Towards Postural Synergies for Caging Grasps

Johannes A. Stork, Florian T. Pokorny and Danica Kragic

***Abstract*—Postural synergies have in recent years been successfully used as a low-dimensional representation for the control of robotic hands and in particular for the synthesis of force-closed grasps. This work proposes to study caging grasps using synergies and reports on an initial analysis of postural synergies for such grasps. Caging grasps, which have originally only been analyzed for simple planar objects, have recently been shown to be useful for certain manipulation tasks and are now starting to be investigated also for complicated object geometries. In this workshop contribution, we investigate a synthetic data set of caging grasps of four robotic hands on several every-day objects and report on an analysis of synergies for this data set.**

I. INTRODUCTION

Robots that can grasp unknown objects in the presence of noise are still not the state of the art. However, to enable future service, household or companionship robots to operate in unstructured environments and to perform useful tasks, such robots need to interact with and manipulate previously unknown objects reliably. While a large amount of effort in the robot grasping community has focused on the automatic synthesis and evaluation of *grasps* that establish contact with an object [1, 2, 3], the benefits of *caging grasps* have recently been rediscovered and exploited for manipulation planning [4]. Caging grasps constrain the object's freedom of motion by preventing it from escaping arbitrarily far [5]. However, they do not necessarily establish contacts. In fact, the related concept of maximal caging [6, 7] has been proposed to maximize the freedom of motion for the object while keeping it trapped in a bounded set. The particular advantage of caging grasps in applications of manipulation planning is that rigidity constraints between an object and the robot can be neglected in planning when the object is caged. The relative pose of the robot hand and object is not fixed and therefore allows for more flexibility. Humans often employ caging rather than force-closed grasps e.g. when holding on to hand-rails, when opening doors etc.

The problem of dexterous grasp planning is high-dimensional and has been approached by randomized search in a low-dimensional hand posture subspace under the notion of *eigengrasps* [8, 9]. A low-dimensional topology-based object representation and a matching posture evaluation for the generation of caging grasps on objects with holes is proposed in our current work at this conference [10]. There we represent fundamental loops in an object using approximated shortest homology generators and devise a method for generating caging grasps on such objects.

This is a submission to the IEEE/ICRA workshop "Hand synergies - how to tame the complexity of grasping". The authors are with the Computer Vision and Active Perception Lab, Centre for Autonomous Systems, School of Computer Science and Communication, KTH Royal Institute of Technology, Stockholm, Sweden, {jastork,fpokorny,dani}@kth.se

Fig. 1: Objects and hands from the data set. From left to right: Objects *Chair*, *Purse*, *Bag*, *Lawn Mower*, *Travel Bag* and robot hands *Armar III* (right hand), *DLR 1*, *Schunk SDH*, *iCub* (right hand).

To explore the prospect of applying the eigengrasp approach to caging grasps, we will here consider a data set of secure caging grasps which we generated on a collection of objects with holes. Example postures of four hands on five every-day objects are investigated for the existence of postural synergies, and the relation of a 'grasp target volume' and these synergies are studied in this work.

Our evaluation shows that postural synergies exist in such kind of caging grasps, and that postures highly depend on the local shape and extent of the caged object part, and in particular namely on the local volume.

