Kinematic Synergy Primitives for Human-Like Grasp Motion Generation

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***Abstract*— Grasping with five-fingered humanoid hands is a complex control problem. Throughout the entire grasping motion, all finger joints need to be coordinated to achieve a stable grasp. Grasp synergies provide a simplified, low-dimensional representation of grasp postures and motions, that can be used for the description of human grasps as well as the generation of novel, human-like grasps. However, the abstract synergy representation complicates the association of relevant high-level grasp parameters, as for example the grasp type and final posture or the grasp speed. Therefore, it is difficult to control these grasp characteristics in the synergy space. This paper presents an adaptable representation for kinematic grasping motions in synergy space, that allows the generation of novel, human-like grasps under direct control of high-level grasp parameters. It is based on via-point movement primitives trained on synergy trajectories of human grasping motions. The representation using synergy primitives allows for a straightforward adaptation of grasp characteristics while preserving the essential grasping motion learned from human demonstration. The kinematic synergy primitives have a low reproduction error of $3.9\,\%$ of the maximum finger joint angle and are able to generate successful grasps on a simulated human hand and a real prosthetic hand.**

I. Introduction and Problem Statement

The human hand is a versatile and complex system with its joints providing 23 *Degrees of Freedom* (DoF) driven by 38 muscles [1], [2], [3]. Despite the complexity of the everyday control tasks, humans are able to perform such versatile grasping motions easily and without much effort. To transfer this intuitive human grasp control onto humanoid robotic hands is one of the great challenges in robotic grasping.

One step towards this goal is the search for an intuitive, adaptable representation of human-learned grasp strategies for the control of humanoid robotic hands. In this work, we aim for such a generalized, adaptable representation of grasp trajectories. These trajectories describe the kinematic configuration of finger joint angles in the human hand throughout the entire grasping process. It thereby starts with the relaxed open hand and describes the finger motion up to the final, stable grasping posture. This grasp motion representation shall be as simple as possible and shall allow the generation of artificial, human-like grasp motions for the control of humanoid robotic hands. It shall therefore provide meaningful parameters to adapt and influence the generated grasp motions.

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(a) (b) (c)

Fig. 1: Human-like grasps generated by the kinematic synergy primitive representation and executed on a robotic prosthetic hand: (a) extension type grasp on a cracker box, (b) large diameter grasp on a ravioli can and (c) sphere 4 finger grasp on a ball

To this end, we leverage the strategy of postural grasp synergies [4], which describe correlations between different joint angles of the human hand during grasping. Postural synergies project a grasp posture $\boldsymbol{g}$ in a lower dimensional synergy representation $\boldsymbol{s}$. Therefore, we seek a synergy space $\boldsymbol{S}$ with m dimensions to represent the grasp posture vector $\boldsymbol{g}$ with n dimensions under the precondition that $m < n$.

To represent an entire grasp trajectory $\boldsymbol{g}(t)$, a synergy trajectory $\boldsymbol{s}(t)$ needs to be described relative to the time t. With the contribution of this paper we aim to frame the synergy trajectory $\boldsymbol{s}(t)$ in a generalized function $\boldsymbol{f}_g(t)$ that is able to describe any grasp from grasp type g. Further, this generalized grasp representation shall be adaptable with respect to relevant characteristics of the grasping motion. In particular, these include the final grasp posture, the grasp speed as well as the hand posture at the beginning of the grasping motion. In addition, the grasping motion itself shall be adaptable in the range of grasp demonstrations provided by humans. This allows to manipulate the exact shape of a human-like grasp trajectory that is generated from the adaptable grasp synergy representation.

By these means, this work introduces a representation of grasp motions learned from human demonstration that is adaptable to high-level grasp characteristics including the start and grasp pose, the grasp speed and timing as well as the shape of the grasp trajectory. At the same time, it leverages the simplification of grasp control provided by kinematic grasp synergies inspired by human motor control. To this end, we learn a set of novel grasp synergy primitives from a single, general kinematic synergy space, as detailed in Section III. Further, we show strategies to adapt and apply these grasp synergy primitives for the generation and control of human-like grasp motions on humanoid robotic or prosthetic hands, as shown in Figure 1 and explained in Section IV. The presented approach is based on a preliminary analysis on grasp motion primitives presented in our previous work [5]. Our contributions are (i) the generalized representation of grasp synergy primitives that provides a precise control of the grasp trajectory path, (ii) a guidance on how to leverage the grasp synergy primitives to adapt different high-level grasp parameters and (iii) the generation of novel, human-like grasping motions from the synergy primitives that have not been demonstrated by a human.

