Motor synergies and object representation in virtual and real grasping

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***Abstract* — Grasping movements directed towards virtual objects have been found to resemble those directed towards real objects. Former studies, however, used natural objects with few controllable features. We investigated hand kinematics and duration of grasping movements directed towards real and virtual spherical objects that systematically vary in size. Kinematic data were analyzed using principal component analysis in order to extract movement synergies and determine invariant movement characteristics for grasping real and virtual objects. Mental representations of grasping movements were analyzed using a hierarchical sorting paradigm (called structure dimensional analysis). Results show that the grasping movement is influenced by object characteristics (i.e., object size) at an early stage of the movement. Clusters that mark objects in PC space can be distinguished early during the grasping movement, long before the final grasping posture of the hand is adopted, in the real and the virtual case. For the final grasping posture, more than 70% of the variance can be described by the first 3 PCs, and more than 80% by the first 5 PCs, for both real and virtual grasping (with slightly higher percentages for the real case). Especially the two or three smallest objects are clearly separated from medium and larger objects in PC space. A separation of small objects from larger ones also occurs in the results of the analysis of mental representation of grasps, which supports the notion that the grasping movement is strongly influenced by conceptual factors.**

Key words: manual action, grasping, hand kinematics, virtual objects, motor synergies, mental representation of movement.

I. INTRODUCTION

Manual action is a skilled behavior that requires intricate control of the musculoskeletal system of the human hand. Especially when we grasp, manipulate and interact with objects, movements of the hand have to be accurately adapted to the object's shape and the task we want to perform. During such skilled movements, the large number of degrees of freedom (DOF) in the human hand has to be controlled in a highly efficient way. It has been proposed that control of human hand movement is organized in a modular way, comprising higher levels that combine and couple several DOF into functional groups (i.e., motor synergies), thus simplifying the execution of meaningful hand postures (e.g., Santello, Flanders & Soechting, 1998). Several studies have supported the notion of motor synergies in manual action and grasping, and principal component analysis (PCA) has proved to be a useful tool in extracting these motor synergies (e.g., Daffertshofer et al. 2004; Tresch et al. 2006). Using a large set of common objects for everyday use, Santello et al. (1998) showed that the kinematics of natural grasping postures could be described by two principal components. Taking into account the fact that they measured 15 DOF, this functional reduction supports the assumption of motor synergies. In a further study, Santello and Soechting (1998) found that hand postures during grasping common objects are not passive adaptations of the hand to the grasped object, but are in fact controlled actively, prospectively with regard to the object that is to be grasped. Santello, Flanders and Soechting (2002) showed that data recorded at the end of the grasping movement is more clearly separable in principle component (PC) space for real objects than for virtual objects. Ansuini et al. (2007) studied the effects that object perturbations during the transport phase have on the evolving hand posture. They found evidence for a global control strategy which corroborates the concept of a modular hand controller. Ingram et al. (2008) analysed human hand movements during everyday activities using a portable motion tracking system. In their study, principal component analysis revealed two first components of the fingers but not the thumb explaining over half of the variance of the data, whereas the thumb contributed to higher order components which excluded the fingers. Their results corroborate and extend results of studies investigating digit independence (Häger-Ross & Schieber, 2000) and force production (Reilly & Hammond, 2000) in reach-to-grasp movements under laboratory conditions.

The view that motor synergies underlie manual actions is also supported by studies that focus more on physiological aspects. Gentner and Classen (2006) used transcranial magnet stimulation to directly stimulate the motor cortex of human subjects and thereby elicited complex finger movements that closely resembled motor synergies found in voluntary hand movements. Weiss and Flanders (2004) recorded the activity of several hand muscles via

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electromyography during grasping movements and spelling in sign language. They were able to extract motor synergies on the muscular level and correlate these to kinematic synergies extracted from simultaneously recorded joint angle data.

In addition to the growing body of evidence for motor synergies and a modular organization of grasping movements, it is known that hand movements are controlled actively, depending on conceptual properties of the to-be-grasped object and the intended task. In task-planning, physical and task-related properties of objects cannot easily be separated from each other, and their relation has been investigated by several authors (e.g., El-Khoury & Sahbani, 2010; Herbort & Butz, 2010). Cohen and Rosenbaum (2004) found that the position of the intended grasp, relative to the grasped object, is strongly influenced by further task planning, e.g., to the position in space at which the object is intended to be placed. Rosenbaum, van Heugten and Caldwell (1996) described an end state comfort effect in object grasping by showing that the grasping posture is adopted in regard to the hand posture during the intended action. In a study by Ansuini et al. (2006), the same object was used in different tasks. Although the object and its initial location were identical in all conditions, significant differences in grasping were found for different intended tasks, supporting the idea that grasping is strongly influenced by task planning even in an early state of the action.