II. RELATED WORK

Postural hand synergies and eigengraps can both be justified based on the well-known results of [11], where principal component analysis (PCA) of grasp joint space data is used to show that the two first principal components (PCs) account for more than 80% of the total variance. There, grasp data is acquired from human subjects shaping their hand as if they grasped a displayed object. The frequently drawn conclusion of these results is that the digits of a human hand are not controlled on an individual level, but rather are commonly actuated by a control that involves few postural synergies for forming general postures. Since the found synergies do not necessarily coincide with a standard grasp taxonomy, it is believed that the hand's shape is controlled independently from the applied forces. So called force synergies are subsequently studied by [12] for lifting, holding and re-placing using a gripper apparatus grasped by human subjects. The findings include that the normal forces of all digits covary linearly and that fluctuations in force are highly synchronized during holding. The temporal aspects of the entire act of grasping is investigated from the perspective of synergies in [13]. Five subjects perform reach-to-grasp experiments with three classes of shapes that are systematically varied in size. Two common patterns in the temporal sequence of marker positions are found: opening and closing of the hand in general, as well as thumb and long finger flexing. The synergies in grasp-to-reach are shown to be different from the postural synergies as the first PC accounts for 99.5% of the total variance and is irrespective of object shape, grasp or subject. Another approach towards grasp synthesis using synergies is given in [8, 9]. Transferring the results for the human hand in [11], eigengrasps for artificial hands are defined. As a result, a stochastic search can be conducted in the highly reduced dimensionality of the eigengrasp space – instead of the full joint space – to generate enveloping pre-grasps. In [9], synergies are used in an on-line interactive manner. A soft synergy model of hands is proposed in [14] to investigate the conjecture that humans learn a series of inner hand representations of increasing complexity. In that approach, the synergetic hand displacement does not directly determine joint angles but instead yields reference points. Mechanical compliance is described as a dynamic equilibrium between attraction towards the synergy-driven reference points of the pose and repulsive contact forces, joint stiffness and body deformation.

In contrast to force-closed grasps, caging grasps, only bound an object's mobility to prevent it from escaping arbitrarily far from the manipulator. A caging grasp provides a way to control an object without immobilizing it completely so that the object will follow the manipulator. Early research on caging has focused on analysis and efficient algorithms for simple hand mechanisms with few degrees of freedoms [15, 16], and considered only simple objects in a plane. Concavity of objects has been exploited for caging to find finger position far away from the object [6]. Later, the study of three-dimensional caging by multi-fingered hands led to the definition of sufficient conditions and resulted in a cage planning system [17]. The notion of stretching and squeezing cages has been introduced for the analysis of caging mobile rigid bodies in a Euclidean space of arbitrary dimension [18, 5]. Caging configurations have been considered as a waypoint towards a full contact establishing grasp [5] and as a method to deal with uncertainty in grasping [19]. Applications in manipulation planning have also recently been found [4], making caging grasps a highly interesting set of postures to investigate.

III. METHODOLOGY AND DATA-SET

To investigate postural synergies in caging grasps we perform principal component analysis of joint space data. Here, we work with a synthetic data set containing 9142 distinct caging grasps of four robot hands. Five real-sized every-day objects are each caged by the hands. We shall not elaborate here on the generation procedure for these caging grasps, which is based on our work in [10] and which uses topological features of the objects which are extracted from point-cloud data. The grasps in our data set have been confirmed as caging grasps by a rigid body simulation where a series of random translations and rotations was applied and was not able to pull the hand away from the object.

A subset of our caging grasp data set is displayed in Fig. 2. A brake-down of the numbers of grasps per hand and object is given in Fig. 3. We used four simulated robotic hands, namely the DLR, iCub, ARMAR III and Schunk hand. The DLR Hand [20] (12 DOF) is a four-fingered articulated robotic hand, about 50% larger than an average human hand. The iCub child-sized humanoid robot hand [21] has nine DOF. The five-fingered IAI-HAND-12 (10 DOF) for the ARMAR III platform [22] is a symmetric three-fingered hand. The Schunk SDH [23] (9 DOF) is a 3-fingered fully actuated industrial robot gripper. The object geometry data was taken from [24, 25]. All robot hands and objects are depicted in Fig. 1.

IV. RESULTS

A principal component analysis (PCA) of the joint space data was conducted separately for each robot hand. The first principal component PC_1 on average captures about 72% of the overall variance and the 2nd PC never accounts for more than 10%. Lower-order principal components account for increasingly less variance. While, for the Armar III, iCub and Schunk hand, the captured variance of PC_1 is about 70%, it is 76% for the DLR 1 hand. The distribution of variance is given in Fig. 4. This quantitative results suggest the existence of postural synergies in the caging grasps of each hand.

