Changing Pre-Grasp Strategies With Increasing Object Location Uncertainty*

Boris Illing[1], Tamim Asfour[1], and Nancy S. Pollard[2]

***Abstract*— Successful and robust grasping for humanoid robots is still an ongoing research topic in robotics. Applying human-inspired grasping strategies does not only correspond with more natural looking motions but can also yield good results regarding task success when having to deal with uncertainty. This study investigates human high-level grasping strategies and how they tend to change for different objects when the uncertainty of object location or orientation increases in between two grasps. We are especially interested in potential gains for humanoid robots in a common household setting. By analyzing collected data from human subject grasp experiments with a set of typical objects found in people's homes, we get better insight into how humans handle uncertainty, as well as when and how they change their applied pre-grasp strategy. By adapting the by far most often observed change from a direct grasp attempt to a tapping strategy when dealing with high uncertainty, we can demonstrate a substantial increase of grasp success rate for our robot system with a Shadow Dexterous Hand mounted on a Motoman SDA10 robot while using less than two hand correction steps on average.**

I. INTRODUCTION

Despite that more and more personal robots are being developed in research, the transfer into people's homes has not happened yet. One of the reasons is that reliably successful, dexterous manipulation is still an open challenge of robotics. Partly due to the growing complexity of robots in regard to increasing degrees of freedom (DOF) and handling of more sensors, there are still a lot of open questions left to be investigated. Thanks to a plethora of different sensor types available, a robot system will usually have a lot of information about its environment. However, when starting to interact with their surroundings, every action will be based on the obtained information and the quality thereof. In case of inaccuracy, measuring errors or simply lag in updating the data, problems will arise. Considering the superior grasping experience of humans compared to robots, observing human high-level grasping strategies and how those change based on the amount of uncertainty seems to be a promising approach.

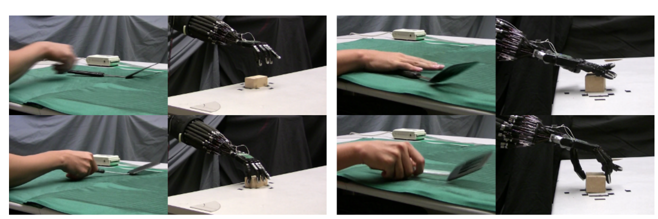
Inspired by the work of Chang et al. regarding human pre-grasp interaction with different objects based on a video survey of 38 participants performing manipulation tasks in a typical home or work setting [1] and a related work about preparatory, pre-grasp object rotation [2], we conducted a series of informal video surveys to explore the impact of uncertainty on human grasping. Based upon our findings we wanted to further investigate how human high-level grasping strategies tend to change for different objects when location or orientation uncertainty increases between two grasp attempts. We conducted a set of experiments gathering data from grasping trials by filming the process with two cameras from different viewing angles. We also collected contact data between the subjects' hands and the table. In addition subjective data was collected to evaluate the participants' thoughts on the grasping strategies they used. As we are especially interested in a common household setting, the considered objects were selected among a set of typical kitchen items and work tools.

Analyzing the data obtained from the experiment provided more details about typical pre-grasp strategies, when and how they change with increasing object location uncertainty and the impact on task completion times, amount of hand corrections, and hand aperture. During the course of the experiment, we observed that participants reused a lot of their pre-grasp strategies, only changing them when forced to by high object location uncertainty. Our findings from the collected data were then evaluated with an anthropomorphic robot hand comparing the two most prominently observed pre-grasp strategies, namely a direct grasp approach and a tapping strategy (Fig. 1).

II. RELATED WORK

When comparing our contributions to related research, there are several aspects to be considered: choice of robotic manipulator, use of sensors, and the general aspect of uncertainty. There has also been work on studying human hand movements and the applied grasp strategies.

Using mainly haptic feedback during grasping has been proposed by [3] for a Shadow Dexterous Hand in simulation and by [4] for a Barrett Hand using force sensors and human



Direct Grasp Strategy   Tapping Strategy

Fig. 1. Evaluating two human pre-grasp strategies with an anthropomorphic robot hand.

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input. Solely relying on haptic information while searching for good finger contact locations has also been applied to grasping objects without a priori knowledge. This has been done in simulation for a robot gripper [5], and in experiments with a PR2 jaw gripper on a large set of 50 household items comparing it to a standard grasping approach using only a vision system [6].

