SOM-based experience representation for Dextrous Grasping

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Keywords: dextrous robot grasping, Grasp Manifold, experience-based and tactile-driven grasping

Abstract— We present an approach to dextrous robot grasping which combines a purely tactile-driven reactive algorithm with an implicit representation of grasp experience to yield an algorithm which can handle arbitrary, partially unknown grasp situations, i.e. vague object shape and position. During the grasp movement, the obtained contact information is used to dynamically adapt the grasping control by targeting the best matching posture from the experience base. Thus, the robot *recalls* and actuates a grasp it already successfully performed in a similar tactile context. To efficiently represent the experience, we introduce the *Grasp Manifold* assuming that grasp postures form a smooth manifold in hand posture space. We present a simple way of providing approximations of *Grasp Manifolds* using Self-Organising Maps (SOMs) and study the properties of the represented grasp manifolds concerning their smoothness and robustness against clustered training data.

1 Introduction

Algorithms for dextrous robot grasping bear the challenge to grasp a large variety of objects possibly unknown in shape, weight, and position. To this end, existing approaches nowadays use imaging techniques to estimate the 3D shape and position of the object, or employ tactile sensors with coarse spatial and temporal resolution.

In general, there are two opposing approaches to address this issue. The first uses object geometry information to plan the grasp beforehand by computing a geometry-specific (optimal) hand posture [1, 7, 9]. The second closes the fingers around the object solely based on tactile feedback until stable object contact is detected [8, 10, 11, 16, 13]. Most of these approaches do not accumulate their grasping experience to employ it for future grasping situations. In the case of "geometry-based" grasping, the algorithm itself inheres the knowledge of how to grasp specific objects, but is not able to match this knowledge dynamically to the presented object. These algorithms only succeed if the geometric representation of the object shape indeed matches the object at hand. If a geometric description of the object is not available in a previously acquired database and cannot obtained on-line, the object cannot be grasped at all. On the other side, "contact-based" grasping reacts on tactile events and dynamically adapts the grasping motion to the actual situation. While they may incorporate additional visual feedback, most approaches of this paradigm employ a fixed finger closing strategy, which does not take advantage of an implicit or explicit representation of the object's shape. Hence, these algorithms fail if the initial assumptions about object position and its coarse shape are wrong or do not match to the observed tactile events.

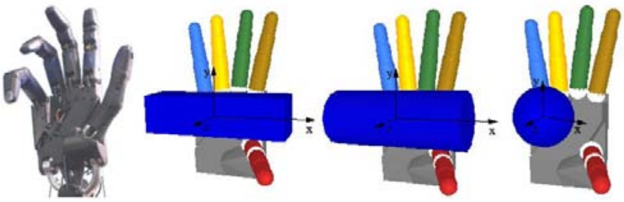

Figure 1: The Shadow Dextrous Hand and its virtual simulation model. Depicted is the initial hand posture with the three studied grasp objects: 1) box ($4 \times 4 \times 16$ cm), 2) cylinder (l: 16 cm, $\varnothing$: 6 cm), and 3) sphere ($\varnothing$: 6 cm).

In the present paper, we propose a new approach to dextrous robot grasping that combines the advantages of geometry-based and contact-based grasping employing an implicit representation of grasping experience using a self-organising map. The SOM is trained with hand postures which previously led to successful grasps. In this manner, it forms an approximation of a smooth grasp manifold representing hand postures which lead to successful grasps. Using tactile information to infer implicit knowledge about the object position, the algorithm dynamically exploits the SOM to adapt the grasping motion to the actual situation. According to observed finger contacts, the most suitable hand posture is selected from the grasp manifold represented by the SOM nodes' reference vectors.

The implementation, acquisition of training data, and evaluation have been realised in a physics-based computer simulation using the proprietary toolkit VORTEX [2] and a model of our 24-DOF SHADOW DEXTROUS HAND [17] shown in Fig. 1. While the kinematics of the hand model exactly corresponds to the real hand, the geometric shape is only coarsely approximated which has proven to be sufficient to obtain results applicable to the real hand.