Motor synergies or motor primitives are supposed to simplify motor control (Bernstein, 1967). However, motor synergies have to be controlled themselves, which requires specific additional structures and control schemes. A simplification of the motor control process as a whole can therefore only be achieved if these structures and control schemes are comparatively simple. Motor synergies of the hand should therefore represent a general level of control that simplifies natural grasping. Their characteristics and temporal contribution to hand posture should accordingly be related to the properties of the handled object and task. One of our goals is to assess the relationship between object properties and hand motor synergies, and to reveal meaningful mappings between these two levels of description. We assume that the layout of grasping postures in motor synergy space should reflect the layout of objects in their associated feature space, with a simple mapping between the two. This also implies that varying the grasping movement according to variations in the nature of object or task should be gradual and continuous, facilitating effective adaptation.

One aim of our research is to develop a quantitative framework for the generation of grasping movements based on motor synergies, taking into account physical and conceptual object properties as well as task characteristics. In the current study, we analyze grasping movements directed towards spherical objects varying linearly in size. Additionally, we compare grasps directed towards real objects and virtual objects, the latter being displayed as images behind the position in which they have to be imagined. According to Santello (2002), mimicked grasping movements show similar characteristics to grasping movements that involve real objects. In order to address the question of grasp conceptualization and how it depends on object characteristics, we apply a method that has been adapted from cognitive psychology to analyze the mental representation of movements (e.g., Bläsing, Tenenbaum & Schack, 2009; Schack, 2004).

II. Methods

Eleven right handed subjects (age: 24-39 years, 4 women) participated in a series of three experiments. All subjects had normal or corrected-to-normal vision and had no known impairments related to arm or hand movement. All subjects gave written informed consent to be part of the study. The experiment was carried out according to the principles laid out in the 1964 Declaration of Helsinki. Subjects performed all three experiments in the same order, starting with Experiment 1, directly followed by Experiment 2, and then Experiment 3.

The experiments were carried out at the Manual Intelligence Lab, making use of its sophisticated multimodal set-up for investigating manual interaction (Maycock et al., 2010). During the data collection, the subjects stood in front of a table (with dimensions 210 x 130 x 100 cm). Subjects wore an Immersion CyberGlove II wireless data glove (Immersion Corp., San Jose, CA; data acquisition rate: 100Hz; sensor resolution: <1°) on the right hand that allowed for the recording of whole hand kinematics (22 DOF). In front of the subject (at a distance of 40cm), a holding device for spherical objects (golf tee) was positioned on the table. A laptop computer screen was positioned behind the holding device. A small round bowl (10cm in diameter) located 40cm to the right of the holding device served as target for placing the objects. A 14 camera Vicon digital optical motion capture system (Vicon, Los Angeles, CA) mounted around the table was used to monitor the trajectories of the hand movements via three retro-reflective markers placed on the back of the data glove (see Maycock et al., 2010).

A. *Experiment 1*

Eight white plastic spheres varying in diameter from 10-80 mm in 10 mm steps were used as the real objects. The spheres were custom made from ABS plastic with a 3D-printer (SST 768, Dimension/Stratasys, Inc., Eden Prairie, MN). Before the onset of each trial, one spherical object was placed on the holding device by the experimenter. During Experiment 1, the computer screen remained blank. The objects were presented in a fixed order, in 10 pseudo-randomized blocks of 8, which was constant for all subjects and identical for Experiments 1 and 2. In both experiments, the subject was instructed to place the right hand at the starting position at the edge of the table and wait for a "go" signal to put the object into the bowl. After placing the object in the bowl, the subjects had to place their hand back at the starting position and wait for the next trial. In order to keep the grasping movement as natural as possible, the term "grasp the object" was deliberately avoided in the instructions as it might have drawn the subject's attention to the grasping action itself.

