On Force Synergies in Human Grasping Behavior

Julia Starke[1], Konstantinos Chatzilygeroudis[2], Aude Billard[2] and Tamim Asfour[1]

***Abstract*— The human hand is a versatile and complex system with dexterous manipulation capabilities. For the transfer of human grasping capabilities to humanoid robotic and prosthetic hands, an understanding of the dynamic characteristics of grasp motions is fundamental. Although the analysis of grasp synergies, especially for kinematic hand postures, is a very active field of research, the description and transfer of grasp forces is still a challenging task. In this work, we introduce a novel representation of grasp synergies in the force space, so-called force synergies, which describe forces applied at contact locations in a low dimensional space and are inspired by the correlations between grasp forces in fingers and palm. To evaluate this novel representation, we conduct a human grasping study with eight subjects performing handover and tool use tasks on 14 objects with varying content and weight using 16 different grasp types. We capture contact forces at 18 locations within the hand together with the joint angle values of a data glove with 22 degrees of freedom. We identify correlations between contact forces and derive force synergies using dimensionality reduction techniques, which allow to represent grasp forces applied during grasping with only eight parameters.**

I. Introduction and Related Work

Throughout the recent decades, humanoid robots have undergone great progress especially in the area of grasping and manipulation. This is fundamentally supported by the development of novel, anthropomorphic hands allowing complex and versatile movements [1]. While a full actuation of all degrees of freedom allows a wide range of manipulation capabilities, it also provokes a high control complexity necessitating extensive knowledge about the configuration of the grasp to acquire. It requires an encompassing grasp planning and grasp synthesis for successful grasping.

By transferring human grasp characteristics, robotic grasp planning can profit from human intuition to increase grasp stability and human-like appearance. This can be done by mapping reference points among the demonstrating human hands [2] or the transfer of grasp type and thumb contact position [3], [4] among other methods. Especially the latter approach demonstrated the high importance of the thumb for grasp stability and appearance.

Analysis of human grasping behavior has however revealed that natural grasps are performed on a notably lower subspace of kinematically feasible grasp configurations. Correlations between the finger joints of the human hand were first observed by Santello et al. [5]. These grasp synergies arise from the mechanical coupling of individual degrees of freedom, but also include motion patterns tailored to the needs of stable grasping. An overview of synergy representations in the context of grasping can be found in [6].

These synergies allow to significantly reduce the complexity either of the control or the controlled hand mechanics. The controller can be simplified based on a low-dimensional grasp representation. By experimentally or mathematically defining synergies for robotic hands, human grasps can be easily transferred onto their individual kinematics [7], [8]. Conversely, the synergies can also be directly implemented in the hand's mechanics using underactuated mechanisms [9], [10], [11]. Besides reducing control complexity, synergies allow the development of anthropomorphic hands with a small number of actuators. By these means, significant reductions in weight and space requirements become possible, which