The plots for each robot hand in Fig. 5 show for each caging grasps the first two coordinates in principal component space (red) as well as the first two coordinates of the principal components themselves. For the Armar III and DLR 1 hands the points form one dominant cluster with comparably little scatter. For the Schunk SDH the points are concentrated on an arc at the top side of a scattered field. The iCub hand produces multiple clusters. To investigate the described clustering in the plots, we color and scale the data points for each posture according to a convex volume approximation of the caged local object part. The resulting plots, displayed in Fig. 6, indicate that the clusters are based on the grasp target volume. For the Armar III and iCub hands, the volume clearly separates two individual clusters. In case of the DLR 1 hand the large volume postures are surrounded by lower volume postures. The lower volume postures themselves are clearly split into two distinct segments. A similar structure can be seen for the Schunk hand, where the large volume postures do, in contrast to the other hands, not form a concentrated blob, but rather a wedge-like connected shape.

Finally, we are interested in the distribution of the principal components on the object shapes. For easy analysis, we color the grasp target positions using a synergy-based RGB color scheme. The 1st coordinate fades from blue to red while the 2nd coordinate determines the amount of green. In this way, we can inspect the distribution of the first two PC's influence on the postures. Fig. 7 shows the resulting maps. Different types of postures are apparently used for vertical and horizontal parts of the *chair* by the iCub and the Armar III hand. The DLR 1 hand uses a different posture for the middle backrest since the long fingers are obstructed from closing due