Many more strategies have been proposed for dealing with uncertainty in regard to object shape. Those include a framework for getting volumetric object models through haptic exploration using a contour-following strategy by a human or robotic hand in [7] and [8], grasping based on visual information using additional haptic feedback in a cluttered environment with a robot gripper and a five-finger anthropomorphic hand [9], and a recent experience-based grasping approach by [10] which uses an initial blind grasping attempt before querying a database with stable grasps for adjustments.

Several related works have offered suggestions on how to deal with additional uncertainty regarding object location and orientation. Strategies include statistical techniques [11], grasp selection using object shape and local features [12], decision-theoretic approaches [13], and planning in belief-space with additional information gain and replanning during the reaching phase [14],[15]. An example of a complete software architecture for reliably grasping household items with a PR2 jaw gripper while dealing with uncertainty is given in [16]. A very specific strategy for handling pose uncertainty has been suggested by [17]. They developed a push-grasp for objects in a cluttered scene with a control scheme to widen the gripper aperture as needed.

Even though these approaches for dealing with uncertainty work quite reliably for simple tasks with mostly lower dimensional robotic hands, they can not simply be applied to a fully anthropomorphic hand. Hence, several studies have been conducted on how to incorporate some form of human input into this process, including direct interaction [18] and the introduction of a rating system for human likeness based on observation through motion tracking [19]. Another approach transfers recorded human motion profiles to a Shadow Hand to achieve movements looking more natural [20]. In subsequent work, they propose a control scheme for the Shadow Hand that autonomously modulates applied contact forces, imitating human grasp behavior [21].

Over the years, there has been extensive work on human grasps and their taxonomy in different fields of research, such as robotics, biomechanics, and occupational therapy [22], [23], [24], [25], [26], [27]. However, these mostly concentrate on categorizing the final grip without taking the preceding pre-grasp strategy into account.

There has also been closely related research investigating through observation how much knowledge about the amount of uncertainty humans tend to use when grasping objects to improve their success rate [28]. They varied the uncertainty by moving an object into peripheral view. However, only a cylindrical object was regarded and only two-finger grasps. The same two constraints were also applied in [29] and [30], showing that humans compensate for object location uncertainty while grasping. In a recent work, utilizing a cylindrical object as well, it has been shown that humans vary their reach-to-grasp behavior based on object orientation uncertainty, leading to an increased amount of sensing prior to grasping [31]. Further research has investigated the effects of peripheral vision on kinematic parameters and hand trajectories [32], [33], [34].

As far as we know there has not been any related research concentrating on human pre-grasp strategies and how they change when dealing with object location or orientation uncertainty for a general set of household items or tools and regarding a natural use of the human hand.

III. EXPERIMENTAL METHODS

The goal of our grasp experiments with human subjects was to get insight into the ways humans tend to use high-level grasping strategies in a common home setting and to evaluate the impact of uncertainty on different strategies for a set of 10 typical household objects.

A. *Setup*

As we were especially interested in observing natural hand movements, we used an unobtrusive experimental setup, specifically avoiding the use of marker-based motion capture or data gloves. As a result we came up with the following overall layout as shown in Fig. 2. During the whole experiment each participant was sitting in front of a desk at a fixed position and was asked to keep looking at a predetermined point at eye level in front of them. Two HD video cameras were set up to film the scene from different angles as occlusions were to be expected during the experiment. Furthermore, we were using two tactile pressure measurement mats, a CONFORMat model by Tekscan with 1,024 sensels each with a 0.5 cm^2 sensel density, to collect all contact data between the participants' grasping hand and the table. Purpose was mostly to try to measure the hand aperture before the fingers start closing around objects lying flat on the table. As only right-handed persons were participating, the setup on the table was arranged accordingly.