The paper is organised as follows: In Section 2 the proposed grasping algorithm is presented. In Section 4 we propose a modification to the best-match search of the original

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SOM algorithm to realise a grasp selection based on current situation knowledge. The training process and the obtained SOM manifolds are presented in Section 5 and finally we end with a conclusion in Section 6.

2 Experience-based Grasping

The main idea of the proposed grasping algorithm is to augment a tactile-driven grasping heuristics with an *experience base of grasp postures* which can be used to guide the grasping process to promising hand postures. In a first approach, we represented this experience as a database of hand postures $\vec{\Theta}$ which previously led to successful grasps of one or more objects in a variety of grasping contexts, i.e. different positions and orientations of the object relative to the hand. Let I be the number of fingers, N_i the most distal joint in finger i, then $\vec{\Theta}$ denotes the vector $[\Theta_{1,1}, \ldots, \Theta_{1,N_1}, \ldots, \Theta_{I,N_I}]^t$ comprising all finger joint angles. Notice, that a grasp posture directly corresponds to a specific object and grasping context. Used in another context, the same hand posture might not lead to a successful grasp.

Comprising a set of successful grasp postures, the experience base implicitly provides knowledge of how to grasp the associated object. As counterpart, the tactile information observed during the grasping process provides implicit knowledge of the actual object shape, position and orientation. A dynamic matching of this context-specific knowledge to the grasping knowledge stored in the experience base yields information about how to grasp the current object in the current situation. We only utilise joint angles for this matching process whose finger segments provide reliable context information. To this end, we employ a *Partial Contact Posture (PCP)* $\vec{\Theta}^{pcp}$ specifying only joints between the palm and finger segments having object contact. If $S_{i,j}$ denotes the finger segment directly attached to and moved by joint j of finger i, the PCP can be defined more formally as:

$$\vec{\Theta}^{pcp} = [\Theta^{pcp}_{1,1}, \ldots, \Theta^{pcp}_{1,N_1}, \ldots, \Theta^{pcp}_{I,N_I}]^t \quad \text{where:} \tag{1}$$

$$\Theta^{pcp}_{i,j} = \begin{cases} \Theta_{i,j} & \text{if a segment } S_{i,(k \geq j)} \text{ has contacts} \\ \text{not specified} & \text{otherwise.} \end{cases}$$

Based on this PCP, we define a modified Euclidean norm d^{pcp} to match a current hand posture $\vec{\Theta}^{pcp}$ to the best matching posture $\vec{\Theta}^{xp,\star}$ in the experience base $\{\vec{\Theta}^{xp}\}$ by minimising d^{pcp}, only taking reliable joints into account:

$$d^{pcp}(\vec{\Theta}^{xp}, \vec{\Theta}^{pcp}) = \sum_{i,j} s_{i,j} \cdot (\Theta^{xp}_{i,j} - \Theta^{pcp}_{i,j})^2 \tag{2}$$

The $s_{i,j} \in \{0,1\}$ only select *specified dimensions* of $\vec{\Theta}^{pcp}$ for comparison. The resulting $\vec{\Theta}^{xp,\star}$ then acts as the target posture for the current control cycle.

As the PCP requires contact information, a precondition for the experience-based control is the existence of at least one contact. Furthermore, as the experience base is a discrete set of hand postures which additionally is affected by noise, a subsequent generic finger closing heuristic similar to our originally used algorithm [13] is necessary to finalise the grasp and establish stable object contacts.

