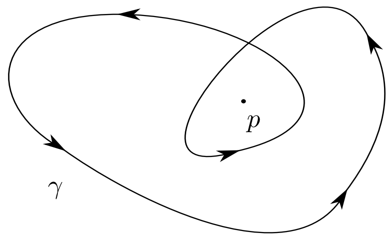

Fig. 2. A closed oriented plane curve $\gamma : [0, 1] \to \mathbb{R}^2$ with $w(\gamma) = 2$.

III. OUR METHODOLOGY

A. Invariant representation

Given a robotic or human hand with $n \geqslant 2$ fingers $f_1, \ldots, f_n$, we assume that one of the fingers, say f_n, can be labelled as a *thumb*. In practice, the thumb for a robotic hand such as the Barrett, Schunk, and Shadow hand, can be easily identified.

We then consider piecewise linear curves $\gamma_1, \ldots \gamma_{n-1}$, such that $\gamma_i(0)$ starts at the tip of the thumb f_n and ends at the tip of f_i by traversing the joints of f_n, then going through the center of the base of the hand and continuing through the joints of f_i (see Figure I, where $\gamma_1(0)$ is depicted in white). Such a curve is also used in [12].

Observing that the traditional winding number $w(\gamma) \in \mathbb{Z}$, for a closed curve γ in $\mathbb{R}^2$ measures the winding around a point $p \in \mathbb{R}^2$ by calculating the total change in angular coordinates, we now define a similar quantity for piecewise linear curves in $\mathbb{R}^3$. Suppose that $\gamma : [0, 1] \to \mathbb{R}^3$ is the piecewise linear curve connecting the points $X_0, \ldots, X_n \in \mathbb{R}^3$ by linear line segments from X_i to X_{i+1}, for $i = 0, \ldots, n-1$ such that a fixed point $p \in \mathbb{R}^3$ is not contained in the image of γ. We define

$$\hat{w}(\gamma) = \frac{1}{2\pi} \sum_{i=0}^{n} \text{angle}_p(X_i, X_{i+1}),$$

where $\text{angle}_p(X_i, X_{i+1})$ denotes the angle between the vectors $X_i - p$ and $X_{i+1} - p$. If γ is a closed curve that lies completely in a plane containing p, the above quantity is just the usual winding number. We will show in this work that $\hat{w}(\gamma)$ can be reliably used in a grasping application to quantify how much a curve is 'wrapped' around a point.

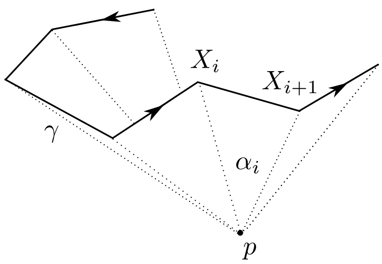

Fig. 3. A non-closed curve $\gamma : [0, 1] \to \mathbb{R}^3$ (solid lines) with reference point p and $\alpha_i = angle_p(X_i, X_{i+1})$.

Motion planning

The introduction of any new representation of a state space directly impacts motion synthesis. One of the motivations for the search for alternate representations is that these might allow us to express "wrapping-type motions", which are typical for grasping, as a simple Gaussian process prior. In this work we shall use the quantities $\hat{w}(\gamma_i)$, as a compact reduced representation of the "wrappedness" of a grasp. In particular, for a human grasp posture p, we shall consider the quantitiy $y = (\hat{w}(\gamma_i), \hat{w}(\gamma_j)) \in \mathbb{R}^2$, where γ_i, γ_j are the two curves with the highest winding $\hat{w}$ around the centre of mass of the grasped object as a "topological state descriptor" of a grasp. We shall record y for a human demonstration grasp and we will then use this topological coordinate to control the Schunk robotic hand to attain the same winding values with respect to the two curves γ_1', γ_2' running through the Schunk robotic hand.

Approximate Inference Control (AICO) frames the problem of optimal control as a problem of inference in a dynamic Bayesian network. Let x_t be the state of the system—we will always consider the dynamic case where $x_t = (q_t, \dot{q}_t)$. The robot dynamics are described by the transition probabilities $P(x_{t+1}|u_t, x_t)$. We introduce an auxiliary random variable z_t with $P(z_t = 1|x_t) \propto \exp\{-c_x(x_t)\}$, that is, $z = 1$ if the task costs $c_x(x_t)$ are low in time slice t. AICO in particular tries to estimate the posterior trajectory and controls. In [18], this is done using Gaussian message passing (comparable to Kalman smoothing) based on local Gaussian approximations around the current belief model.