The sequence during each of the experiments was as follows: every participant was asked to execute a specific task for one object placed at location 1 (either move it to

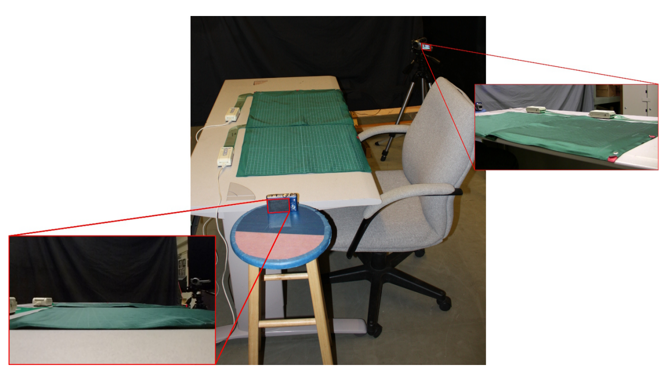

Fig. 2. Overview of the experimental setup.

a target location or use it there). This was repeated three times, changing the object's position from location 2 to 4. Afterwards, a fifth trial was exectued, which was a blind grasping attempt. The complete cycle was repeated for each of the 10 objects with initial object rotation being randomly selected at the beginning of the trials. We then chose a subset of our objects and conducted four additional trials for each one selected, placing them with varying orientation at location 4. We observed early on that object rotation was influencing the applied pre-grasp strategies, so we extended the set of objects until using nearly all of them for rotational trials. Due to symmetry reasons we did not include the plate and used the bowl only twice per participant, totaling up to a maximum of 34 rotational trials per subject. After the experiment every participant was asked to complete an exit questionnaire to gather impressions from their point of view.

To control the level of uncertainty, participants were asked to briefly shut their eyes inbetween two trials while the current object was moved to another location. The exact placement spots for the objects were varied slightly during the course of the experiment, so as to make their locations less predictable. In general, the viewing angle changed from a central one to an increasingly peripheral one, as there has been extensive work in vision and neuroscience research showing that this clearly corresponds to a degrading performance in position and orientation judgment [35], [36], [37], [38], [39]. Location 1, 2, and 3 were positioned on an approximate quarter of a circle resulting in mid-peripheral vision from moving into the lower visual field. Location 4 was set further away to the right using the second pressure measurement mat and resulting in far peripheral vision. For the blind grasping attempt, the object was placed somewhere in front of the participant. Fig. 3 shows all different object locations used throughout the trials.

The objects included in the experiments were selected among usual kitchen items and common tools to make sure that every participant would be familiar with them. The choice of objects was also determined by the fact that all of them should be big enough to be grasped by a robot hand as well, and should not be fragile. Fig. 4 pictures the 10 household items used for the experiments, with the group in the top row being the ones that the participants had to move to a specific target location, and the bottom group being tools which had to be used at the target location.

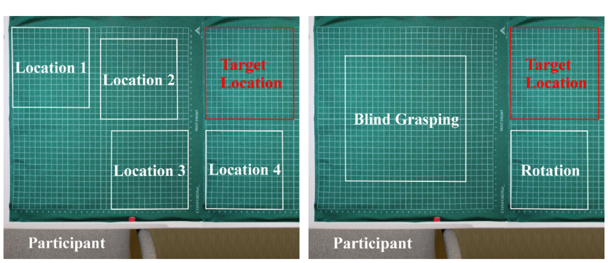

Fig. 3. All different locations used for object placement throughout the trials.

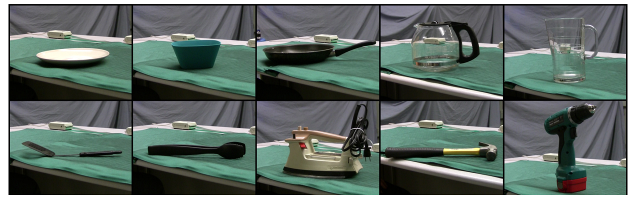

Fig. 4. The set of 10 household items used for the experiments.

B. Hypotheses

Based on preliminary experiments, we formulated several hypotheses for the selected set of objects. Possibly depending on size, shape, and the applied grip, we should be able to observe the following in case of increased object location uncertainty:

- a tapping movement from the top to verify object location,
- a midair sweeping motion on one or two axes,
- increasing task execution time due to slower hand movement,
- a wider hand aperture while approaching the object, and
- less preliminary object rotation depending on initial orientation.

The inclusion of a blind grasping trial should also be helpful in making observable strategy changes more visible. We expect the subjective results from the questionnaires to support our hypotheses through the participants' perception.

IV. RESULTS

In the following, we will present the results we obtained by analyzing the data we gathered from the experiments with 15 participants. This includes both objective results from the video data and subjective results from the questionnaires.