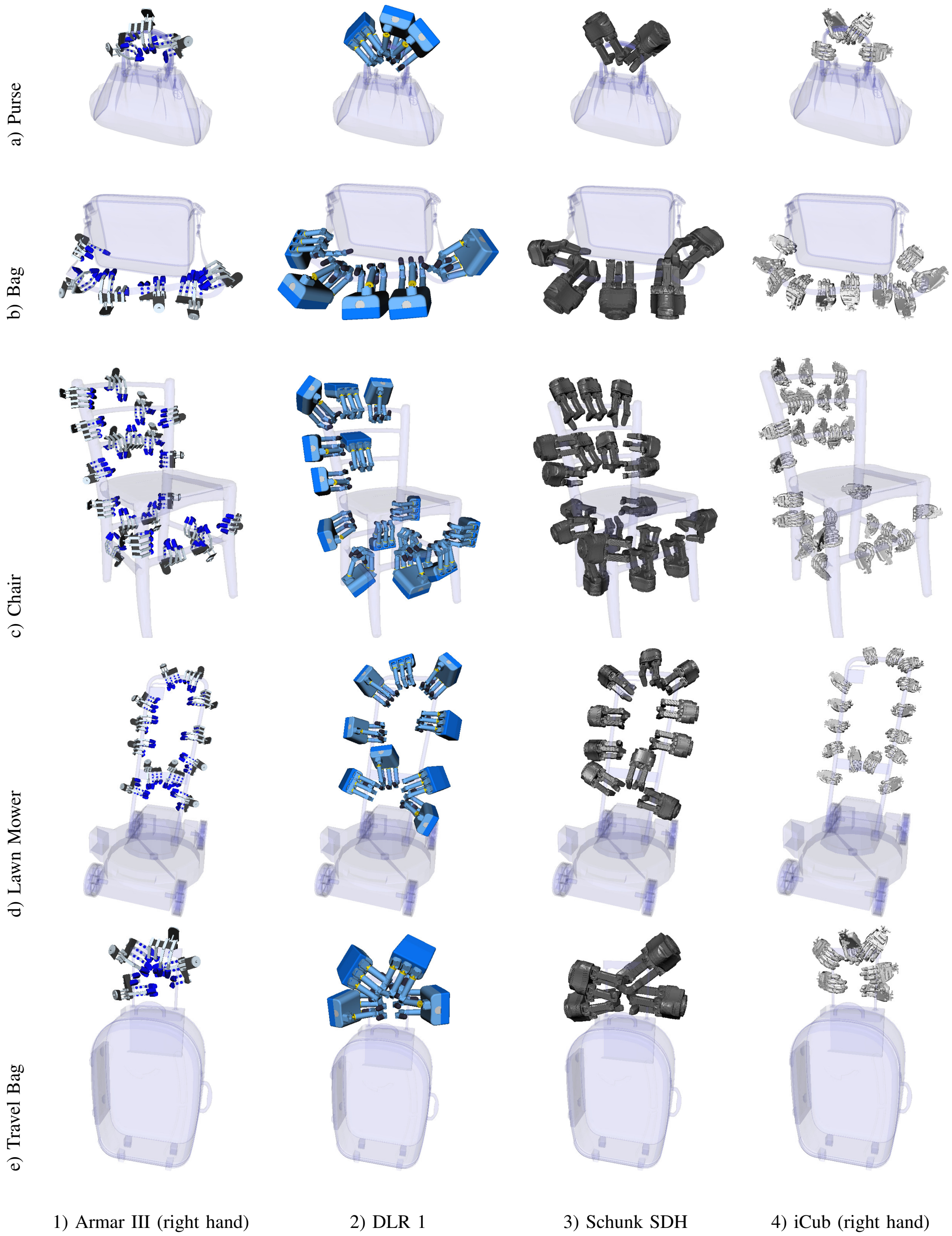

Fig. 2: Randomly selected examples of grasps from the caging data set. The different sizes of the robot hands can clearly be seen in relation to the objects. While some areas cannot be reached by the large hands because of obstruction, some smaller hands cannot reach around large volumes.

Endeffector	Armar III (2586)	DLR 1 (1971)	Schunk SDH (2249)	iCub (2336)
Purse	102	66	75	102
Bag	335	194	221	344
Chair	1402	961	1188	1216
Lawn Mower	598	613	623	532
Travel Bag	149	137	142	142

Fig. 3: The data set contains 9142 caging grasps of four robot hands on five objects. The table above shows how the grasps are distributed over hands and objects. To explore the synergies all postures of a single robot hand are considered at once, separately of each hand.

Hand	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6
Armar III	70.2	8.6	4.8	3.8	3.4	3.2
DLR 1	76.7	8.1	4.1	2.9	2.2	1.5
Schunk SDH	68.8	9.9	7.1	6.3	4.7	2.9
iCub	71.2	6.2	3.7	3.1	2.5	2.1

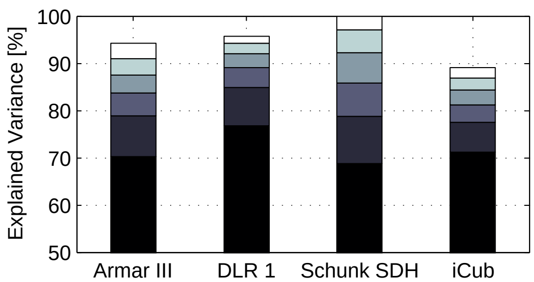

Fig. 4: Synergies can be found by consider the share of total variance that the first n principal components (PC) of the joint space data explain. For each robot we show the first six PC. The first two PC explain 78, 74, 67, 72 percent and the first three explain 85, 86, 80, 80 percent of the total variance.

to the object's geometry. On the *lawn mower* the DLR 1 and the Schunk hand have elongated gripper-like postures around the power switch box because that part is too wide to be properly enveloped. Such a posture can be seen for the Schunk hand at the 9 o'clock position in Fig. 8.