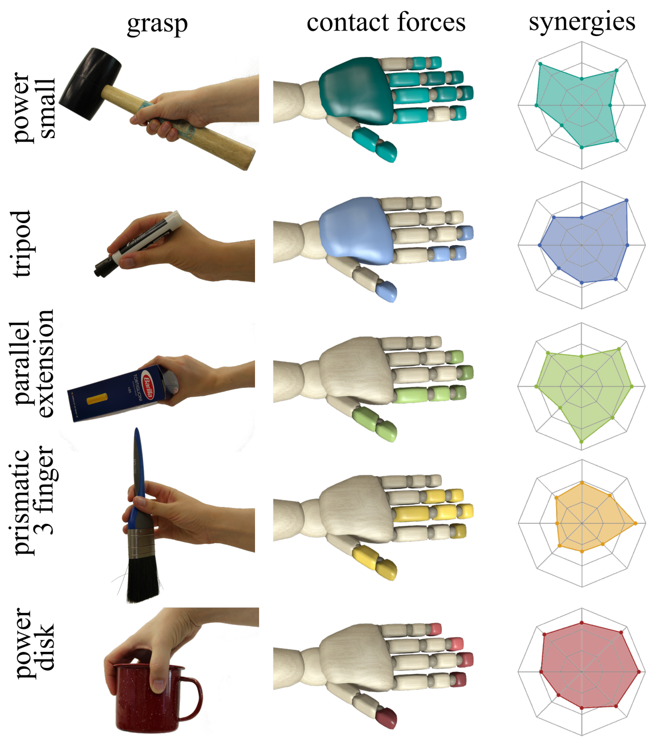

Fig. 1: During different types of human grasps (left), the location and amount of contact forces (center) exhibit coupled behavior allowing to represent them as force synergies (right); the activation of these synergies differs between grasp types, but also between individual grasps

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[1]Julia Starke and Tamim Asfour are with the Institute for Anthropomatics and Robotics, Karlsruhe Institute of Technology, Karlsruhe, Germany, {julia.starke, asfour}@kit.edu

[2]Konstantinos Chatzilygeroudis and Aude Billard are with the Learning Algorithms and Systems Laboratory, Ecole Polytechnique Federale de Lausanne (EPFL), Switzerland

are especially important in modular, lightweight robotics and prosthetics.

While there are comprehensive studies on finger joint configurations for both static observations [5], [12] and entire grasping motions [13], [14], little is known about the role of contact forces in synergy-based grasp descriptions. Santello and Soechting proved that such synergies generally exist by observing normal forces at the fingertips in power grasps [15], [16]. They showed a linear covariance in the forces of all fingertips over time by varying finger contacts and applied forces in dedicated tasks. The work concentrates on cylindrical power grasps on a dedicated measurement device. It proves an influence of the grasp posture on the contact force pattern, which we are investigating further in this paper.

Based on the consideration of oppositional force configurations in palm and fingers a recognition of grasp intention from human grasp postures and forces was proposed in [17], [18]. While distinguishing 41 different opposition types, a configuration of overlaid types can be derived from the interaction forces between hand and object. As different opposition types are applied to reach task specific goals, the grasp intention can be recognized by a considering the opposition configurations. An analysis of correlations between grasp forces was also presented in [19].

Moreover, the estimation of grasp forces was also considered in relation to the concept of soft synergies by Bicchi et al. [20]. Soft synergies are proposed to apply kinematic synergies on physical hands. They close the gap between the low-dimensional overall grasp control and the fine-granular adjustments necessary to firmly enclose the object with all fingers. As this is implemented by two counteracting force fields, the method of soft synergies also allows to estimate grasp forces by including a model of the mechanical compliance of the hand, see [21], [22]. The mechanical implementation of these concepts in robotic hands is defined by the model of adaptive synergies [23]. Especially in human hands having a deliberately variable compliance, the specific consideration of grasp forces is important for grasp stability. By varying the compliance of the human hand, several sets of force synergies can be applied to a grasp retaining the same grasp pose and postural synergy representation. Thereby the grasp stability and overall force applied on the object can be deliberately influenced by the human. Such an encompassing direct observation of grasp forces and their coherence regarding different grasp characteristics is still missing.

In this paper, we analyze human grasp contact forces, as shown in Fig. 1, for a wide range of grasping conditions. We perform a comprehensive study of force patterns taking into account different grasp types and object shapes. In addition, we consider varying object weights by considering different contents and filling levels for container objects. In comparison to kinematic hand postures we strive to find a universal description of force synergies. Moreover we present novel combined postural force synergies to mutually express all relevant characteristics of grasping. We examine our results with respect to the interdependence of grasp forces, the derived synergy representation and a derivation of grasp types from those contact forces.

II. Human Grasp Study

To get a comprehensive overview of the characteristics of human grasping actions, we perform a large study of grasp motions involving eight subjects executing 466 grasps on 14 objects. The demonstrations are performed by one female and seven male right-handed subjects. In the following we describe the technical sensor setup and the procedure of data acquisition.