A. Objective Results

From analyzing the experiment data we created a database where we indexed every valid grasp from the trials, considering several different variables for each grasp. We had to exclude some of the trial data where participants were not fully following the instructions. For the results we obtained we have been using a total of 1130 grasps.

First of all we were interested in the different pre-grasp strategies applied by participants throughout the trials. We could observe the fact that people tend to reuse a lot of grasps resulting in only a few distinctive approaches, which worked well enough for our whole set of objects. Trying to explicitly name them, we came up with the following list of overall strategies:

- direct grasp (Fig. 5),
- tapping (Fig. 6),
- sensing (Fig. 7),
- sideways movement with flat hand,
- hit or miss (Fig. 8),
- approaching with preshaped hand (Fig. 9),
- left-right-sweeping, and
- forward movement with flat hand.

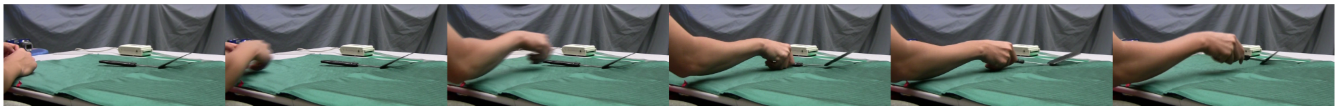

Fig. 5. Direct grasp strategy at location 2: 1.4s grasp completion time.

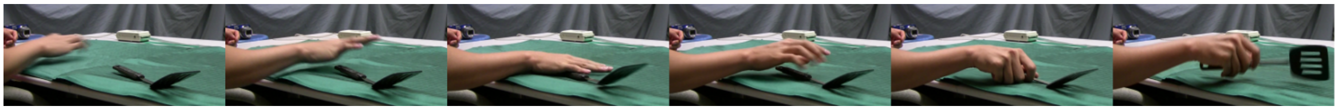

Fig. 6. Tapping strategy at location 4: 2.4s grasp completion time.

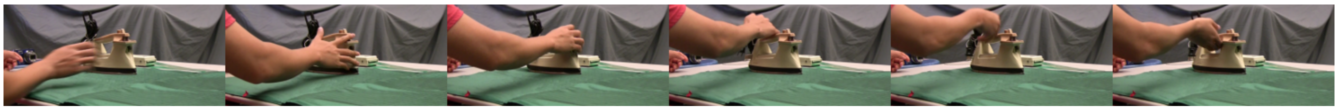

Fig. 7. Sensing strategy during blind grasping: 3.4s grasp completion time.

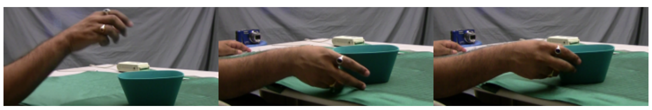

Fig. 8. Hit or miss strategy at location 4: 2.2s grasp completion time.

Fig. 9. Approaching the object with preshaped hand during blind grasping: 2.2s grasp completion time.

TABLE I

DISTRIBUTION OF STRATEGIES APPLIED DURING BLIND GRASPING.

Pre-grasp strategy	**Count**	**Percentage**
Tapping	91	51.4
Sensing	31	17.5
Flat hand forwards	21	11.9
Left-right-sweeping	16	9.0
Preshaped hand approaching	12	6.8
Hit or miss	2	1.1
Other	4	2.3
Total	177	100.0

Analyzing the distribution of pre-grasp strategies per location, we found that the most prominent strategy with low object location uncertainty was by far a simple direct grasp attempt (77.9 % of usage at location 1): moving the hand straight to the object while changing the finger posture into a pre-grasp state just before making contact. The most used pre-grasp strategy when dealing with high uncertainty, however, was a tapping movement with a flat hand (51.4 % during blind grasping). The tapping strategy varied though based on the amount of uncertainty, as it heavily relies on the quality of the initial guess. For example at location 4 we could observe a lot of participants executing only a single tap to check an object's exact position before directly grasping the target. During blind grasping we could at times observe this behavior as well, resulting in very fast grasp attempts, but also the other extreme happened where the tapping strategy yielded among the worst results in terms of time to grasp due to many failed guesses trying to locate the object.