II. Related Work

The related research in the area of adaptable grasp representations learned from human demonstration concentrates on two main representation strategies. First, we will explain the concept of grasp synergies, which provide a lower-dimensional representation of the complex control space of the human hand. Thereafter, we will discuss movement primitives as a method for the representation of motion trajectories, that can be adapted according to task and motion characteristics.

A. Grasp Synergies

Postural grasp synergies have been originally found in neuroscience [4], [6]. It has been shown that the joint angles of the human hand are correlated in static grasp postures and can thereby be described by few synergy variables. By these means, a high-dimensional grasp posture can be described in a lower-dimensional grasp synergy space. Postural synergies have since been applied for the design [7], [8], [9], [10], [11] and control [12], [13], [14], [15] of numerous robotic hands.

To achieve a static hand posture described by such postural synergies, a suitable finger motion needs to be adopted throughout the grasp acquisition process. Several approaches have been presented in literature to describe this kinematic grasping motion based on trajectories in a static synergy space [16], synergistic eigenmotions [17], [18] or joint-wise function approximation [19]. All these approaches provide low-dimensional representations of finger joint angle trajectories to describe temporal grasping motions. However, the applied dimensionality reduction decreases the intuitiveness of the representation and makes it harder to deduce and control high-level grasp characteristics. Moreover, all listed approaches concentrate on a lower dimensional description of either the finger joint angle configuration or the timing of the grasp. The respective other aspect still needs to be defined manually.

To improve the intuitive representation of high-level grasp characteristics, structured postural synergy spaces have been developed [20], [21], [22]. A non-linear mapping of the joint angles to the synergy parameters allows to shape the latent synergy space according to other high-level grasp characteristics. Nevertheless this structured postural synergy space is designed solely for the representation of static grasp configurations and does not take the finger approach motion into account.

A temporal synergy representation for grasp contact forces provides an encoding of both temporal and force characteristics directly in a non-linear synergy space learned by a neural network [23]. This temporal latent synergy representation is also capable of embedding additional grasp characteristics into the structure of the synergy space during learning. As an alternative, the method of representing grasping motions in a static synergy space has been successfully transferred also to temporal grasp force patterns [23], [24].

B. Movement Primitives

Dynamic Movement Primitives (DMPs) [25], [26] allow for the adaptation of a represented motion trajectory regarding the system's start and end pose as well as the velocity of the motion execution. Due to this flexibility, they are widely used in robot programming by demonstration. The derivative models of *Probabilistic Movement Primitives* (ProMPs) [27] and *Via-Point Movement Primitives* (VMPs) [28] improve the original representation by preserving the variance of human motion demonstrations within the MP representation.

Similar to DMPs, VMPs consist of an elementary trajectory $\boldsymbol{h}(x)$ and a shape modulation $\boldsymbol{f}(x)$. The shape modulation, which enables the adaptability of the resulting motion trajectory, is described by kernel functions $\boldsymbol{\psi}(x)$ weighted based on the weight parameters $\boldsymbol{w}$ with

$$\boldsymbol{f}(x) = \boldsymbol{\psi}(x)^T \boldsymbol{w} \tag{1}$$

The VMP representation is the sum of this shape modulation offset and the real elementary trajectory with

$$\boldsymbol{y}(x) = \boldsymbol{h}(x) + \boldsymbol{f}(x) \tag{2}$$

By the directed adaptation of waypoints in the elementary trajectory $\boldsymbol{h}(x)$ – the via-points – VMPs provide direct control over the path of the trajectory.

Motion primitives, like DMPs, ProMPs and VMPs, are widely used to represent and control arm trajectories during robotic reaching and manipulation motions. To control finger grasp motions, Ben Amor et al. apply a dimensionality reduction to human grasping data to describe grasp movement primitives in a lower-dimensional subspace [29]. However, an individual low-dimensional representation is learned for each grasp type, thereby giving up the universality of the human grasp synergies. From a more general point of view, Bitzer and Vijayakumar have shown that a well-parameterized dimensionality reduction on the original motion data can significantly improve the specificity of task characteristics in the resulting movement primitive representation [30].