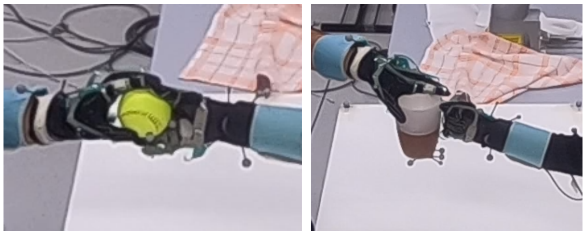
A. Data Acquisition

Throughout the grasp procedure, subjects wear a sensorized data glove (CyberGlove III, CyberGlove Systems LLC, USA) to measure 22 joint angles of the human hand. Although all subjects describe themselves as right-handed, half of them wear the CyberGlove on their left hand. This setup is chosen to perform handover motions involving grasping with the dominant and non-dominant hand. However, according to our experience and previous analysis in literature [16], handedness of the subjects has no significant influence on the characteristics of grasping tasks.

The gloves are calibrated applying a procedure derived from the scheme proposed in [24]. Wooden reference angles are pressed sequentially against the individual joints and a linear interpolation is provided for each sensor value. The procedure is enlarged for the thumb circumvention, adduction and flexion in the metacarpophalangeal joint to capture the strong interference between the superimposed sensors performing these joint measurements. For each pair of sensors, the interaction is modeled by a linear interpolation, allowing the elimination of influences of one motion on the sensor readings of the other ones.

Grasp forces are measured by a Grip System (Tekscan Inc., USA) including 18 resistive pressure sensors attached to the palmar side of the data glove. This allows a high spatial resolution of contact force measurements including two sensors on the thumb, three on each finger and four within the palm.

In addition, the poses of the object and the subjects' wrist, elbow and shoulder are recorded with an optical motion capture system (Optitrack, NaturalPoint Inc., USA). As this system captures the 6D pose of the wrist, the wrist pronation/supination and flexion/extension of the CyberGlove are not used within this study. Furthermore, the entire grasping process is recorded by three static cameras within the room and two first-person perspective cameras mounted on the head of the subjects. All subjects wearing the left glove are additionally equipped with an eye tracker. The study setup is shown in Figure 2. In this work we only use the grasp forces from the Grip System and the hand pose from the CyberGlove. We focus on static grasping force at the point the object is stably held within the hand. To extract this position from the recorded continuous motion, the instance of maximum overall grasp force is considered. All individual



(a) (b)

Fig. 2: Setup of the human grasp study: two subjects hand over different objects like a softball (a) or a pitcher (b) with different filling level, the hands are sensorized with a tactile sensor array measuring contact forces at 18 locations within the hand

contact forces are extracted at this point and are normalized over the size of the measured surface.

B. Performed Grasp Procedure

To record a natural and balanced set of grasps and to avoid unnatural behavior due to the artificial situation, we record the grasps in a task-based setting. Subjects are recorded in pairs performing grasp motions for handover and tool use tasks. Both subjects are standing comfortably on opposite sides of a table with the object placed in between them.

The person wearing the measurement devices on their right hand, *presenter* hereinafter, grasps the object from the table and hands it over to the second subject, the *receiver*. After taking the object with the left hand, the receiver puts it down on the table between the subjects again. Both subjects are asked to grasp as they would naturally yet making sure to vary the way they grasp the object across trials. No restrictions are made to the strategy chosen for each individual grasp.

To understand the influence of the object's weight especially on the grasp forces applied, several boxes, cups and glasses are filled with liquid or granulate material up to varying filling levels. By these means, the same object shape is captured with different overall weights. For tools two distinct recordings are done. First the presenter is asked to pass the object over to be used by the receiver. In a second trial the presenter shall use the object before passing it over to the receiver. On each object configuration six to 14 grasps are recorded by the same pair of subjects.

In total 14 objects from household and workshop environment are recorded. The set is selected from the YCB Object Set [25] and the KIT Object Database [26] enlarged by additional drinking vessels and food packagings of different weights and shapes. A complete list of object properties can be found in Table I.