Notable other strategies we encountered were sensing, where all fingers were used to follow the object's contour before grasping, moving the flat hand sideways while having it vertically oriented for trials at location 4, changing the hand early on into a pre-grasp state and approaching the object very slowly, and a hit or miss strategy trying a direct grasp approach first, then either correcting the hand position or completely changing the strategy in case that failed. During the blind grasping trials we could also observe a left-right-sweeping motion in search of the object and people slowly moving their flat hand forwards while having their palm oriented towards the object. Table I shows the distribution of strategies used for blind grasping. This includes 37 times where two strategies were used during one trial, mostly tapping in combination with sensing. Interestingly, we found that sensing was barely used on its own (only 2.1 %).

After categorizing the more frequent pre-grasp strategies, we investigated how they would change based on the level of uncertainty. As some of the strategies were used more often at specific locations (direct grasp at location 1 to 3, tapping and sideways movement with flat hand at location 4 and after, sweeping and forward movement with flat hand for blind grasping), we could mainly differentiate three cases of changed pre-grasp strategy: at location 4, for blind grasping, or both. Even though the uncertainty did already increase from location 1 to 3 it was not enough to force people to change their grasping strategy up to this point. Exceptions were mostly due to some participants testing out several grasps for a new object and the change of rotation connected with the placement of the different locations.

To be able to measure the observable effects from changing pre-grasp strategies, we mainly used two variables: grasp completion time and amount of hand corrections until fully grasping an object. For both of these we were considering the span between the first visible movement of the right hand and the object being lifted up from the table in a usable state, which could include additional object rotations midair. For the amount of hand corrections we were only counting very visible movement changes of the whole hand or several fingers at once, and only relative to the object, plus every occurence of accidentally hitting the object with a following correction. We can show that, as expected, grasp completion time goes up with increasing object location uncertainty. This can be seen in Fig. 10, however, the trend is not as visible as we hoped for. One reason for this is due to our experimental setup, as we will discuss later on, and another reason is that we could not clearly observe a reduced hand movement speed until the uncertainty increased a lot. Furthermore, we measured slightly higher values at location 1 compared to location 2 and 3, because the participants often tried out several hand poses before finding a good grip when given a new object. In line with our previous finding Fig. 11 shows the same trend for the mean amount of hand corrections to increase along with the object location uncertainty. Additionally, the effect of uncertainty was a lot more visible. Both variables highly correlate with each other: the more corrections are needed, the longer it will take to grasp an object resulting in a correlation coefficient of 0.807. We also discovered that the trend of increasing amount of hand corrections depending on the uncertainty was observable seperately for each of the 10 objects and also for each of the 15 participants.

We further analyzed the data with repeated measures analysis of variance (ANOVA) tests using the software SAS, to test our results for statistical significance. An ANOVA test can be used to compare the levels of variance between and within a factor under observation, with further post-hoc tests needed in case of a significant difference. For all our ANOVA tests we used a significance level of $\alpha = 0.05$. To conduct post-hoc tests we used Tukey's Honestly Significant Difference test (Tukey's HSD). At first we tested grasp completion time and amount of hand corrections regarding the different locations and both yielded a statistically significant difference of means (p <0.0001, F = 76.17 and p <0.0001, F = 114.96 respectively). Tukey's HSD test showed that in the first case there are three different groups: location 1 to 4, location 4 and rotation, and blind grasping, while in the second case the outcome was more distinct with location 1 to 3 as one group, location 4 and rotation as another one, and then blind grasping as a third group. We also conducted further ANOVA tests for different combinations of our two main variables with other factors regarding the different locations, such as object, participant, object orientation, gender of the participant, and using the handle of an object, but neither of those yielded statistical significance except for the two different groups of objects. The overall trend of increasing grasp completion time and amount of hand corrections was clearly visible for both groups, with the means of the five tools being a lot higher than those of the other five objects, possibly due to them being overall more complicated to grasp.

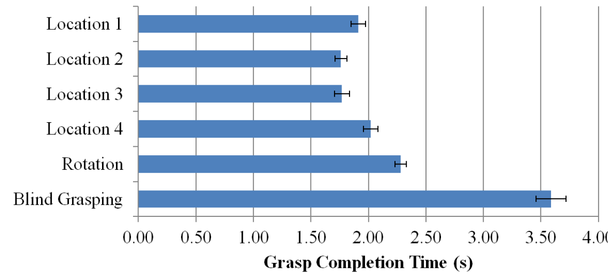

Fig. 10. Mean grasp completion times and standard error of the mean for all objects and participants.