Expressing motion priors in topology-based spaces and coupling spaces: Employing AICO with a linear Gaussian motion prior in a topologically motivated space is not sufficient to solve general motion synthesis problems, we need mechanisms to couple inference in topology-based space and state space. Figure 4 displays a corresponding graphical model. The top layer represents a process in alternate space and is coupled with the state-space layer by introducing additional factors

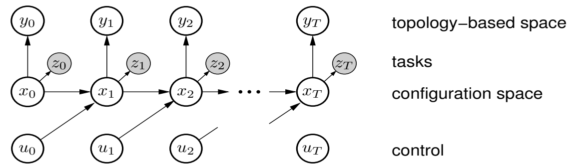

Fig. 4. AICO in configuration and topology-based space. The new topology motivated space represented as an additional task variable.

$$f(x_t, y_t) = \exp\{-\frac{1}{2}\rho\|\varphi(q_t) - y_t\|^2\}, \tag{1}$$

which essentially attempt to minimize the squared distance between the topology-based state y_t and the one computed from the joint configuration $\varphi(q_t)$, weighted by a precision constant ρ. Note that for Gaussian message passing between levels using a local linearisation of φ (having the Jacobian of the topology-based space) is sufficient. These factors essentially treat the topology-based state y_t, namely the winding values $(\hat{w}(\gamma_1), \hat{w}(\gamma_2))$, as an additional task variable for the lower level inference, analogous to other potential task variables like end-effector position or orientation.

IV. EXPERIMENTS

For our experiments we will use libORS, a freely available robot simulator incorporating routines for planning trajectories in the AICO framework. We use two kinematic models.

Firstly, a model based on a 3d scan of a human hand with 20 DOF (Figure I, left) which serves as our "demonstrator" and secondly a model of the Schunk robot hand (Figure I, right) which is the target of our transfer method. The Schunk hand is connected to the Schunk arm and motion are generated for the full 14 DOF robot.

Instead of generating training motions from human subjects, we have opted to automatically generate a large set of grasps in simulation in order to obtain a statistically significant amount of test data.

Test data generation

The test data consists of a set of stable grasps with a human hand model and with two object models: a bottle and a hammer as shown in the left column of Figure 6. The grasps are generated using a part-based grasp planning system – BADGr [9].

For each object, its 3D shape and dimension is first approximated through a constellation of oriented bounding boxes. These boxes decompose the object according to a convexity index, so that each box encapsulates a compact part of the object that is the candidate for grasp generation. For each reachable facet of the boxes, 4 grasp hypotheses are

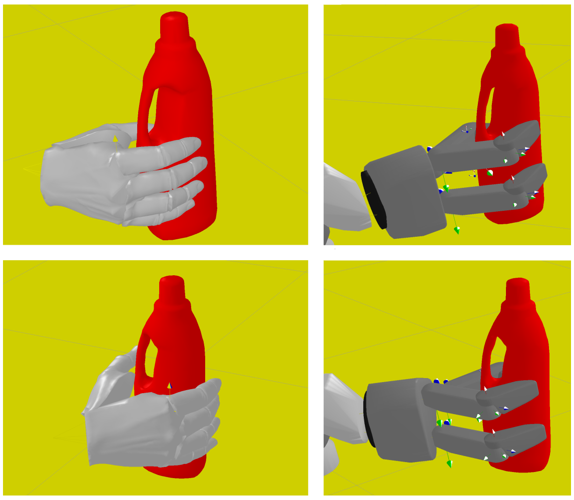

Fig. 5. Left side: examples of bottle grasps generated with human-like hand. Right side: Results of motion planning with a 3-finger Schunk hand.

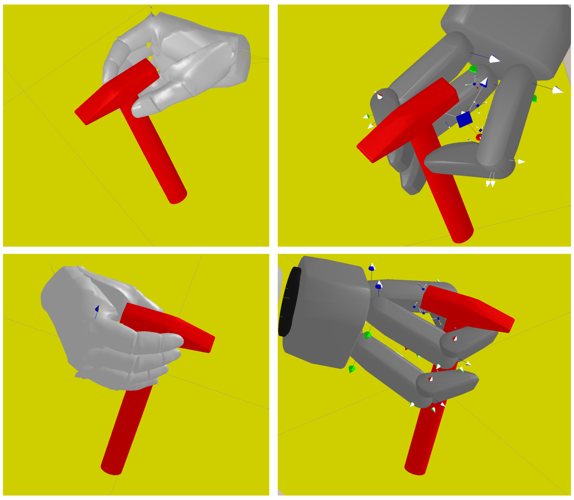

Fig. 6. Left side: examples of hammer grasps generated with human-like hand. Right side: Results of motion planning with a 3-finger Schunk hand.

generated by aligning the approach vector to its normal and the 4 orientations to its 4 edge vectors. Details of the grasp planning process can be found in [9]. The hypotheses are executed on the objects in the simulator which gives a grasp quality measure for stability assessment. We tested those grasps for physical stability using the simulation environment PhysX by moving the hand with the object by random rotational motions. A grasp was accepted as stable if the object did not fall out of the hand during this process. Using this procedure, we first generated 251 grasps for the hammer and bottle object. After testing for stability in PhysX, this resulted in 67 stable grasps for the Hammer and 32 such grasps for the bottle (see Figure I). We shall use this set of stable human grasps as our candidate data set for transfer to the Schunk robot hand.