As subjects are asked to perform different grasps feeling natural to them without any further restrictions, a wide variety of grasp postures is recorded on the same object. All grasps are assigned to an appropriate grasp type manually according to the GRASP taxonomy [27]. The majority of grasps is performed with the thumb abducted in the categories *palm power* including *power small diameter* and *power disk* grasps as well as *precision pad* including *palmar pinch*, *tripod* and *prismatic 3 finger* grasps. Yet also less frequent grasps like the *adduction grip* or the *fixed hook* are observed. The number of recorded grasps within each category is shown in Fig. 3. In the following we will concentrate on the depicted nine most frequent grasp types. The label others subsumes seven additional grasp types, namely *adduction grip*, *middle palmar pinch*, *tripod variation*, *power sphere*, *power large diameter*, *little palmar pinch* and *fixed hook*. Those grasps are recorded in less than ten samples each. The frequency of the adopted grasp postures matches with previous studies described in [28] and [29] with small variations due to the different selection of objects.

TABLE I: PROPERTIES OF THE GRASPED OBJECTS

Object	Configurations	Weight	Object Set
Bowl	E / F	163 g / 297 g	YCB
Brush	HO / TU	75 g	KIT
Champagne Glass	E / HF / F	31 g / 71 g / 138 g	
Clear Plastic Cup	E / HF / F	18 g / 82 g / 142 g	KIT
Hammer	HO / TU	796 g	KIT
Mug	E / HF / F	107 g / 278 g / 423 g	YCB
Pasta Box	E / HF / F	46 g / 324 g / 497 g	
Pen	HO / TU	16 g	YCB
Pitcher	E / HF	125 g / 715 g	KIT
Plate	E	87 g	KIT
Red Plastic Cup	E / HF / F	27 g / 225 g / 389 g	
Screwdriver	HO / TU	159 g	KIT
Softball	HO	138 g	YCB
Wineglass	E / HF / F	151 g / 207 g / 277 g	

E: empty   HF: half full   F: full
HO: hand over   TU: tool use

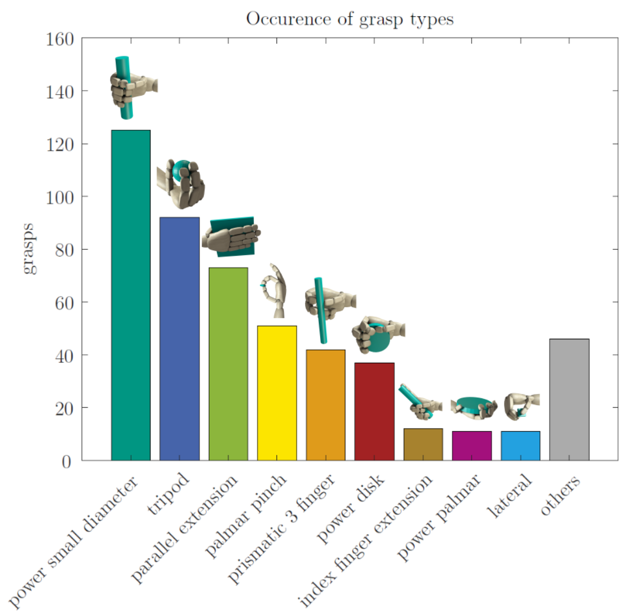


Fig. 3: Occurrence of grasp types within the human handover study; palm power and precision pad grasps are predominant, while a wide range of 16 grasps is incorporated in the study; the category others contains seven grasps with less than ten demonstrations each.

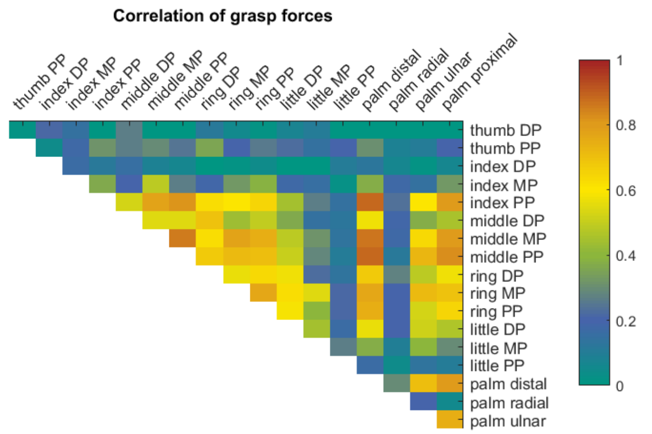


Fig. 4: Patterns of linear correlation between contact forces at the individual locations; a high dependency is mainly notable within the middle and ring finger forces and for the fingers and the palm.