III. Synergy Primitives

The generation of kinematic synergy primitives will be explained in the following, starting with the human demonstrations of grasping motions. A universal postural synergy space is learned from human demonstrations. A VMP is trained on several grasp synergy trajectories from the same grasp type and the adaptation capabilities of the resulting kinematic synergy primitive are explained.

A. Grasp Recordings

To learn grasp synergy primitives, we record a dataset of 911 human grasp motions on 30 objects of different shapes and sizes. The twelve male and three female subjects with an average age of $24.7 \pm 3.0\,\mathrm{years}$ performed all 33 grasps included in the GRASP Taxonomy [31]. In addition, a functional grasp to push a trigger or button on a tool while holding it in a cylindrical power grasp is recorded. This grasp type will be called *Trigger Grasp* in the following. Subjects were standing comfortably in front of a table with the object placed before them. At the beginning of each recording, the subject placed both hands flat on the table surface. The grasp type for each recording was predefined and was shown to the subject using a picture with the same grasp type applied to another object. Subjects then grasped the object with their dominant right hand adopting the demonstrated grasp type, lifted it from the table and placed it back down. Finally, the subjects placed their hand back flatly on the table.
Grasping motions were recorded by a sensorized glove measuring 22 joint angles within the human hand (CyberGlove III, CyberGlove Systems Inc., USA). In addition, the glove was equipped with reflective markers, which were recorded by a motion capture system (Vicon, Vicon Motion Systems Ltd., UK). For reference, a video recording of the grasp procedure was acquired in addition. The sensorized glove was calibrated by measuring two reference angles per joint and determining a linear correlation of the sensor value with respect to the joint angle. For the thumb, cross-correlations between the three degrees of freedom (DoF) of the metacarpophalangeal joint have been taken into account. The calibration procedure is described in detail in our previous work [32]. The grasp recordings are publicly available in the Kinematic Grasping Dataset[1] within the KIT Whole Body Human Motion Database [3].

B. Learning Synergy Primitives

The grasp synergy primitives are learned from the human grasp demonstrations in a two-step-procedure. First, synergy trajectories are learned from the finger joint angle motions. Then, VMPs for the different grasp types are trained on those synergy trajectories.

The synergy trajectories are defined in a static synergy space using the method proposed by Romero et al. [16]. The static synergy space is learned by performing a principal component analysis over all joint angle configurations in the Kinematic Grasping Dataset regardless of their timing. The 22 joint angles are projected into six dimensions in synergy space, which represent $85.8\,\%$ of the overall variance. The first synergy predominantly represents the general degree of hand closing, the second synergy allows more specific control of the distal interphalangeal joints and the higher order synergies provide adjustments of finger abduction and the joint posture of individual fingers. Grasp trajectories are

[1] https://motion-database.humanoids.kit.edu/list/motions/?datasets=3534

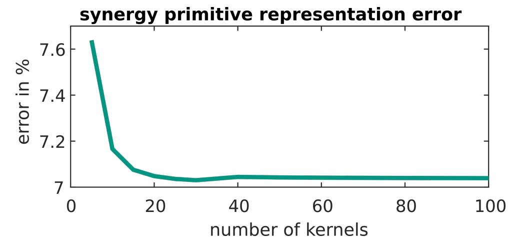


Fig. 2: Representation error of synergy primitives learned with a varying number of weighted kernel functions.

represented by a timed sequence of static synergy configurations, thereby describing a trajectory in synergy space.

Subsequently, one VMP per grasp type is learned. To this end, all synergy trajectories of the same grasp type are used to train a single VMP for that particular grasp type. Since the grasp type defines the coordination of the fingers throughout the grasping motion, the corresponding trajectories represent a single grasp strategy. Hence, each weight of the VMP can be encoded by a single Gaussian distribution. The number of weighted kernel functions required to represent the synergy primitives has been evaluated based on the reproduction error on learned demonstrations. As shown in Figure 2 a significant impact in correct motion representation is achieved by 20 weighted kernels. Increasing the number of weights beyond that does have a very small impact on the representation accuracy of the primitive representation. Therefore, the synergy primitives are learned by a VMP with 20 weighted kernel functions.