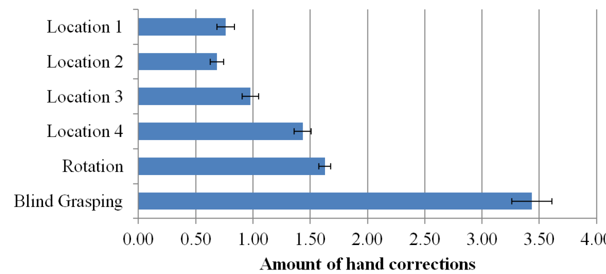

Fig. 11. Mean amount of hand corrections and standard error of the mean for all objects and participants.

As we already noticed during the experiments that due to our setup the initial object orientation influenced the applied pre-grasp strategy, we also had to analyze the impact on our results. For the different trials we had mostly oriented the objects to the diagonal directions, hence we had the most accurate data for these four. As an example an object with a handle, such as the pan, could have been oriented with the handle to the right and forward relative to the participant. Looking at the mean amount of hand corrections only for those four main directions, we can still see that the amount goes up along with the uncertainty (Fig. 12). However, the effect is a lot less visible for objects oriented to the left as that made objects harder to grasp at location 1 to 3 and on the contrary easier at location 4. Conducting multiple ANOVA tests on the impact of orientation on the amount of hand corrections did not show a statistical significance though. It should still be noted that overall the mean values from the rotational trials yielded a lot more accurate results than the ones from location 4, simply due to the greatly increased amount of data.

According to our hypotheses, we also expected to see a general increase in hand aperture. We could indeed confirm that, based on the video data, as it was quite visible throughout most of the trials, partly due to changing pre-grasp strategies though. Fig. 13 shows three examples of how the hand typically opens up as the object location uncertainty rises. Unfortunately, we could not measure this general behavior with the data we gathered from the tactile pressure measurement mats for the objects lying flat on the table. The sensor resolution of the mats would have been sufficient for this, but due to random noise and the mats

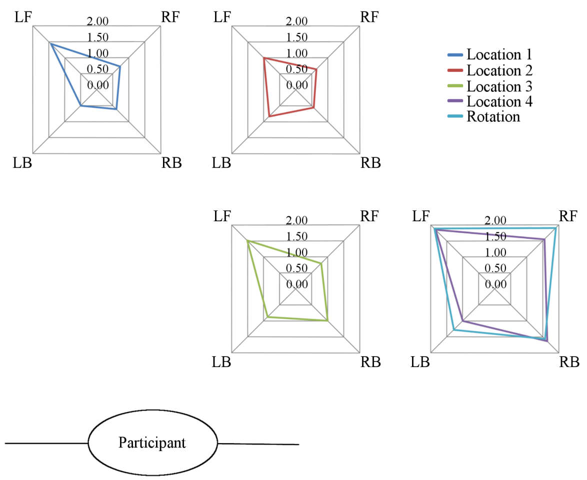

Fig. 12. Mean amount of hand corrections based on the four most used initial object rotations, oriented to the left and forward (LF) or backward (LB), or to the right and forward (RF) or backward (RB).

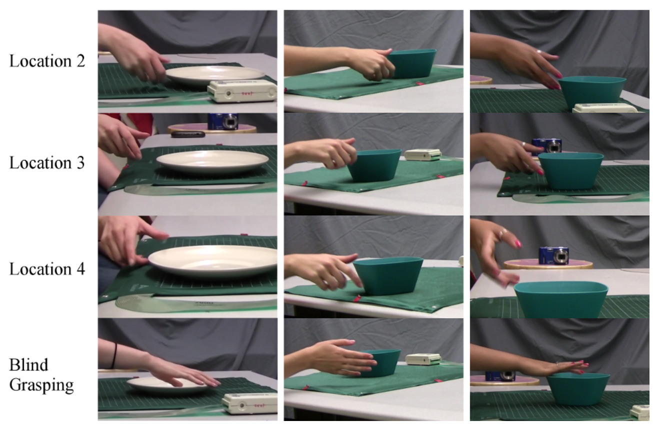

Fig. 13. General increase of hand aperture for three different participants.

not being very sensitive to low pressure the data was mostly unusable.