III. Force Correlation Analysis

To understand the occurrence of different contact locations and contact forces, we analyse correlations between the grasp forces obtained from the measurements. We compare the forces taking into account the grasp type they are associated with. In addition, we study the force trend for different object weights.

A. Force Location Context

The overall dependencies between contact forces are considered by having a closer look on their mutual context. The existence of force synergies is to be expected from former research [15]. Nevertheless the similarities in force behavior and the consideration of correlations between the contact locations spread over the palmar side of the hand are a necessary precondition for the extraction of synergies.

A thorough analysis of forces over the different contact locations reveals significant correlation between the middle and ring finger as well as the distal, proximal and ulnar palm. We analyze the correlation between two contact forces $\overrightarrow{x}$ and $\overrightarrow{y}$ using the *sample Pearson correlation coefficient* r_{xy}:

$$r_{xy} = \frac{\sum_i (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_i (x_i - \overline{x})^2}\sqrt{\sum_i (y_i - \overline{y})^2}} \tag{1}$$

The full correlation matrix is shown in Fig. 4 with the finger contacts denoted at the proximal (PP), medial (MP) and distal phalanges (DP). A particularly strong correlation is notable between the index and middle finger proximal phalanges and the distal part of the palm. These positions exhibit a *Pearson correlation coefficient* r of 0.84 and 0.86 respectively. But also within middle finger contacts an r above 0.83 is observed. The thumb however, acts mostly individually and exposes no notable correlation with the finger and palm contact locations. The highest correlation of the thumb with an r of 0.40 is observed with the tip of the middle finger.

The low correlation results for the thumb and the index finger reflect their highly task-specific operation. As noted in previous work [4], the thumb placement plays a central role for grasp stability. In all grasps with the thumb abducted, it has to oppose all other fingers involved, causing it to react as a counterpart to the sum of all finger forces. Consequentially, a correlation to individual finger forces is not visible due to the changing number of fingers involved in different grasps. In this work we did only consider the correlations between the 18 contact forces individually, but did not analyze overall finger forces. However, a high correlation of thumb and opposing fingers would be expected in such an analysis. The index finger is similarly involved in $92.7\,\%$ of all grasps and forces especially at the fingertip are subject to change depending on the number of supporting fingers. In addition, index finger forces are highly task specific as the index is guiding object manipulation necessary in the tool use recordings.

B. Force Synergies

Similar to the basic postural synergy analysis described in [5], a *principal component analysis (PCA)* is performed on the hand contact forces. In contrast to the kinematic hand configuration, the grasp forces exhibit a higher diversity and require a more complex representation. However, force synergies do exist and allow to reduce the 18 contact forces considered to eight synergy parameters while accounting for $91.9\,\%$ of the overall information transmitted. The total variance accounted for depending on the number of synergies is shown in Fig. 5 a). The arrangement of the recorded grasps within the space of the first eight synergies calculated from grasp forces is depicted using a *t-Distributed Stochastic Neighbour Embedding (TSNE)* in Fig. 5 b). This method describes the eight-dimensional data of the force synergies in two-dimensional space by optimizing the Kullback-Leibler-Divergence of the similarities of data points within the two-dimensional output Q from input similarities P. The optimization loss is therefore described by

$$\mathcal{L} = \sum_{i \neq j} p_{i,j} \cdot log\left(\frac{p_{i,j}}{q_{i,j}}\right) \tag{2}$$

Fig. 6 shows an overview of the mean position of the most frequent grasp types in those first eight synergies. Similar to the postural synergies, natural human grasps are arranged in an oriented shape within this eight-dimensional subspace. In both postural and force synergies there is no clear distinction between the grasp types. However, for force synergies there is a slight tendency for separation of power and precision grasps identifiable. A notable distinction between the most frequent grasp types is only visible in synergies one and four. Other than in the postural synergies, which show a higher selective functionality in the overall less informative, higher order synergies, some differentiation of the palmar pinch and power disk grasp can be seen in the first force synergy.