B. *Experiment 2*

In Experiment 2, the experimental procedure was exactly the same as for Experiment 1, but this time no real objects were used, and the holding device remained empty throughout the experiment. Instead, images of objects were displayed on the computer screen, which corresponded exactly in shape and apparent size to the real objects from Experiment 1. The participants were instructed to imagine the displayed object lying on the holding device and act accordingly. All subjects performed Experiment 2 directly after completing Experiment 1. The duration of a typical session, including both experiments, was approximately 90 minutes.

The data analysis for Experiments 1 and 2 was identical in order to compare real grasping with virtual grasping. Grasping movements were defined as starting with the hand accelerating (i.e., reaching a velocity threshold) from the starting position and ending as the hand starts to accelerate, after grasping the object.

We analyzed velocity profiles of the hand movement in space during the grasp as measured by the Vicon motion capture system. Velocity profiles were calculated using the x-component of one of the markers on the hand as it moved through the Vicon volume (i.e., the movement component away from the subject's body and towards the object). Total durations of real and virtual grasping were compared using repeated measures analysis of variance (ANOVA) with factors object TYPE (i.e., real vs. virtual) and object SIZE.

Motor synergies of the grasping movement were calculated from the Cyberglove data via principal component analysis (PCA). We recorded 22 DOF encompassing the movement of all five fingers of the human hand and the palmar arch during defined grasping movements. Two DOF were omitted from the analysis as they represented the wrist and did not contribute to the grasping movement. Based on pooled joint angle data from each trial, we computed PCA for Experiment 1 and Experiment 2 separately in order to extract movement synergies. As a pre-processing step the means were subtracted from the joint-angle data and the PCA was performed on the correlation matrix. The hand posture measured at any given time during the grasping movement can be described as a single point in a 20-dimensional joint angle space; therefore, the grasping movement can be regarded as a series of vectors within this 20-dimensional space. We analyzed this set of postures defining points in joint angle space with PCA, yielding a new set of unity vectors (or PCs). These PCs form a new orthogonal coordinate system whose dimensionality is equal to the dimensionality of the underlying data set. Both coordinate systems are equivalent descriptions of the underlying data, however, in the PC coordinate system the unity vectors are aligned with the axes of largest variance of the analyzed data set. In this way, PCs reflect or "capture" the datas' variance.

C. *Experiment 3*

In a third experiment, we analyzed the subjects' mental representations of the applied grasping movements by means of the *structure dimensional analysis* (SDA) method (see Schack 2004, 2010). Ten out of the eleven subjects who had taken part in Experiments 1 and 2 also took part in Experiment 3. All 10 subjects (age: 24-39 years, 3 women) performed Experiment 3 after Experiments 1 and 2. The duration of a session of Experiment 3 was approximately 30 minutes. For Experiment 3, the subjects were seated in front of a laptop computer screen. On the screen, the same images as in Experiment 2 were displayed as stimuli in the following way: a fixation cross was displayed for 1 second, followed by one of the objects for 3 seconds, then another fixation cross was displayed for 1 second, followed by a second object. The subjects were instructed to make a grasping movement towards the first object, the reference object, as soon as it appeared, as they had done in Experiment 2, then make a grasping movement towards the second object as soon as it appeared. Subjects had to answer the following question: are the two grasping movements you just performed similar to each other? This question was delivered via a question mark which appeared on a white screen asking the subject to press one of two marked keys for a positive or negative answer, with a positive answer indicating similar and a negative answer indicating dissimilar grasps (note that we did not ask for similar and dissimilar objects!). After the subject had answered the question by key press, the reference object was displayed again, followed by the next object, and then by the subject's response. Each object was displayed as a reference (i.e., first object in the tuple) with every other object (i.e., second object in the tuple), resulting in 56 object tuples (and therefore 56 decisions) in total.

Using this splitting procedure, eight decision trees were created, as each object occupied the reference position once. Subsequently, the algebraic branch sums were determined on the partial quantities per decision tree, submitted to a Z-transformation for standardization, and combined into a Z-matrix. This matrix formed the starting point of all further data analysis that was carried out according to the SDA method (Schack 2004, 2010). In the first step, the binary decisions applied by each subject were used as a basis for a metric distance scaling between the items (i.e., the grasps). Secondly, the Z-matrix was transferred into a Euclidian distance matrix, on which a hierarchical cluster analysis (in accordance with the average-linkage-method) was carried out to determine a hierarchical structure based on Euclidean distances within the given set of items. This resulted in individual cluster solutions on the N-concepts formed as dendrograms. Cluster solutions were calculated for all individual subjects and for the whole group. Each cluster solution was established by determining an incidental Euclidian distance (d_{crit}), with all junctures lying below this value forming the apical pole of an underlying concept cluster.