B. Subjective Results

Having analyzed the experiment data, we were also interested in comparing our results to the subjective data we had gathered from the questionnaires. We had mainly asked the participants to rate the perceived amount of object location uncertainty for location 1 to 4 with the numbers going up from 1 (low uncertainty) to 10 (high uncertainty), state with which objects they were not familiar with, and try to tell for which objects they could notice a change in their grasping strategy.

As some of the participants misunderstood how we asked the rating question and obviously swapped low with high uncertainty, we had to correct the answers of 5 participants by mirroring them. The mean ratings did confirm our experimental setup to be working as intended, with the amount of uncertainty increasing only slowly for the different locations: the rating goes up from a 2.7 for location 1 to a 6.4 for location 4 (Fig. 14). We also conducted multiple ANOVA tests to see if being familiar with an object or the perception of a change in pre-grasp strategy had a statistically significant impact on grasp completion time or amount of hand corrections, but without avail.

V. ROBOT EXPERIMENTS

The robot setup we used for our evaluation is a 15-DOF dual-arm Motoman SDA10 industrial robot with a Shadow Dexterous Hand mounted on the right arm, as to be seen in Fig. 15. Hence, only 7 DOF of the SDA10 robot had to be considered. The Shadow Hand is an anthropomorphic five-finger robot hand resembling a typical human right hand in size and is actuated by antagonistic pneumatic muscles in the forearm offering 24 DOF. To move both robots together we use a framework based on the Robot Operating System (ROS), with the ROS master running on an Intel Pentium 4 processor at 3.60 GHz and having seperate controllers for the Motoman arm and the Shadow Hand.

As a proof of concept we translated our findings from human observation to this robot setup based on grasping a simple object in cuboid form (10.16 cm x 5.08 cm x 2.79 cm). The two pre-grasp strategies most prominently observable were a direct grasp approach when dealing with low uncertainty and switching to tapping in case of increasing uncertainty. To evaluate the effectiveness of that human-inspired change in pre-grasp strategy based on the amount of uncertainty, we compared overall grasp success, grasp completion time, and amount of hand corrections for both strategies. As our system does not have any visual sensors, we had to artificially impact the object location uncertainty. Low would relate to the object being at a fixed position, which is known before grasp execution (center location). To increase uncertainty to a medium level, we would move the object one time its width, 5.08 cm, along one axis (left, right, forward, backward) and increasing it even further to a high level by moving the cuboid 5.08 cm on two axes (left and forward or backward, right and forward or backward). As a result we got nine different test cases for comparing both strategies.

Implementation of the direct grasp strategy was done via an open-loop control, sending explicit joint angles to arm and hand controller for several key poses of the grasp. We obtained the joint angles by manually grasping the object at the center location using an Apple iPad and the multi-touch interface for dexterous telemanipulation presented in [40], which relies on a TUIO-based finger tracker application to

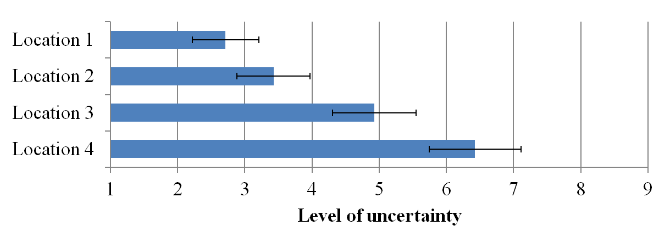

Fig. 14. Mean ratings of the participants' perceived amount of object location uncertainty and standard error of the mean.

map finger movement to the Shadow Hand. In the process we got a quite natural arm and hand movement and could identify important poses for the grasp: start position, moving over the block, bending the fingers, moving down, closing the fingers and lifting the object. We then used this series of poses to repeatedly execute the exact same grasp for all our nine test cases several times. Our simple, direct grasp strategy was always successful at the center position, could by chance grasp the object when it was moved backwards, and failed in all seven other cases. Mean grasp completion time was 11.0 s and amount of hand corrections was fixed at 0 by design.