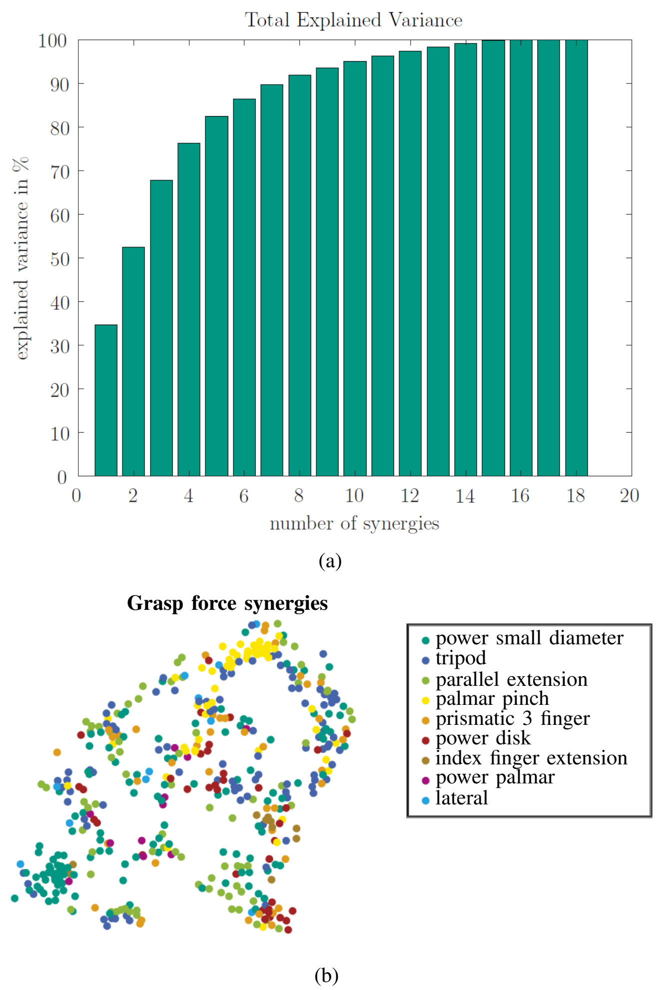


Fig. 5: The first eight principal components of grasp interaction forces account for 91.9 % of the variance (a); they are visualized in two dimensions calculated by TSNE (b); similar to the postural equivalent, a separation of grasp types is not inherently performed, however a slight separation between power grasps in the lower left corner and precision grasps in the upper right corner is notable.

C. *Influence of Object Weight*

As the object weight force has to be counteracted by the grasp to successfully lift it from the table, a dependency of the overall grasp force on the object's weight is to be expected. This is clearly confirmed by the present grasp study. The average force exerted by one grasp contact ranges from 0.71 N for a pen with 16 g to 14.66 N for a hammer with 796 g. The grasp force applied on average increases linearly with the weight by a factor of 0.016. This factor is calculated by performing a linear interpolation of the mean contact force averaged over all measured contact locations based on the object weight.

However, the maximum exerted grasp force shows a quadratic dependency with the maximum contact force for the same hammer being 48.80 N in the palm within the process of hammering. The increasing variance for heavier objects is mainly visible when comparing different grasp types. Thereby it can be assumed that the forces necessary