The interpretation of the fist two principal components can be investigated in Fig. 8. For the Armar III hand the first component mainly describes flexing of the short finger joints while the 2nd component governs the longer fingers. The thumb of the DLR 1 hand is controlled by the first component and the 2nd component describes bending of the long fingers. For the Schunk SDH the first component decides the distal joint bending. The 2nd component controls whether the fingers towards the left are more bent than the fingers towards the right. The opening of the longer fingers of the iCub hand relates to the first component while the 2nd component is concerned with the shorter fingers.

V. CONCLUSIONS

Research on caging has so far mainly focused on industrial applications and on simple hand representations while robot grasping research was largely concerned with stable contact-based grasps. We have explored synergies of a caging grasp data set on objects with holes and with complex geometry. We found that the first two synergies account for a large percentage of the variance in our data set. The first two postural synergies were found to describe the general shape of the hands indicating that they might be well-suited to be used in the planning of caging grasps on complex objects.

ACKNOWLEDGMENT

This work was supported by the EU project FLEXBOT (FP7-ERC-279933) and the Swedish Foundation for Strategic Research.

REFERENCES

[1] A. Bicchi and V. Kumar, "Robotic Grasping and Contact: A Review," in *IEEE ICRA*, 2000.

[2] A. Sahbani, S. El-Khoury, and P. Bidaud, "An overview of 3D object grasp synthesis algorithms," *Robotics and Autonomous Systems*, vol. 60, no. 3, pp. 326–336, 2012.

[3] D. Prattichizzo and J. C. Trinkle, "Grasping," in *Springer Handbook of Robotics*, B. Siciliano and O. Khatib, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2008, ch. 29, pp. 671–700.

[4] R. Diankov, S. Srinivasa, D. Ferguson, and J. Kuffner, "Manipulation planning with caging grasps." in *IEEE-RAS Humanoids*, 2008, pp. 285–292.

[5] A. Rodriguez, M. Mason, and S. Ferry, "From caging to grasping," *The International Journal of Robotics Research*, vol. 31, no. 7, pp. 886–900, 2012.

[6] P. Pipattanasomporn and A. Sudsang, "Two-finger caging of concave polygon," in *IEEE ICRA*, 2006, pp. 2137–2142.

[7] ——, "Two-finger caging of nonconvex polytopes," *Robotics, IEEE Transactions on*, vol. 27, no. 2, pp. 324–333, 2011.

[8] M. Ciocarlie, C. Goldfeder, and P. Allen, "Dexterous grasping via eigengrasps: A low-dimensional approach to a high-complexity problem," in *Robotics: Science and Systems Manipulation Workshop-Sensing and Adapting to the Real World*, 2007.

[9] M. T. Ciocarlie and P. K. Allen, "Hand posture subspaces for dexterous robotic grasping," *The International Journal of Robotics Research*, vol. 28, no. 7, pp. 851–867, 2009.

[10] F. T. Pokorny, J. A. Stork, and D. Kragic, "Grasping objects with holes: A topological approach ," in *IEEE ICRA*, 2013.