To implement the tapping strategy we used a closed-loop control, relying solely on the hall effect sensors of the Shadow Hand to accurately and constantly measure the values of the finger joints with a resolution of 0.2 degrees and the discrepancy to the current target value. Starting in the same pose as the direct grasp with all fingers straight, we moved the hand by only using the Motoman arm. We then conducted several tapping movements while adjusting the hand position based on the finger joint sensor readings. In case no contact was made or only the middle finger, ring finger, or the fingertips hit the object, the hand was moved slightly forwards. If only one or two fingers on one side of the hand made contact, the hand position was corrected accordingly to the left or right. This strategy for the corrections resembles approximately what we could observe during our human subject experiment. The process of adjusting the hand position was continually repeated until an appropriate position was found to grasp the object. This was determined by a distinct deviation of the wrist joint values corresponding to a dorsiflexion of the hand caused by the palm making full contact with the object. In this case a grasp attempt was executed, similar to the one used for the direct approach. We could show that the success rate for our tapping strategy compared to the direct grasp was significantly higher when dealing with increased uncertainty. We could repeatedly execute successful grasps for eight out of the nine test cases while maintaining an average of only 1.75 hand corrections per trial, which is comparable to the ones of humans with 1.44 (location 4) or 1.63 (rotation).

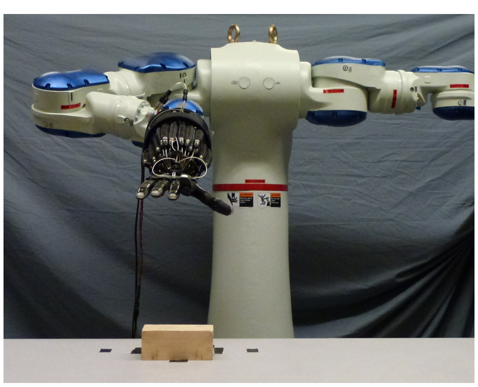

Fig. 15. Overview of our robot experiment setup with the object being placed on the table in front of the robot (in this case in the center position).

Mean grasp completion time increased with 48.8 s a lot more compared to the direct grasp, which is about four times as high, but that was partly due to slower hand movement and security stops during the tapping to avoid any damage to the hardware. Please also refer to the accompanying video for a comparison between both strategies executed by a human and by the robot.

It should be noted that during our experiments we had some issues with the Shadow Hand, such as the overbent first joint of the index finger as to be seen in Fig. 15, but that did not impact our results any further.

VI. DISCUSSION AND FUTURE WORK

We have presented the insight we have gotten from our experiments into human pre-grasp strategies and changes applied to them when dealing with uncertainty. We observed that people tend to reuse their same strategy as often as possible, only changing it when being forced to by a high amount of object location uncertainty. Through our analysis we found that main task parameters, such as grasp completion time and amount of hand corrections, significantly increase in case of high uncertainty, which relates to the underlying change of pre-grasp strategy. We could already show that applying our findings from human observation to our robot setup substantially helped when considering object location uncertainty for robotic grasping.

During the human subject experiments we could also see that some pre-grasp strategies were used more often for specific objects. Sensing played a considerably more important role when participants were asked to grasp one of the objects for which the initial orientation was not easily visible, most notably the jug, the iron, and the hammer. We believe that the choice of applied strategy relies on several factors, with object location uncertainty being only one among them. Further investigation of the additional impact of object size, shape, or grasp history remains to be done. Even though tapping seems to be the by far most used strategy for high uncertainty due to working reliably well, getting more information about the whole set of human pre-grasp strategies and understanding the different factors involved in choosing a specific one to apply, seems to be a valueable direction of subsequent research.

Regarding future work we suggest several improvements to the experimental setup we used. During our analysis we found that the obtained values for grasp completion time were not as distinctive as expected. We believe that having a fixed hand start position for all participants could help with making the overall trend more visible. Furthermore, improving the setup to account for the changing relative object rotation and varying distance to the start position would surely be of help. An interesting idea is also to find different ways of controlling the amount of uncertainty other than moving the target objects into peripheral view. Possible alternatives could be limiting stereoscopic vision or varying the illumination. Additional improvements include using high-speed cameras to ensure a better quality of the visual data and finding a way to reliably measure hand aperture while maintaining an unobtrusive setup. Overall we could already show with our rather small grasp sample size the usefulness of applying human pre-grasp strategies based on the amount of uncertainty and getting even more data by considering other objects and additional participants should make this approach even more viable.

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