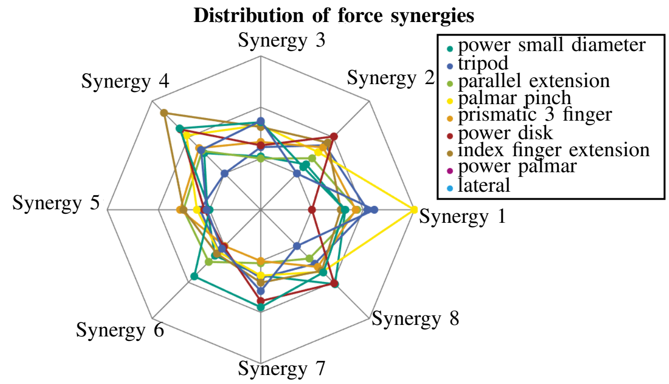


Fig. 6: Mean representation of grasp types in the first eight synergies; a differentiation of grasp types is mainly notable in the first and fourth synergy.

for grasp stability and the trust in the grasp are strongly depending on the way of grasping and the task to be performed. The heavier the object, the stronger the grasp depends on an adequate amount of grasping force, making the subjects vary their finger force significantly according to the dynamic characteristics of the chosen grasp type.

IV. Grasp Classification and Force Definition

Understanding forces in human grasping is a crucial for the natural, efficient grasping in anthropomorphic humanoid and prosthetic hands. To transfer the synergies observed from humans, this section provides further insights on grasp force patterns and a derived classification of grasp types.

A. *Grasp Force Patterns*

To evaluate the capability to distinguish individual grasp types by their force patterns, the activation of each force sensor with a threshold of 1 N is considered. As shown in Table II, all grasp types except for *parallel extension* and *prismatic 3 finger* have distinguishable force activation patterns. The similarity in the two mentioned grasp types is based on their affinity in task application. Both are used for simple grasping and lifting tasks. Therefore there is a fluent passage between both types, which is hardly separable in segmentation. Very broad force activation in at least 50 % of the force sensors is notable in power grasps like *power small diameter* or *power palmar*.

On the other hand precision grasps show a very limited number of contact locations applying forces to the object. *Palmar pinch grasps* with the index finger and thumb have only two contact points at the tips of those fingers.

Similar to the *sensorimotor efficiency index* for hand postures [5], we calculate the percentage of all possible information that is transmitted by contact forces. This index provides a quantitative measurement of the discriminability of grasp types based on their contact forces as qualitatively analysed with the force patterns. With a mean of 93.9 % it clearly indicates the feasibility to distinguish different grasps.

TABLE II: CONTACT LOCATION PATTERNS OF THE DIFFERENT GRASP TYPES

	thumb DP	thumb PP	index DP	index MP	index PP	middle DP	middle MP	middle PP	ring DP	ring MP	ring PP	little DP	little MP	little PP	palm distal	palm radial	palm ulnar	palm proximal
power small diameter	●	○	●	●	●	●	●	○	●	●	●	●	○	○	○	○	○	○
tripod	●	○	●	●	○	●	○	○	○	○	○	○	○	○	○	○	○	○
parallel extension	●	○	●	●	○	●	○	○	●	○	○	○	○	○	○	○	○	○
palmar pinch	●	○	●	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
prismatic 3 finger	●	○	●	●	○	●	○	○	●	○	○	○	○	○	○	○	○	○
power disk	●	○	●	○	○	●	○	○	●	○	○	○	○	○	○	○	○	○
index finger extension	●	○	○	○	○	●	●	○	●	○	●	○	○	○	○	○	○	○
power palmar	●	●	●	○	○	●	●	○	●	●	●	●	○	○	○	○	○	○
lateral	●	○	●	●	○	○	○	●	○	●	●	○	○	○	○	○	○	○

B. Grasp Classification

Motivated by the high information content of the studied contact forces we perform a multi-class classification of applied grasp types using decision trees with a minimal leaf size of four and multiway splits. We develop an approach for predicting the applied grasp type directly from the forces and contact locations between the hand and the object. It achieves a classification accuracy of $92.3\,\%$.

This shows the general predictability of grasp strategies from the measured forces and therefore allows to analyse grasping behavior by only considering the object contacts. Furthermore, it emphasizes the correlation between both characteristics and their mutual significance for stable, task-oriented grasping. By implication this also indicates the ability to define adequate contact forces for a given object weight and grasp based on the analysed data.