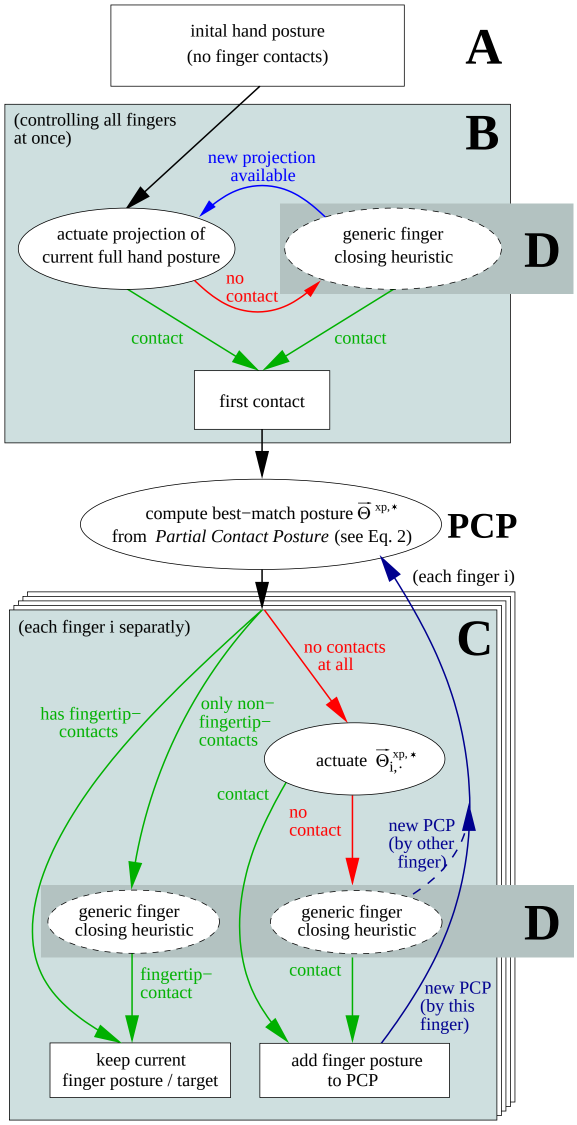

Figure 2: Overview of the grasp control algorithm.

Subsumed, there are four different control phases of the algorithm: A) Actuating an initial hand posture, B) Establishing first contact in an already experience-influenced process, C) Performing experience-based grasp control and D) Applying a generic finger closing heuristic (embedded in phases B and C). The whole grasp control is embedded in an action-perception-loop which allows a dynamic adaptation to the current grasping context. A schematic overview of the control algorithm is given in Fig. 2. A detailed description and evaluation of the grasp control is given in [15].

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3 SOM notation

In this paper, the following notation is used: the SOM lattice is denoted as A with node indices $\vec{a}$ and attached reference vectors $\vec{w}_{\vec{a}}$. $\vec{a}^{\star}(\vec{x})$ is the index of the best-match node according to the input $\vec{x}$ determined by the standard equation using a distance metric $dist(.)$:

$$a^{\star}(\vec{x}) = \arg\min_{\vec{a}\in A} dist(\vec{w}_{\vec{a}}, \vec{x}). \quad (3)$$

4 SOM Grasp Manifolds

Grasping experience was introduced in Section 2 as a set of grasp postures represented by vectors of hand joint angles and stored in a database. To appropriately cover all possible grasping situations, this database must comprise a multitude of corresponding postures, which increases both the computational costs and required storage capacity. To obtain a more compact representation of the grasping knowledge, we assume that all valid grasp postures for at least one object form a low-dimensional smooth manifold $\mathcal{GM}$ embedded in hand posture space and denote it as *Grasp Manifold*. Thus, if such manifold exists, it represents the set of hand configurations in the hand posture space that is of special interest in a specific grasping context. The task of grasping then can be described as modifying the current hand configuration in an appropriate way such that it converges to a *grasp configuration* in the manifold.
The SOM as discrete approximation of such manifold provides efficient means to accomplish this task. By projecting the current hand configuration onto the SOM by performing the best-match search, we can recover the closest grasp configuration in the set of SOM reference vectors. In addition, the SOM provides an elegant way to recover grasp postures based on incomplete grasp data – meaning hand postures which only partly describe a grasp in the actual context – and thus to pull incomplete grasp configurations onto the manifold. This mechanism of an "associative completion" was introduced first in [18] in the context of the PSOM [12]. It can be realised by a simple modification of the Euclidean Norm in the distance metric $dist(.)$ in Eq. 3:

$$dist(\vec{x}, \vec{x'}) = \sum_i p_k (x_k - x'_k)^2 \quad (4)$$

with $p_k > 0$ if component k should be considered for the projection and $p_k = 0$ otherwise. Hence, by setting the $p_k = 1$ for those dimensions k of the current hand posture that already coincide with a grasp posture and setting $p_k = 0$ otherwise, we can *activate* the grasp part of the hand posture for the SOM best-match search and *deactivate* the rest. In this form, Eq.4 resembles the PCP distance metric in the previous section (Eq.2). Thus, the SOM with the modified distance metric (Eq.4) for the best-match search implements the same projection onto the experience base as the PCP matching (Eq. 1-2), but for the manifold representation of the experience. This extension of the best-match search comes with no additional computational costs. Fig. 3 depicts an extract of a two-dimensional SOM-based *Grasp Manifold* trained on 4220 cylinder grasp postures. Each hand picture represents the reference vector $\vec{w}_{\vec{a}}$ of a particular SOM node. The visualisation of the SOM shows that similar hand postures are grouped together and change smoothly to other postures which supports our initial assumption of a smooth low-dimensional *Grasp Manifold*. Nevertheless, there are less smooth areas which will be interpreted in the next section.

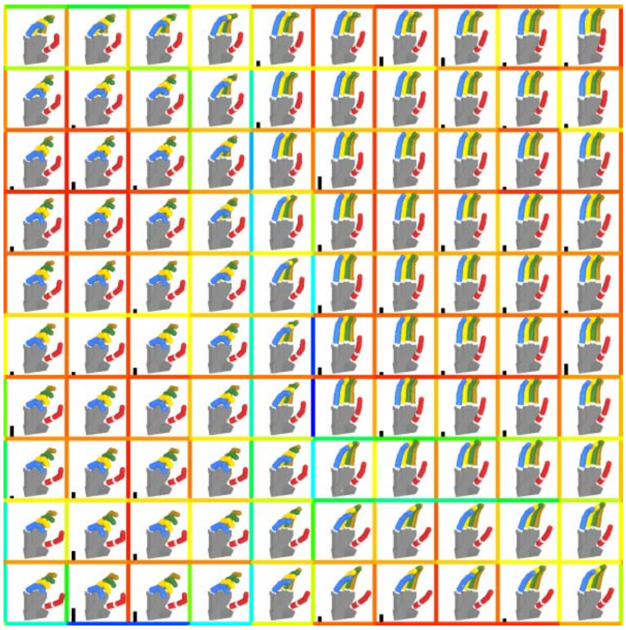

Figure 3: 10x10 extract of a cylinder-specific 25x25 SOM *Grasp Manifold*. Each hand posture visualises the reference vector $\vec{w}_{\vec{a}}$ of one SOM-node. The smooth changing of the postures supports the assumption of the *Grasp Manifold*. The colour of the sub-figure borders encode the internode distance: red: min.distance, green: medium dist., blue: max.dist. Black bars left from the hand indicate the relative amount of training data that fall on the SOM node; no bars indicate the lack of supporting training data.

5 Properties of the Grasp Manifold

In our experiments, we use object-specific 25x25 SOMs trained on grasp postures for one specific object shape. Hence, a particular SOM is only adequate for grasping objects of the matching type, requiring a prior classification of the object. This has the advantage, that the extension of the system by new objects does not change the behaviour for already learned objects. Nevertheless, we have shown that representing all grasp postures corresponding to various objects *within a single SOM* is possible as well [14].