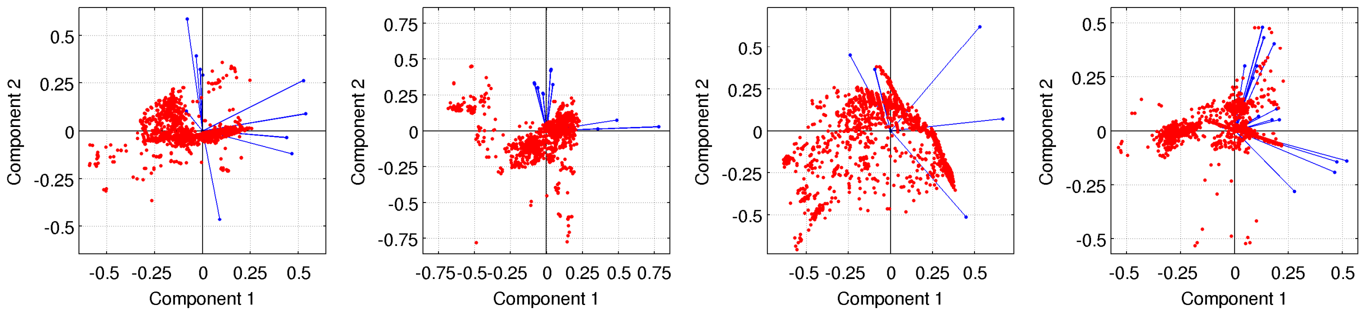

Fig. 5: From left to right: First two first principal components of the joint space data (red) and principal components (blue) of *Armar III* (right hand), *DLR 1*, *Schunk SDH*, *iCub* (right hand).

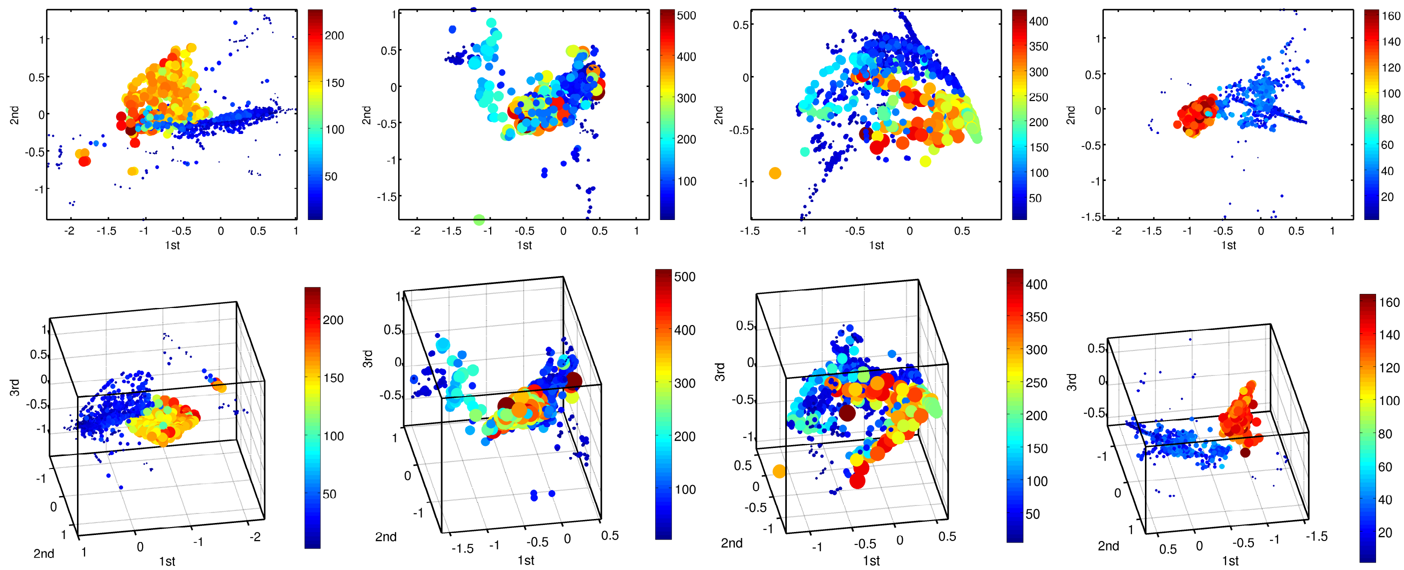

Fig. 6: First principal components of the joint space data set, color and size are defined by the volume of the grasping target. Top row: first two PC. Bottom row: First three PC.