V. DISCUSSION AND INSIGHTS

The force synergies in the presented data are notably less marked than reported by Santello et al. [5] for grasps on imaginary objects. However, these force synergies are more widespread and broader correlations are clearly visible, promising a force synergy representation similar to the postural synergy description.

The presented force synergies allow an informative low-dimensional representation of grasp characteristics emphasizing the balance of forces crucial for stable grasping. Especially in the human hand, the consideration of both grasp postures and forces is essential for an encompassing grasp description as the human can vary the compliance of their hand to intentionally change contact forces applied. This allows the human to apply a wide range of force patterns while keeping the grasp posture fixed.

Still, neither postural nor force synergies encode descriptive information like the applied grasp type in an apparently readable manner. As shown in section IV, common grasp types can be distinguished based on their contact force patterns. Force synergies are appropriate for the separation of such individual contact areas. On the other hand the distribution of information among the forces is more balanced requiring six to eight synergies to appropriately describe the complete information available.

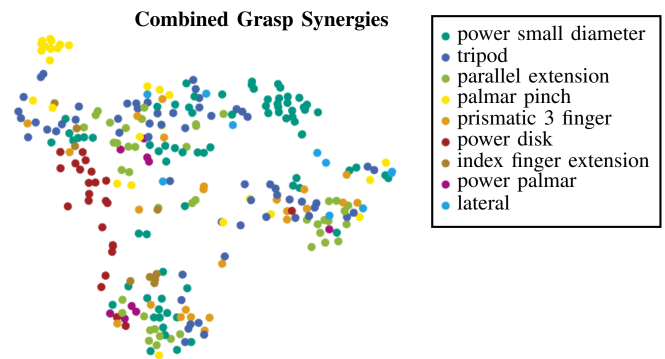


Fig. 7: First eight combined postural force synergies visualized in two dimensions using TSNE.

A combined postural force synergy description derived by calculating the PCA over the combined and normalized data of both modalities allows to describe both characteristics in a compact representation. Fig. 7 shows a representation of the first eight combined postural force synergies calculated by TSNE. This representation enhances the selectivity of grasp contact positions encoded in the grasp forces by the shape information contained in the grasp posture, which eases the interpretation of grasp parameters notably. However, Fig. 7 also shows that more complex interpretation strategies are needed to isolate the individual adopted grasp configurations.

VI. CONCLUSION

This paper presents a study of human grasp force patterns including 466 grasps by eight subjects on 14 objects. It analyses the forces at 18 different contact locations within the human hand. In addition, the grasp forces are compared with the corresponding kinematic hand postures of the performed 16 grasp types.

This study reveals significant correlations between the individual contact forces of the palm and the four fingers. The thumb shows an individual force behavior being mostly decoupled from the opposing fingers. Inspired by the postural synergy description we confirm the existence of force synergies and to the best of our knowledge we present their first characterization. We derive individual force synergies, which are less related than the postural synergies but show a higher tendency to segregate individual grasp strategies. We present combined postural force synergies, which combine the most important characteristics of grasping.

In addition, we characterize the dependency of grasp forces and object weight presenting a linear approximation for the average grasp force applied. While this relation between weight and applied force is to be expected, a key observation is the notable increase of grasping force variance with object weight. The task dependency of contact forces therefore evolves with the overall weight. By analyzing the patterns of applied contact forces, a clear discriminability between individual grasp types can be shown. These findings on grasp-related force patterns provide the basis for force controlled grasping algorithms exploiting the full potential of humanoid robotic hands while applying human grasp characteristics. Conversely, we also show the capability to classify individual grasp types from the contact forces. This enables the association and influence on grasp types based on finger force sensors in a humanoid robotic hand.

We believe that these analyses bring us a significant step further in the understanding of human grasp behavior, allowing the design of human-inspired control schemes for robotic and prosthetic hands. In continuation we are planning to compare postural and force synergy representations in detail and further analyze the combination of their informational content. The study presented herein encourages us to further enhance the integration of contact forces into the human grasp synergy description as part of the controllable variable space for humanoid robotic and prosthetic hands.

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