As training data, we generated grasp postures in simulation. To obtain postures with hand/object contacts at every

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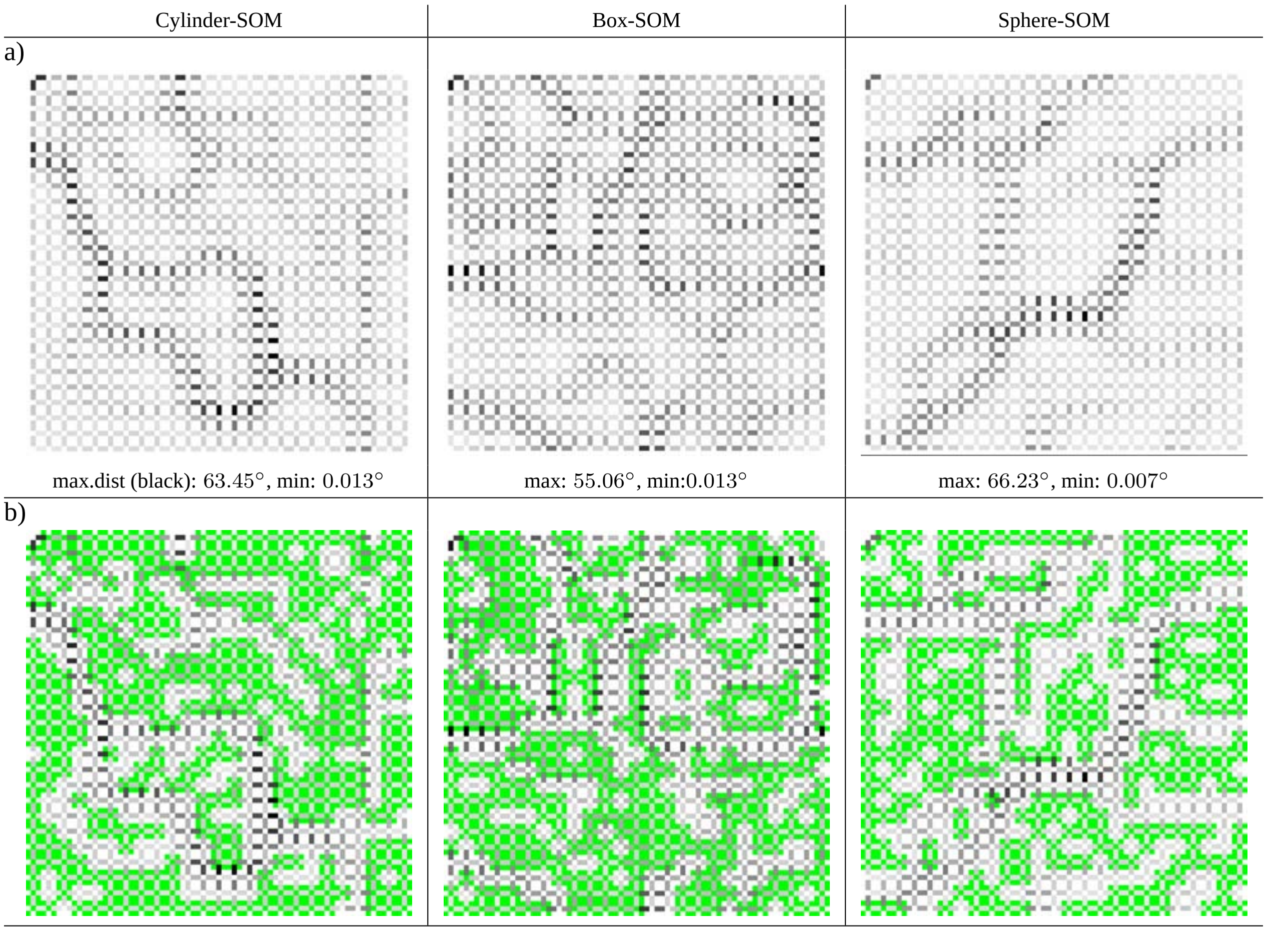