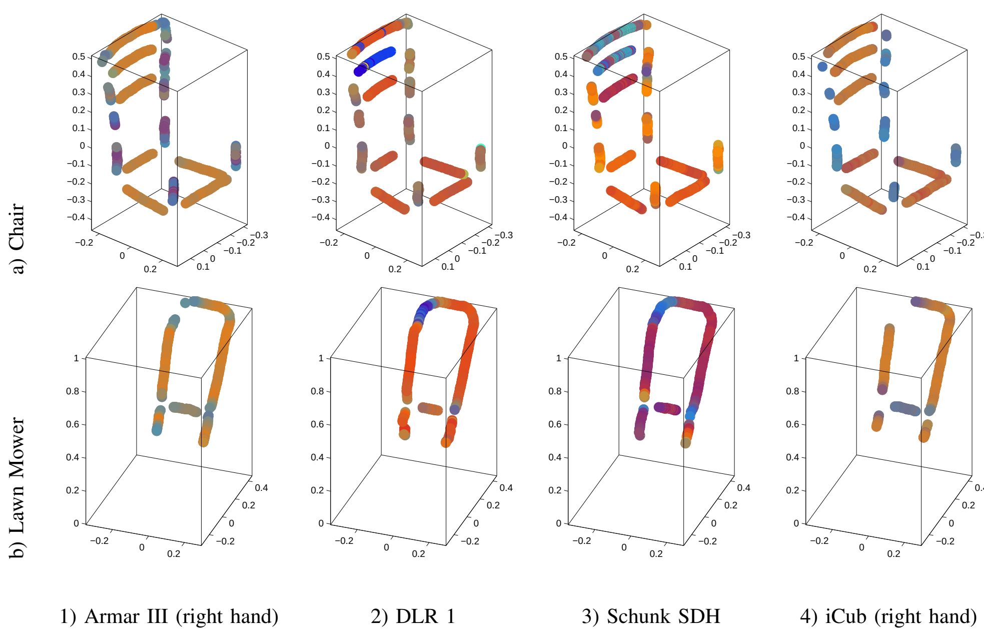

Fig. 7: Coloring of intended grasp center points by the first two principal components of the joint space data. The RGB color scheme maps the 1st PC from blue (min) to red (max) and decides the amount of green by the 2nd PC.