III. Results

A. Experiment 1 and 2: Duration of hand movements

Total grasping durations were similar for the real and virtual object 1 (both slightly above 1400 ms), but durations decreased to a much greater extent over the set of real objects rather than for the virtual objects (object 8: real 860 ms; virtual 1230 ms) (see Figure 1). Durations of real and virtual grasping differed for objects 3 to 8 (objects 3 and 4: $p< .05$; objects 5-8: $p< .01$; paired t-tests). Repeated measures ANOVA revealed effects of object TYPE (real, virtual) ($F_{[1,10]}$=13.64; p<.01; partial η^2=0.577) and object SIZE ($F_{[1.61,16.13]}$=68.92; p<.001; partial η^2=0.873), as well an interaction between the two factors ($F_{[2.63,26.27]}$=39.55; p<.001; partial η^2=0.798). Mauchly's test revealed that the assumption of sphericity was violated for SIZE ($X^2_{(27)}$=55.6; p<0.001) and for TYPE*SIZE ($X^2_{(27)}$=47.8; p<0.05), therefore the degrees of freedom were corrected (Greenhouse-Geisser; SIZE: e=0.23; TYPE*SIZE: e=0.38). Bonferroni pair wise comparison of objects sizes showed differences between object 1 and all other objects (all p<.001), object 2 and all other objects except object 3 (all p<.01), object 3 and objects 5, 6, 7 and 8 (all p<.05), and objects 4 and 7 (p<.05).

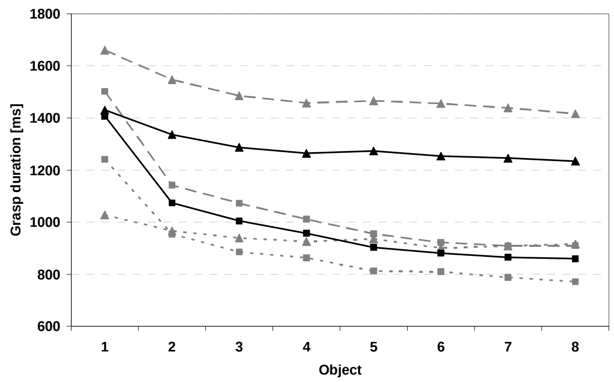

Figure 1: Durations of grasping movements; squares: real objects; triangles: virtual objects; black: mean of all subjects; grey, dashed line: male subjects; grey, dotted line: female subjects.

When analyzing the data from male and female subjects separately, the results of the male subjects showed the same characteristics as the results for the whole group (with effects of object TYPE and SIZE and an interaction between the two, all p<.001), whereas the data from the female subjects showed significant effects only for object SIZE and the interaction (both p<.001).

Velocity profiles of hand movement in space showed a similar shape in both conditions, with an initial acceleration lasting approximately one quarter of the grasp duration, and a following deceleration, comprising a more or less distinctive plateau phase, for real and virtual objects. For medium and large objects, the shapes of the profiles for virtual and real grasping were more similar than for small objects, despite the difference in total duration. For small objects, deceleration occurred more slowly in the virtual grasping case than in the real grasping case. Velocity profiles of one subject grasping object 1 are shown in Figure 2.