Transfer

The transfer itself consists of two phases: motion planning using AICO and the closing of the fingers. This distinguishes our approach from similar methods, which focus mainly on the last phase or which try to find good contact points. We instead let the planner decide what an optimal configuration of the hand should be. For the optimization problem we use the winding numbers extracted from human hand example grasps as goals - in particular, we choose the winding with respect to the two curves γ_1, γ_2 with the largest winding numbers around the centre of mass of the object (out of the four curves $\gamma_1, \ldots, \gamma_4$, running along the human hand). We have also included a collision task variable, which defines a potential in the neighbourhood of the object and which has very high costs for states penetrating the object. Since not all orientations are reachable by the robot arm, we imitate the approach direction of the simulated human grasp by rotating the object so that the grasp approach direction is feasible for the robot arm. In the final phase, the fingers are closed until contact with the surface occurs.

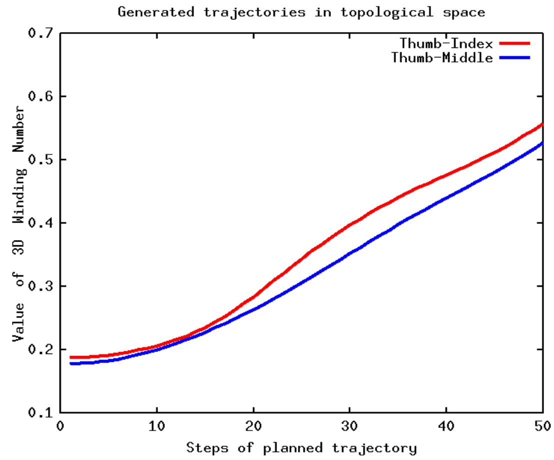

Fig. 7. A complex grasping trajectory in configuration space is represented by a pair of simple monotonically increasing curves in our topologically motivated state space consisting of $y_t = (\hat{w}(\gamma_1(t)), \hat{w}(\gamma_2(t)))$. The graph displays steps t in the simulation (horizontal axis) against the values of $\hat{w}(\gamma_1(t))$ and $\hat{w}(\gamma_2(t))$.

TABLE I
COMPARITIVE STABILITY ANALYSIS

Objects	Hammer	Bottle
Total number of grasps	101	151
Stable grasps	67	32
Autoclose based on initial human hand configuration	13%	25%
Grasp transfer using topological synergies	53%	63%

Evaluation

In order to benchmark the transfer of grasps, we applied a realistic simulation within PhysX. The object and the hand (without the arm) were copied to the physical environment with gravity and friction forces. We simulated random rotational motion of the hand in 100 simulation steps and measured if the object was still inside the hand. This procedure then results in a success classification of the grasp.

We have mentioned in the previous section that our approach consists of two phases: Control via AICO and a final automatic closing of the fingers. One could argue that transplanting the Schunk hand to the same position as the human hand and an automatic closing of fingers might be enough for reliable transfer. For comparison, we first tested such a direct 'transplantation'. For this, we put the Schunk hand into the same position and orientation as the human hand and performed automatic finger closing. As can be seen from table I, this, in a sense, naïve method, has a very low success rate w.r.t the total number of stable grasps.

Topological synergies, on the other hand, yield a much higher percentage of successful grasps. At least half of the transferred grasps are stable under realistic physical conditions. It is worth mentioning that the amount of information needed for our method is significantly less than required by other approaches - only two winding numbers and the orientation of the object is sufficient for simple objects. The trajectory in topological space (see Figure 7) is also very simple, but as a result of the non-linear properties of the mapping between layers of our Bayesian network, we obtain a relatively complex behaviour in the configuration space.

V. CONCLUSIONS

In this workshop contribution, we have begun to investigate a novel grasp representation based on the notion of *winding numbers* which measures how much a hand wraps around a target object. We have used this representation to transfer a large percentage of stable human grasps to stable grasps of a 7 degree of freedom Schunk hand. Our method incorporates planning using the AICO framework, which allows us to combine our topological task goals with traditional constraints such as collision avoidance. An initial evaluation of our approach using the PhysX simulation framework suggests that such "topological synergies" can be used to successfully transfer grasps between a human hand model and a Schunk hand. The strength of our approach lies in the fact that we are able to use topological task goals in conjunction with more traditional task variables in order to synthesize complex motions. In future, we would like to investigate how to incorporate additional information about object structure into our method and we are interested in exploring further how ideas from topology, such as winding numbers, linking numbers and writhe can be used for the purpose of grasping in robotics.

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