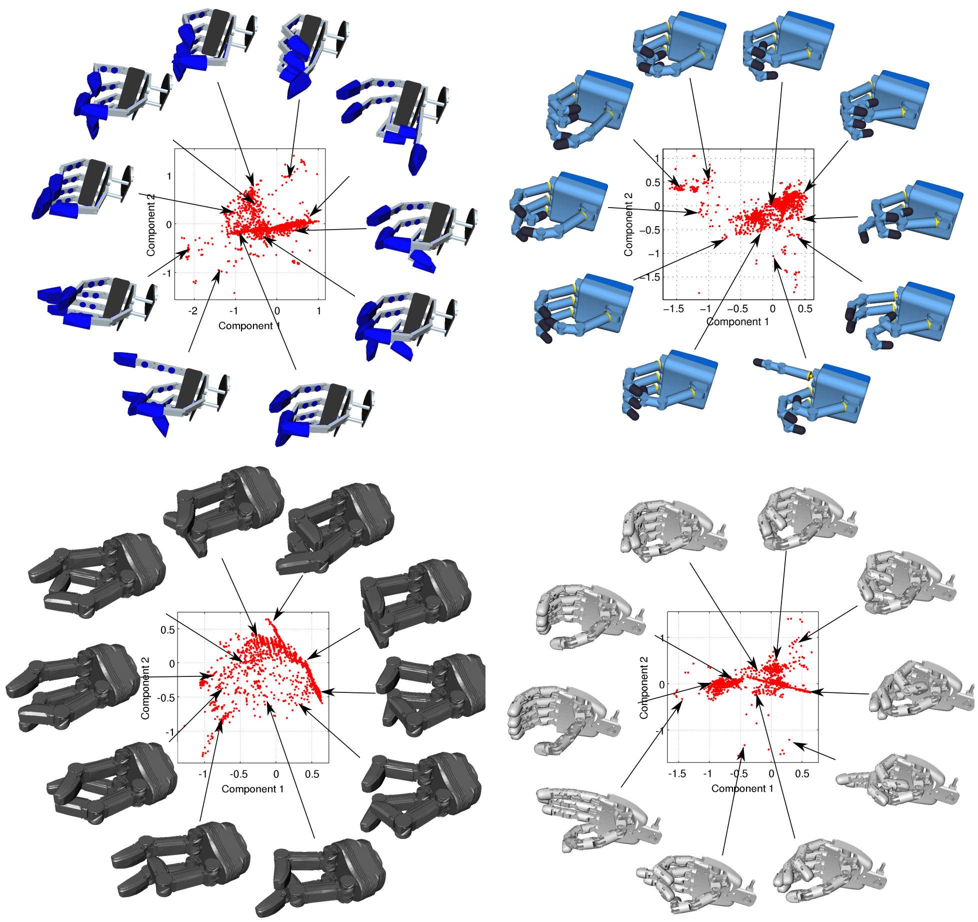

Fig. 8: Example postures from the secure caging data set together with their first two principal component coordinates.

[11] M. Santello, M. Flanders, and J. Soechting, "Postural hand synergies for tool use," *The Journ. of Neurosc.*, 1998.

[12] M. Santello and J. Soechting, "Force synergies for multifingered grasping," *Exp Brain Res*, 2000.

[13] C. Mason, J. Gomez, and T. Ebner, "Hand synergies during reach-to-grasp," *Journal of Neurophysiology*, vol. 86, no. 6, pp. 2896–2910, 2001.

[14] M. Gabiccini, A. Bicchi, D. Prattichizzo, and M. Malvezzi, "On the Role of Hand Synergies in the Optimal Choice of Grasping Forces," *Autonomous Robots*, 2011.

[15] E. Rimon and A. Blake, "Caging 2D bodies by 1-parameter two-fingered gripping systems," in *IEEE ICRA*, 1996, pp. 1458–1464.

[16] C. Davidson and A. Blake, "Caging planar objects with a three-finger one-parameter gripper," in *IEEE ICRA*, 1998.

[17] S. Makita and Y. Maeda, "3D multifingered caging: Basic formulation and planning," in *IEEE/RSJ IROS*, 2008.

[18] A. Rodriguez and M. Mason, "Two finger caging: squeezing and stretching," *Algorithmic Foundation of Robotics VIII*, pp. 119–133, 2009.

[19] W. Wan, R. Fukui, M. Shimosaka, T. Sato, and Y. Kuniyoshi, "Grasping by caging: A promising tool to deal with uncertainty," in *IEEE ICRA*, 2012, pp. 5142–5149.

[20] G. Hirzinger, J. Butterfaß, S. Knoch, and H. Liu, "DLR's multisensory articulated hand," in *Experimental Robotics V*, ser. Lecture Notes in Control and Information Sciences. Springer, 1998, pp. 47–55.

[21] G. Metta, L. Natale, F. Nori, G. Sandini, D. Vernon, L. Fadiga, C. von Hofsten, K. Rosander, M. Lopes, J. Santos-Victor, A. Bernardino, and L. Montesano, "The iCub humanoid robot: An open-systems platform for research in cognitive development." *Neural Networks*, vol. 23, no. 8-9, pp. 1125–1134, 2010.

[22] I. Gaiser, S. Schulz, A. Kargov, H. Klosek, A. Bierbaum, C. Pylatiuk, R. Oberle, T. Werner, T. Asfour, G. Bretthauer, and R. Dillmann, "A new anthropomorphic robotic hand," in *IEEE-RAS Humanoids*, 2008.

[23] C. Parlitz, "Hardware for Industrial Gripping at SCHUNK GmbH & Co. KG," in *Grasping in Robotics*, ser. Mechanisms and Machine Science. Springer, 2013, pp. 363–384.

[24] Archive3d.net, http://www.archive3d.net/.

[25] Trimble 3D Warehouse, http://sketchup.google.com/3dwarehouse/.