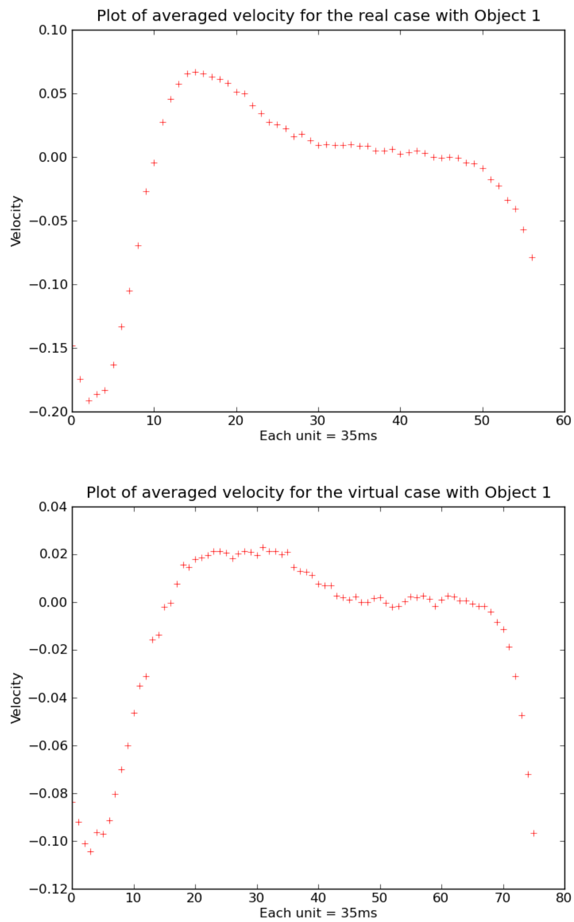

Figure 2: Velocity profiles of one subject grasping object 1, averaged over 10 trials; top panel: grasping the real object; bottom panel: grasping the virtual object (for larger objects, the profile of the virtual case becomes more similar to the real case).

B. Experiments 1 and 2: Motor synergies in grasping

The results of the PCA analysis indicated that on average, more than 70% (real objects: 77.6%, virtual objects: 73.1%) of the variance can be described by 3 principal components (PCs), and more than 80% can be described by 5 PCs (real objects: 88.3%, virtual objects: 84.3%). The data from grasping real objects recorded at the end of the grasping movement (i.e., when object contact is established) was in general more separable in PC space than the data from grasping virtual objects. Object size was coded by a combination of PCs 1 and 2, with a major influence of PC 1 especially for the three smallest objects (see Figure 3) in most of our subjects. Nine out of eleven subjects clearly showed this pattern for the real case data (with the group of smaller objects including object 4 in two of the subjects). In the two remaining subjects the pattern was reversed, with a major influence of PC 2 for the three smallest objects. Even though this finding was more obvious in the real data than in the virtual data, the virtual data showed the same pattern, with the three or four smallest objects being clearly separated from the larger ones.

When not only the end posture but also intermediate postures of the grasping movement were taken into account, it became apparent that object-specific clusters in PC space became separable from each other early during the movement. Figures 4 and 5 show the clustering of objects 1, 5 and 8 for a single subject, starting from the end grasp positions back to a point in time close to the start of the movement. It is noticeable that good clustering and separation in PC space was not only observed at the end grasp point in time, but also along the majority of the trajectory as the hand moves towards the object. This was true for both the real and virtual cases. The separation in PC space broke down for objects 5 and 8 near the beginning of the trial (see Figures 4 and 5), but was maintained for object 1. This trend was observed for all subjects, regardless of the case (real or virtual), which means that it is possible to recognize grasp types not only at their end grasp positions, but at much earlier points along the trajectory of the movement.

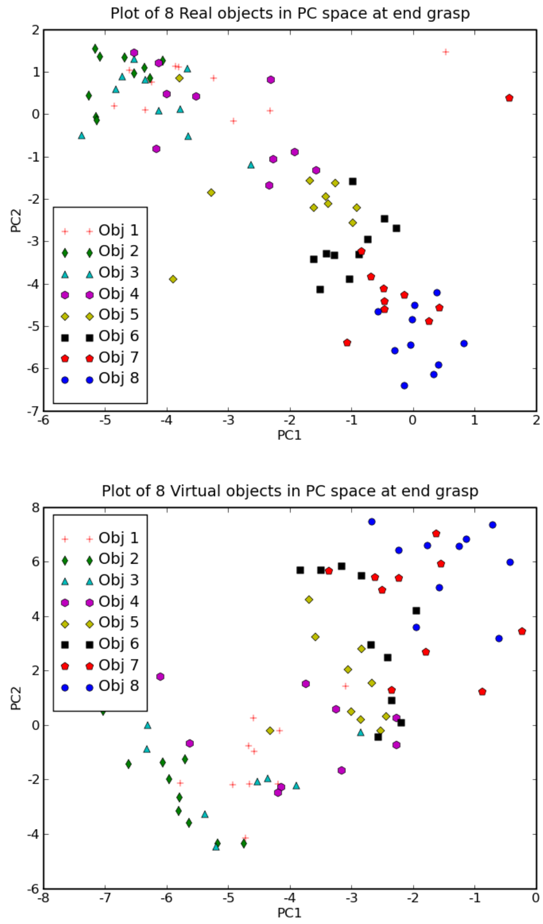

Figure 3: All 8 objects in PC space (PCs 1 and 2) at end grasp position; top panel: grasping real objects; bottom panel: grasping virtual objects (one subject).