C. Grasp Parameterization

The learned synergy primitive can be executed on a humanoid robotic or prosthetic hand to control a grasping motion of the primitive's grasp type. The adaptability of the VMP allows to parameterize the grasping motion according to the specific object and situation while preserving the human-learned grasp strategy. To this end, the inherent adaptation capabilities can be leveraged to customize the different characteristics of the primitive grasping motion.

Start: By adapting the start of the synergy primitive, the initial position of the hand can be influenced. Most often, the start pose will be the open hand. This is also the case in the human demonstrations the synergy primitives have been trained on. However, the starting pose could also be set to a slightly curved, relaxed resting pose. If the grasp shall be executed within a longer series of manipulation actions, the starting pose can be defined to match the hand pose after the execution of the preceding manipulation step.

Goal: The goal of the synergy primitive describes the final, static grasp posture. Thereby, goal adaptation has to be applied to adjust the grasp to the object. To define a suitable goal pose, any grasp planner can be applied, ranging from standardized analytical grasp planners [33], [34] to human-like synergy grasp generators [21], [22]. Alternatively, a more reactive grasp planning and control inspired by the concept of soft synergies can be applied [13]. For this option, the goal posture is chosen as the maximally closed human hand posture observed for this grasp type. Then the grasp execution is performed in an adaptive manner, either by reactive, sensor-based control or a mechanically adaptive hand actuation.

Temporal scaling: The temporal scaling factor τ of the synergy primitive describes the execution speed of the grasping motion. A factor of $\tau = 1$ causes an execution at the exact speed learned from human demonstration, while $\tau < 1$ results in a slower execution and $\tau > 1$ speeds up the grasping motion. This grasp speed can be defined directly. Instead, the temporal scaling can also be derived from measurements of the task progress. Especially in assistive and rehabilitation robotics, the temporal scaling can be directly controlled by user input to allow the user to retain control of the task execution.

Via-points: By explicitly setting via-points, it can be ensured that the grasping trajectory passes a specific hand posture at a specific time during the grasping process. Apart from the direct enforcement of postural adaptations in the grasping motion, this concept can be leveraged to shape the general motion characteristics in several ways. First of all, via-points allow to naturally adapt the grasping motion to different starting conditions. When the fingers are partially flexed at the beginning of the grasping motion, humans enlarge their hand aperture within the first $60\,\%$ to $70\,\%$ of the reaching phase, before closing the hand again [35], [36]. This behavior is not present in the human grasp recordings our synergy primitives are trained on, because these start with the hand fully opened. Nevertheless, such behavior can be provoked by setting a via-point representing a more open hand position with respect to the starting posture. This will cause the hand to open first throughout the grasping motion before closing around the object.

On a synergy level, a via-point can be used to structure and alter the amount of motion done before and after the via-point. Thereby, the timed coordination of synergies can be changed by speeding up the motion caused by one synergy and delaying the motion caused by another synergy. The same can also be achieved on a kinematic level, if the desired intermediate hand posture is transferred into the synergy space. To give a practical example, an intermediate hand posture can be set by a via-point to define whether the thumb or the fingers close inside for a small diameter power grasp.

Finally, via-points may even be used for regrasping between two different variants of the same grasp type. This can be achieved by varying the characteristics of the grasp posture between the goal and an additional via-point. Thereby, the synergy primitive is forced to primarily aim at the via-point posture, but alter it again later in the grasping process to reach the final goal posture. For example, such regrasping within the same grasp type can be used to rotate a small object in a pinch grasp or to adapt a cylindrical grasp from an initial configuration that allows to pick an object from a surface to a more stable configuration for following manipulation actions. However, since each synergy primitive is trained on a specific grasp type, grasp variations can only be enforced within the same grasp type to ensure the resulting grasping motion is sensible and human-like.

All of these adaptation capabilities are not available in the classical synergy representation, where trajectories would need to be altered by hand. However, manually changing trajectories does not ensure the human likeness of the resulting motion, which is guaranteed with the synergy primitives.

IV. Evaluation

The kinematic synergy primitives are evaluated to assess their validity and merit for the representation and control of human-inspired grasping motions for robotic hands. To assess the general validity of synergy primitives, the reproduction error of human grasping motions represented by synergy primitives is evaluated. Further, the capability of synergy primitives for robotic grasp generation is assessed by evaluating the grasp success in simulation and on a physical robotic hand.