Figure 4: Visualisation of the inter-node distances and the data-projection-nodes of the trained 25x25 cylinder-, box- and sphere-SOM. a) inter-node distance structure: black node connections denote maximal, light gray connections denote minimal inter-node distances. The small white squares mark the node positions in the lattice A, the large white squares are background. b) overlaid node matches (green background) when projecting the training data set onto the SOM. The nodes on the cluster borders are only roughly supported by training data.

fingertip, we connected the fingertips to the corresponding object with springs that pull the fingers in the direction of the object. The object is fixed and by moving the hand manually in a variety of relative hand/object positions and orientations, we generated a total of 10.174 postures, 4.069 for the box, 4.220 for the cylinder and 1.885 for the sphere. As the springs are only able to establish contacts for small deviations of an initially manually actuated five-fingertip-contacts posture, several of such ”starting postures” had to be used. While this method allows for generating a big amount of data representing different regions of the hand posture space it results in man-made clusters of data around these starting postures. But if our assumption of a smooth manifold holds, the algorithm has to be able to cope with these clustered training data and the inter-cluster gaps, respectively.

To train the object-specific SOM-*Grasp Manifolds*, the grasp postures associated with the corresponding object were presented within all 300 learning epochs according to a random distribution (learning rate $\varepsilon(t)$ decreasing from 0.95 to 0.05, standard deviation $\sigma(t)$ of gaussian neighbourhood function decreasing from 6 to 0.7). The magnification effect of the SOM learning results in a higher density of nodes in the clusters of training data, while there remain some nodes in the space in between. Onto these nodes, no training data is mapped at all and their distance to neighbouring nodes is much larger than on average. Hence, the clusters of the training data and cluster borders are clearly visible (cf. Fig. 3 and 4a). Fig. 3 is a 10x10 extract of a node visualisation of a cylinder-specific 25x25 SOM where each hand picture represents the reference vector of the corresponding SOM node. The clusters are the areas where the depicted grasp postures remain similar, cluster borders can be identified by highly differing postures from one node to the next. The colours of the sub figure borders describe the inter-node distances: bright red denotes the minimal inter-node distance in the SOM, green a medium and bright blue the maximal distance. A more distinct picture of the inter-node distance structure of the whole SOMs is depicted in Fig. 4a where only the inter-node connections are shown.

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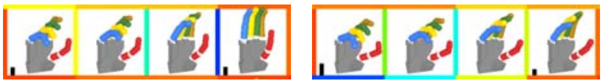

Figure 5: Two 1x4 extracts of Fig. 3. The left and right nodes are supported by training data (black bars left from the hand). The middle nodes do not have data support and represent inter-cluster nodes. Though not supported by training data, they represent useful grasp postures and interpolate nicely between adjacent cluster nodes.

High inter-node distances are represented by black connections (maximal distances: cyl: $63.45°$ in 22 dimensions, box: $55.06°$, sph: $66.23°$) and small distances by very light gray connections (minimal distances: cyl: $0.013°$, box: $0.013°$, sph: $0.007°$). Thus, the black "lines" represent the cluster borders where the reference vectors have high inter-node distances.

In Fig. 4b, in addition to Fig. 4a, the nodes which are supported by training data are marked with green background. In contrast to the nodes in data clusters, the nodes on the cluster borders are mainly not supported, but as shown in Fig. 5, these inter-cluster nodes represent meaningful grasp postures as well and nicely interpolate between adjacent cluster nodes. Thus, the SOM training achieves to learn meaningful bridges between the clusters, representing intermediate grasp postures.

Interestingly, during application of the experience-based grasping algorithm (keeping the SOM fixed), those inter-nodes are more often winners than the cluster nodes used during training (cf. Fig. 6). This suggests, that during testing, much more grasp situations are discovered than in training. By resuming the learning phase of the SOMs with the grasp postures generated in testing and performing few learning epochs with small learning parameters (10 epochs, $\varepsilon(t)$ decreasing from 0.1 to 0.05, $\sigma(t)$ decreasing from 3 to 0.7), the SOM structure becomes noticeably smoother. Fig. 7 and Fig. 8 depict the result for the cylinder-specific SOM used for Fig. 3 and Fig. 4 after performing a second training phase with new grasp postures. The inter-node distance structure depicted in Fig. 8a is very homogeneous. The second training phase resulted in more nodes that are unsupported by the original training data (cf. Fig. 8b) but better represent the grasp postures generated by the grasping algorithm (cf. Fig. 8c).