C. Experiment 3: Mental representation of grasping

The results of the cluster analysis via SDA (α=1%, d_{crit}=4.44) revealed a representation structure for the whole group in which grasps directed towards objects 1-3 (the three smallest objects) were combined in one cluster and grasps directed towards objects 4-8 were combined in the second cluster. Comparing the results of the individual subjects revealed that five out of ten subjects showed the same cluster solution as the group (cluster 1: objects 1-3, cluster 2: objects 4-8), one subject produced a similar cluster solution in which the second cluster was split (cluster 1: objects 1-3, cluster 2: objects 4+5, cluster 3: objects 6-8), and four subjects showed deviating binary cluster solutions (2 subjects: cluster 1: objects 1-4, cluster 2: objects 5-8; 2 subjects: cluster 1: objects 1-5, cluster 2: objects 6-8). The cluster solution of the whole group of 10 subjects is displayed as a dendrogram in Figure 6.

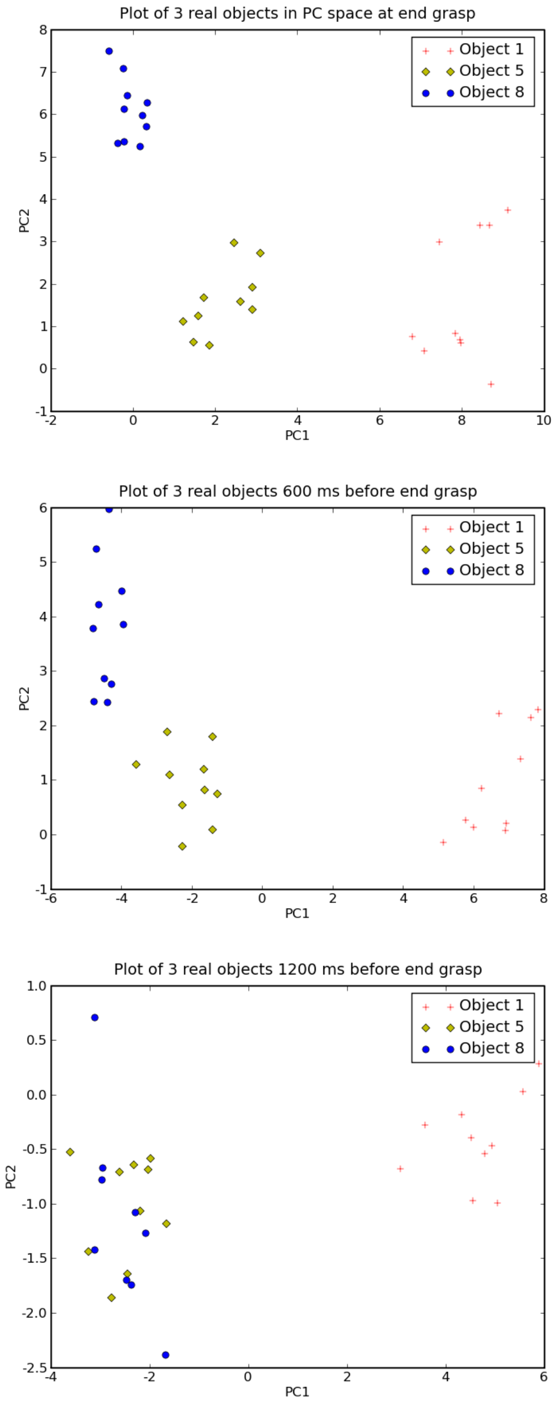

Figure 4: Objects 1, 5 and 8 in PC space (PCs 1 and 2) at different sampling times in grasping real objects (one subject). We have depicted three points in the grasping motion: end grasp, halfway to end grasp and close to the beginning of the grasping motion.