A. Representation Quality

The representation quality of demonstrated human grasping motions is measured by calculating the *Mean Squared Error* (MSE) between the original grasp trajectory and the trajectory represented by the corresponding synergy primitive. The MSE measures both spatial and temporal similarity, since the human and generated trajectory are compared at each timestep without considering any time shifting. The synergy primitive is parameterized according to the demonstrated grasping motion. If only the start and goal pose of the hand is adapted, the primitive causes a representation error of $7.0\,\%$, as shown in Figure 2. However, this error can be reduced significantly by adapting the general primitive to the specific characteristics of the grasp trajectory with via-points. By setting three via-points after one, two and three quarters of the trajectory progress, a reproduction error of $3.9\,\%$ can be achieved. The PCA-based synergy representation has a reproduction error of $3.9\,\%$. The combined reproduction error caused by both PCA and VMP representation in sequence amounts to $5.9\,\%$ under the same conditions. This error is smaller than the sum of the individual errors, because the inaccuracies of both methods are not necessarily accumulated, but may also compensate each other. An overview of the reproduction error for different grasp types is presented in Figure 3.

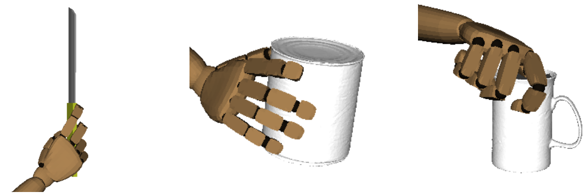
The largest errors can be seen in frequent grasps, e. g. *Medium Wrap* and *Small Diameter*. Due to the larger amount of human demonstrations, these grasps have larger variations in the demonstrated data, which need to be represented by the synergy primitive. For the same reason the *Lateral* grasp shows a higher error. In this grasp only the thumb and index finger postures are functionally relevant and therefore the joint angles of the other three fingers have a high variance. On the other hand the *Palmar Pinch*, *Power Disk*, *Prismatic 2 Finger* and *Ring* are easy to replicate using a primitive motion and exhibit a lower primitive error.

B. Grasp Quality on a Simulated Humanoid Hand

The grasp quality of motions generated from the kinematic synergy primitives is assessed on a simulated humanoid hand. In order to eliminate any influence of mapping errors, we apply the generated grasps on the simulated human hand model of the Master Motor Map [3].

For each grasp type, novel, human-like grasp trajectories are generated from the respective kinematic synergy primitive. The grasp trajectories are adapted based on the variance observed in the human grasp demonstrations for the same grasp type and object. In total, 728 grasps have been evaluated.

The grasp quality is evaluated on the static, final grasp achieved by the generated grasp trajectory. The arm motion and hence the position and orientation of the hand with respect to the object is taken directly from a human demonstration of a grasp from the same grasp type on the same object. All grasps are executed in the kinematic grasp simulator Simox [34]. To ensure that contact is made between the fingers of the hand and the object surface, an approach inspired by the soft synergy model [13] is applied. Once the hand has reached a grasp aperture corresponding to $90\,\%$ of the final finger closing angle, the finger motion is controlled taking into account both the trajectory generated from the kinematic synergy primitives as well as the object surface. By these means it can be ensured that the fingers involved in the grasp are in contact with the object surface.



(a) (b) (c)

Fig. 5: Simulated grasps on a human hand model generated from the kinematic synergy primitives: (a) index finger extension grasp, (b) large diameter grasp and (c) palmar pinch

The quality of the grasps is measured by the ε-metric [37]. Over all grasps, it results in a quality of $\epsilon = 0.13$. Because the ε-metric encourages grasps with a higher number of grasp contact points, it is naturally higher for power grasps than for precision grasps. Due to this characteristic, the grasp quality increases to $\epsilon = 0.18$ when considering only power grasps. The ε grasp quality for the grasps of all different grasp types can be seen in Figure 4. Some exemplary grasps are shown in Figure 5. While the two power grasps in Figures (a) and (b) yield a high grasp quality of $\epsilon = 0.38$ and $\epsilon = 0.25$ respectively, the precision grasp in Figure (c) yields a grasp quality of $\epsilon < 0.01$, but nevertheless provides a qualitatively acceptable result.