By comparing Fig. 4b(left) and Fig. 8b, it becomes clear that after the second training phase a noticeably smaller amount of nodes is used to represent the original training data resulting in a coarser posture resolution in these regions. On the other hand, as in the testing phase a regular position/orientation grid was used covering the main part of the expedient position/orientation space, it is more desirable to represent the resulting test data with a stable resolution (as depicted in Fig. 8c) than the clustered original training data in a very high resolution under-representing the meaningful inter-cluster grasps not covered by it.

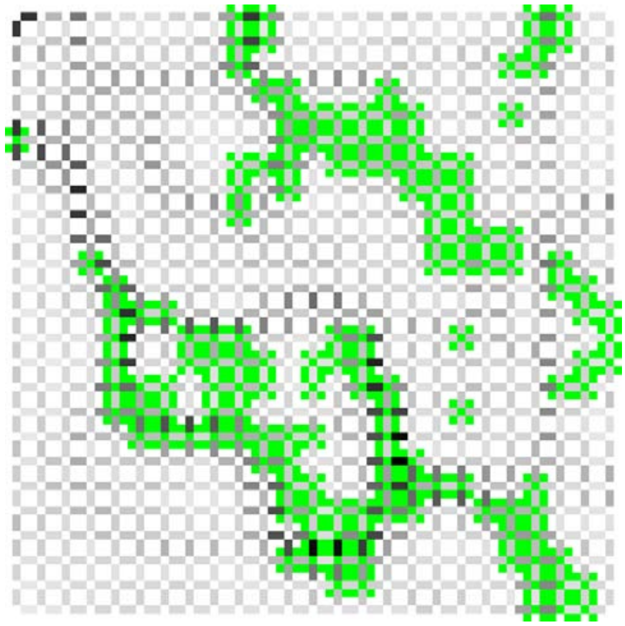

Figure 6: Visualisation of the inter-node distances and the data-projection-nodes of the 25x25 cylinder-SOM. Depicted is Fig. 4a extended by the node matches (green background) when projecting all successful grasp postures from evaluation (force closure grasps characterised by non-zero positive magnitudes of the worst-case disturbance wrench within the L1 grasp wrench space, cf. [3]). The grasp postures match mainly on the inter-cluster nodes.

Figure 7: 10x10 extract of the cylinder-specific 25x25 SOM *Grasp Manifold* used for Fig. 3 and Fig. 4 after resuming the learning with grasp postures generated by the experience-based grasp control. The node structure is now very smooth, the hand postures fade smoothly from one node to the next.

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Figure 8: Visualisations of the inter-node distances and the data-projection-nodes of the 25x25 cylinder-SOM used for Fig. 3 and Fig. 4 after resuming the learning with grasp postures generated by the experience-based grasp control. a) besides one outlier (which was an outlier already before), the inter-node distance structure of the whole SOM is very homogeneous. b) overlaid node matches (green background) when projecting the training data onto the SOM and c) with overlaid node matches (green background) when projecting the new grasp postures generated by the control algorithm.

6 Conclusion

We presented a new approach to dextrous robot grasping that dynamically combines grasping experience with current tactile object information. Searching for the grasp posture which best matches the current *Partial Contact Posture* the algorithm dynamically bridges the gap between general grasping knowledge and actual object perception. As efficient experience representation, we introduced the *Grasp Manifold* being a smooth manifold in hand posture space.