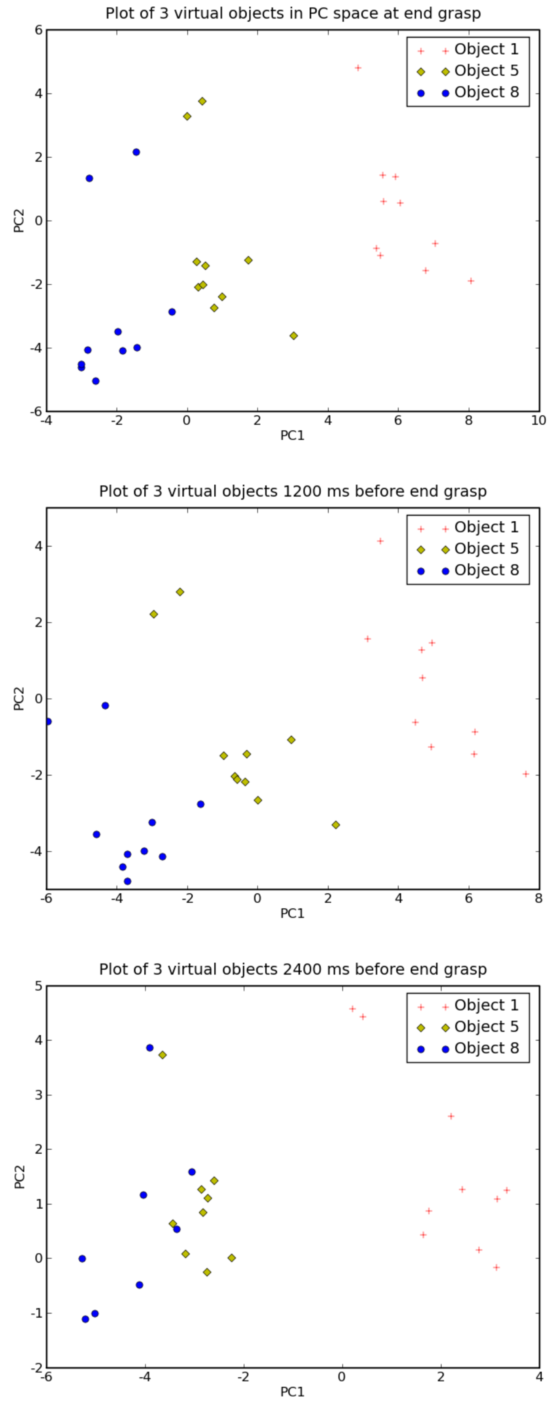

Figure 5: Objects 1, 5 and 8 in PC space (PCs 1 and 2) at different sampling times in grasping virtual objects (one subject, the same as in Figure 4). We have depicted three points in the grasping motion: end grasp, halfway to end grasp and close to the beginning of the grasping motion. Note that this (male) subject took significantly longer in the virtual condition (2400ms on average).

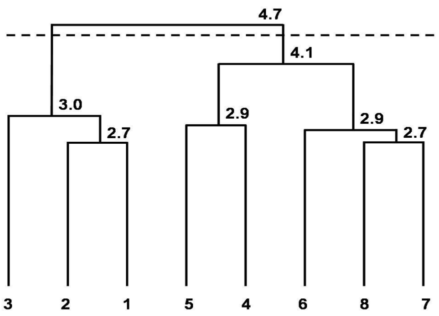

Figure 6: Mental representation of grasping movements towards virtual spherical objects; results of cluster analysis (SDA) displayed as dendrogram. Numbers on the bottom line mark object diameter (mm), horizontal bars in the dendrogram indicate Euclidean distances between concepts (the lower the link between items, the lower the distance between the corresponding concepts); the horizontal dashed line indicates the critical value for the given alpha probability (α=1%, d_{crit}=4.44), only structural links below the critical value are considered relevant.

IV. Discussion

We compared grasping movements directed towards real and virtual spherical objects that varied linearly in diameter, based on grasp durations, velocity profiles and motor synergies as revealed by PCA calculated on 20-dimentional joint angle space; additionally, we analyzed the mental representation of grasping movements directed towards the virtual objects using the SDA method. Our results suggest that the grasping movement is influenced by conceptual factors from a very early state onward. This becomes obvious from the motor synergies revealed by the PCA of joint angle data from the entire movement. Clusters in PC space become distinguishable at an early stage of the movement, long before the object is reached and the hand's end posture is adopted. When the final grasping posture has been reached, more than 70% of the variance can be described by the first 3 PCs (real: 78%; virtual: 73%), and more than 80% can be described by 5 PCs (real: 88%; virtual: 84%), for both real and virtual grasping, with data from real grasping being more clearly separated in PC space than virtual grasping data.