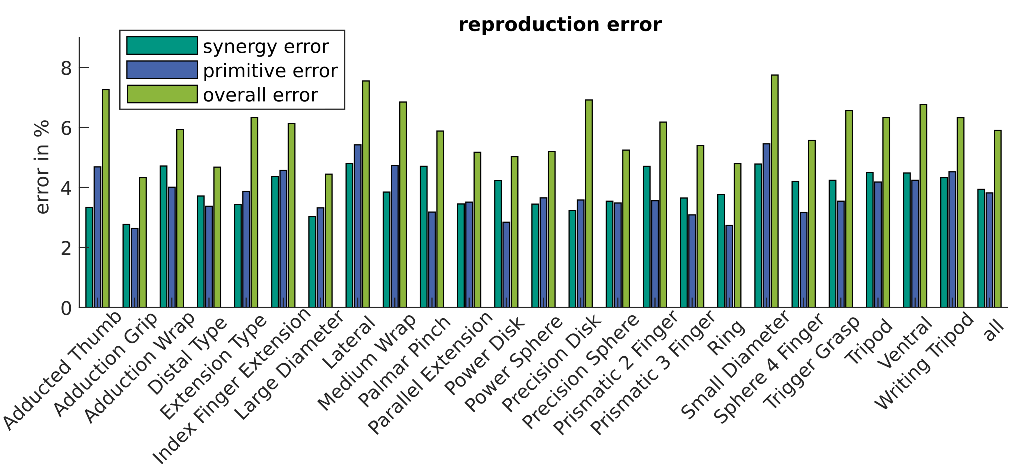


Fig. 3: Reproduction error for different grasp types caused by the synergy representation, the primitive representation and the overall error of the synergy primitives

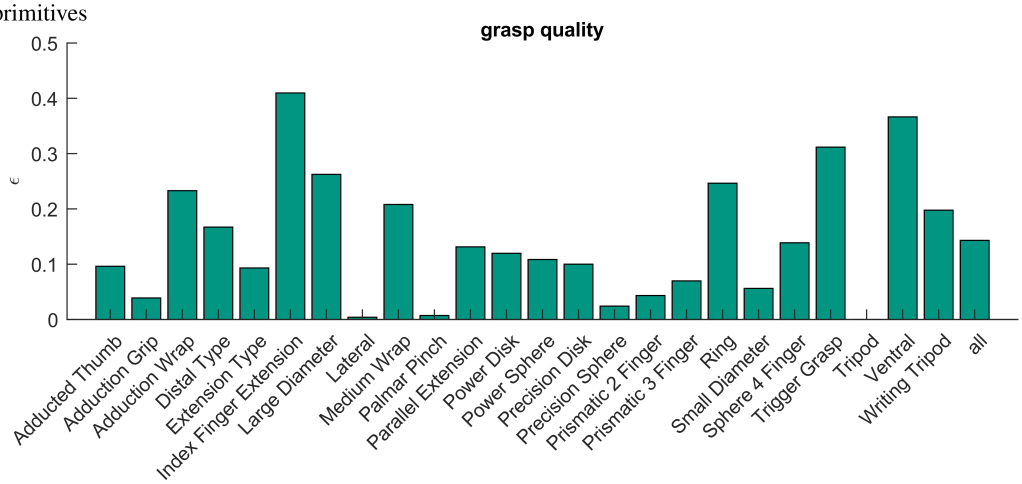


Fig. 4: ε grasp quality of grasps generated from the kinematic synergy primitives and simulated on a human hand model for the different grasp types

C. Grasp Quality on a Robotic Hand

Further, we evaluate the quality of generated grasp trajectories on the female KIT Prosthetic Hand [11]. This robotic prosthetic hand provides an actuated thumb flexion as well as the underactuated closing of all four long fingers. The adaptivity of the underactuation mechanism driving the fingers allows for different power grasps depending on the interaction between the hand and the object. Grasps generated from all power grasp primitives are executed on the prosthetic hand. Overall, 63 grasps from eight different grasp types are executed on 14 objects. The grasp synergy primitives are adapted according to the object size. For each grasp a grasp trajectory is generated using the respective synergy primitive for that grasp type. The 22-dimensional trajectory of joint angles is then mapped to the two DoF of the robotic prosthesis by a kinematic mapping. The prosthesis thumb trajectory is calculated from the motion of the three thumb flexion joints. The prosthesis finger trajectory is calculated based on the flexion joint trajectories of all four long fingers. For both finger and thumb trajectory the mean over all considered joint angles is calculated and mapped to the motor position corresponding to the same joint angle in the prosthetic hand. The grasp trajectory is then executed on the robotic prosthesis using a feedforward control.