With the Self-Organising Map, we provided one powerful example of a *Grasp Manifold* approximation. By studying the properties of the resulting SOMs, we could fortify our assumption of the existence of smooth grasp manifolds. We have shown that the SOM learning is able to smoothen the clustered training grasp postures to more general grasping contexts which are not covered by the training data. Further on, by resuming the learning phase for the trained SOMs with grasp postures resulting from the application of the described experience-based grasping algorithm, we could homogenise the inter-node distance structure of the SOMs even more and obtained a very smooth SOM approximation of a *Grasp Manifold*.

Future work will address an extension to more objects and more complex object shapes as well as a realisation of the presented grasp strategy with our real *ShadowHand* which does not meet the precision and sensitivity requirements of the presented control algorithm yet. Finally, the performance of continuous manifold representations like the *Unsupervised Kernel Regression* [4][5][6] will be evaluated concerning the effect of the continuity and the ability to represent whole movement trajectories instead of final grasp postures only.

References

[1] C. Borst, M. Fischer, and G. Hirzinger. Calculating hand configurations for precision and pinch grasps. In *Proc. IROS*, 2002.

[2] CM-Labs. Vortex 2.1. www.cm-labs.com/products/vortex, 2005.

[3] R. Haschke, J. J. Steil, I. Steuwer, and H. Ritter. Task-oriented quality measures for dextrous grasping. In *Proc. Conference on Computational Intelligence in Robotics and Automation*. IEEE, 2005.

[4] S. Klanke and H. Ritter. A Leave-K-Out Cross-Validation Scheme for Unsupervised Kernel Regression. In *ICANN 2006*, volume 4132 of *LCNS*. Springer, 2006.

[5] S. Klanke and H. Ritter. Variants of Unsupervised Kernel Regression: General Cost Functions. In *Proc. ESANN*, 2006.

[6] P. Meinicke, S. Klanke, R. Memisevic, and H. Ritter. Principal Surfaces from Unsupervised Kernel Regression. *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 27(9), 2005.

[7] A. Miller, S. Knoop, P. Allen, and H. Christensen. Automatic grasp planning using shape primitives. In *Proc. ICRA*, 2003.

[8] L. Natale and E. Torres-Jara. A sensitive approach to grasping. In *6th Intl. Conf. on Epigenetic Robotics, Paris, France*, 2006.

[9] R. Pelossof, A. Miller, P. Allen, and T. Jebara. An SVM Learning Approach to Robotic Grasping. In *Proc. ICRA*, 2004.

[10] R. Platt, A. Fagg, and R. Grupen. Nullspace Composition of Control Laws for Grasping. In *Proc. IROS*, 2002.

[11] R. Platt, A. Fagg, and R. Grupen. Manipulation Gaits: Sequences of Grasp Control Tasks. In *Proc. ICRA*, 2004.

[12] H. Ritter. Parametrized self-organizing maps. In S. Gielen and B. Kappen, editors, *ICANN 93-Proceedings*. Springer, 1993.

[13] F. Röthling, R. Haschke, J. J. Steil, and H. Ritter. Platform Portable Anthropomorphic Grasping with the Bielefeld 20-DOF Shadow and 9-DOF TUM Hand, 2007. accepted for IROS 2007.

[14] J. F. Steffen. Erfahrungsbasierte Greifstrategie für anthropomorphe Roboterhände. Master's thesis, Bielefeld University, Dec 2005.

[15] J. F. Steffen, R. Haschke, and H. Ritter. Experience-based and Tactile-driven Dynamic Grasp Control, 2007. accepted for IROS 2007.

[16] J. Steil, F. Röthling, R. Haschke, and H. Ritter. Situated robot learning for multi-modal instruction and imitation of grasping. *Robotics and Autonomous Systems*, Special Issue on "Robot Learning by Demonstration"(47), 2004.

[17] The Shadow Robot Company. Shadow Dexterous Hand. www.shadowrobot.com/hand, 2002.

[18] J. Walter. *Rapid Learning in Robotics*. PhD thesis, Faculty of Technology, Bielefeld University, 1996.

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