Our suggestion that the grasping movement is influenced early by conceptual factors is borne out by the results of our third experiment. The mental representation of the applied grasping movements measured in our group of subjects consists of two clusters that reflect the same separation of small and medium-to-large objects, one containing the three smallest objects 1 to 3, the other one containing objects 5 to 8. Within the larger cluster, a non-significant differentiation into medium-sized objects 4 and 5 and large objects 6 to 8 occurs in the dendrogram. A differentiation between small and medium-to-large objects can also be seen from the results of PCA in Experiments 1 and 2. Even at a very early stage of the grasping movement, a clear separation occurs between the smallest object (diameter: 10mm) and the two larger objects, both in the real and the virtual case (see Figures 4 and 5). The medium-sized object (50mm) and the largest object (80mm) are separated halfway through the grasping movement (this separation at a later stage could probably be related to the non-significant separation between medium-sized and large objects in the dendrogram). When we look at the data of all real objects at end grasp position (see Figure 3), it is clear that objects 1 to 3 vary mainly along the first PC, whereas objects 4 to 8 vary along both PCs, and more strongly along the second, which results in a "bended" shape of the plot. This pattern occurred in the real case for all subjects and in eight out of eleven subjects in the virtual case. We interpret this as an additional indicator of a general separation between grasping small and medium-to-large objects. From the finding that the cluster solution found by the SDA method closely matches the results of the PCA we conclude that the general grasp type is determined at an early stage of motion planning influenced by the conceptual level, whereas a further specification (in terms of an adaptation to object size) is developed during a later phase of the grasping movement. The questions if this later phase might correspond to the plateau phase observed in the velocity profiles (see Figure 2), and if the general grasp type can be related to established grasp taxonomies (e.g., Cutkosky, 1989) will be addressed in a future publication.

Grasping duration (measured from the beginning of hand movement to object contact) decreased with increasing object size and took generally longer in the virtual case (with grasping durations for objects 1 and 2 showing no significant difference between real and virtual objects). For the comparison between durations of real and virtual grasping movements, we have observed an unexpected difference between female and male subjects in our study: when data from men and women are analyzed separately, only the men show significantly longer durations for virtual grasping movements. Durations of virtual versus real grasping differ for all males but only for one of the females. As the comparison of real and virtual grasping on the basis of motor synergies does not reveal any systematic difference between female and male subjects, the difference in timing might suggest that females can more easily image the object lying on the holding device or adapt their grasp to the virtual object than the males, and therefore do not need extra time for the virtual grasping. However, as the number of subjects is rather small, further investigation is necessary at this point.

We have shown that whole hand grasping kinematics are low dimensional and can efficiently be described by only three PCs indicating strong linear relationships between the involved joints. Subjects use similar movement synergies that reflect the physical properties of the grasped object during real and virtual grasping (see Santello, 2002). Our findings allow for a compact description of grasping movements in terms of movement synergies. Furthermore, our results corroborate the view that grasp characteristics are specified at an early state of the movement. This has also been found by Winges, Weber and Santello (2003) who showed that hand shape modulation to object volume can be detected very early in the grasp, and by Herbort and Butz (2010) who investigated anticipatory forearm orientation in a knob-turning task. Our results expand previous works by suggesting that grasp is adapted to object size (as the only varying factor) in a step-wise manner, with an early pre-adjustment that might relate to the general grasp type and a later adaptation to absolute object size, both occurring before object contact is established (enabling tactile adaptation as a third step).

Studies of human grasping, often in the context of robotic applications such as the control of robot hands, have often used natural objects that vary strongly in many different parameters (e.g., Steil et al. 2004; El Khoury & Sahbani, 2010). Although there are studies that investigate the influence of systematic variations of object shape and intended action on grasping movements (e.g., Mason et al. 2001), none so far have systematically varied more than one parameter in a combinatory manner thereby constructing an object space in which objects vary systematically. Furthermore, to our knowledge there are no studies that analyze such object variations with regard to motor synergies in a quantitative manner. Another aspect that we want to add to the spectrum of grasp characteristics is intended action; we plan to analyze grasping movements towards the same object, but with different intentions (i.e., grasping the same object in order to execute different following tasks), thereby combining object space with task space.

In the future, we aim to investigate the adaptive process that generates grasping movements based on these parameters, varying selected object properties systematically in order to understand how they contribute to grasp specification. In forthcoming studies, we will investigate grasping movements directed towards objects that vary different parameters, such as weight, texture, shape or roundness. Experiments with objects varying in roundness, interpolating between sphere and cube, are currently being carried out in our project group.

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