For the grasping evaluation the prosthesis is mounted on a shaft and worn on the arm of the experimenter below their own hand. The grasp motion is triggered externally. The objects are placed on a table. Each grasp trajectory is executed three times to grasp the corresponding object. The objects are lifted, held for three seconds, turned by $90°$ and held for another three seconds, before placing them back onto the table. For grasping up to two points are given for a successful and correct grasp, if the object moves within the hand or the grasp type is significantly different, only one point is scored. After rotation another two points are given for firmly holding the object. If the object moves within the hand after rotation, only one point is scored.

Overall 237 out of the achievable 252 points are obtained. This corresponds to a grasp success of $94.0\,\%$. Figure 6 shows a detailed overview of the grasp success achieved with grasps of different grasp types on the robotic prosthetic hand. Most grasps were performed stably in all trials. Some exemplary grasps are shown in Figure 1. Major problems occurred only when grasping the small mixing bowl, because the bowl was too wide to be grasped from atop in a *disk grasp* with the 50^{th} percentile female-sized prosthesis. Further, the golf ball slipped out of the hand in one occasion in the *sphere 4 finger grasp* and object motion within the hand occurred for the small clamp in the *small diameter grasp* and the cracker box in the *parallel extension grasp*.

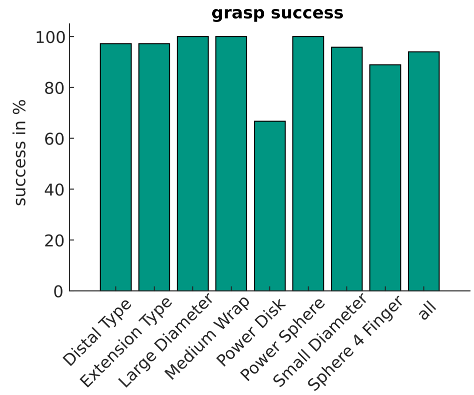


Fig. 6: Grasp success rate for different power grasps generated by the kinematic synergy primitives on a robotic prosthetic hand

V. Conclusion

This paper introduces a novel method to describe human grasping motions in a general and adaptable way and allows to generate new human-like grasping motions for the control of humanoid robotic hands that have not been directly demonstrated by a human. Using a static postural synergy space, that is learned from human demonstration, grasping motions can be described as simplified, low-dimensional trajectories. The selection and adaptation of these grasp motion trajectories is performed by applying a motion primitive representation.

For each grasp type, a single VMP is learned from a range of varying human grasp demonstrations. The VMP thereby provides a generalized description of the trajectory and variance of the grasping motion. In addition, its adaptation capabilities allow to accurately control high-level grasp characteristics. The start and final grasp postures can be modified directly in the VMP representation. By these means, a grasp can also be adapted to different objects that vary e. g. in size or overall shape. Grasp speed and timing can be controlled via the canonical value of the VMP representation. Finally, the trajectory path can be influenced by using via-points. This may be used to adapt the grasping motion within the variance of the human demonstrations, but also to achieve intermediate grasp poses for regrasping or object manipulation.

The presented kinematic synergy primitives exhibit good representation capabilities for grasp motions demonstrated by humans. A representation error of less than $6\,\%$ can be achieved. In addition, novel, human-like grasping motions can be generated from the kinematic synergy primitives. These achieve suitable grasp configurations with an average grasp quality of $\epsilon = 0.13$ in simulation. On a real prosthetic hand, generated grasps achieve a grasp success rate of $94\,\%$.

In future work, we would like to extend the application of via-point trajectory control to more complex manipulation tasks that consist of a series of simple grasp postures. Further, we also plan to leverage the adaptation capabilities of the kinematic synergy primitives to personalize grasping motions in the interaction with humans. We believe that the presented kinematic synergy primitives provide a powerful tool for the generalized representation, adaptation and control of human-like grasping motions for humanoid robotic hands.

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