Force Control During the Precision Grip Translates to Virtual Reality

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Abstract— **When grasping and manipulating objects we implicitly adapt grip forces according to the physical parameters of the object. We integrate visual, cutaneous, and force feedback to estimate these parameters and adapt our control accordingly. Using virtual reality, both feedback integration and control can be investigated in ways that are not possible using real-life objects. Here, we present our custom-built virtual reality setup and show its validity for use in human studies of fine motor control. Participants grasped and lifted virtual objects with different weights. We show that, consistent with lifting real objects, all participants adapt their grip forces to the object mass, and do so on a trial-by-trial basis. Compared to similar studies with real objects and full feedback, grip forces were increased, and adaptation required more trials. This study successfully demonstrated that grip force control in the precision grip translates to virtual reality. While our setup can be used for similar work in the future, subsequent virtual reality experiments should include a longer adaptation phase compared to classic setups.**

I. INTRODUCTION

Grasping and manipulating objects are essential skills in everyday life. When interacting with novel objects we are able to adapt our predictive and feedback control of grip force (GF) according to the physical properties of the object [1]. The adaptation of predictive components occurs on a trial-by-trial basis while feedback control is achieved during a movement.

Rapid development of virtual reality (VR) tools is leading to an increasing popularity of setups using this technology researching strategies of the sensorimotor system. While setups using this technology offer a plethora of opportunities to investigate different aspects of human motor control (e.g. [2]), users' experience does not resemble the real world. For example, without the use of VR glasses, the participant's view of a scene is limited to 2D. Further, a delay and potential asynchronies in provided feedback modalities can lead to a distorted perception [3].

We built a VR setup including haptic robots that provided position and force feedback and a 2D monitor-mirror system. In order to use such a setup to investigate the sensorimotor system, we must first verify that motor behaviour in grasping of physical objects translates to the virtual environment. In [4] we showed that participants were able to predictively adjust digit positions and fingertip forces to compensate for torques in an inverted T-shaped object. Here, we chose to investigate the grip force adaptation to objects of different weight, as initially presented in [5]. Further, we investigated whether trial-by-trial adaptation of several metrics could be extended to grasping in our system.

In the present study, to validate our own setup we show that (A) participants apply a static grip force proportional to the object weight and (B) adapt to new object properties on a trial-by-trial basis.

II. METHODS

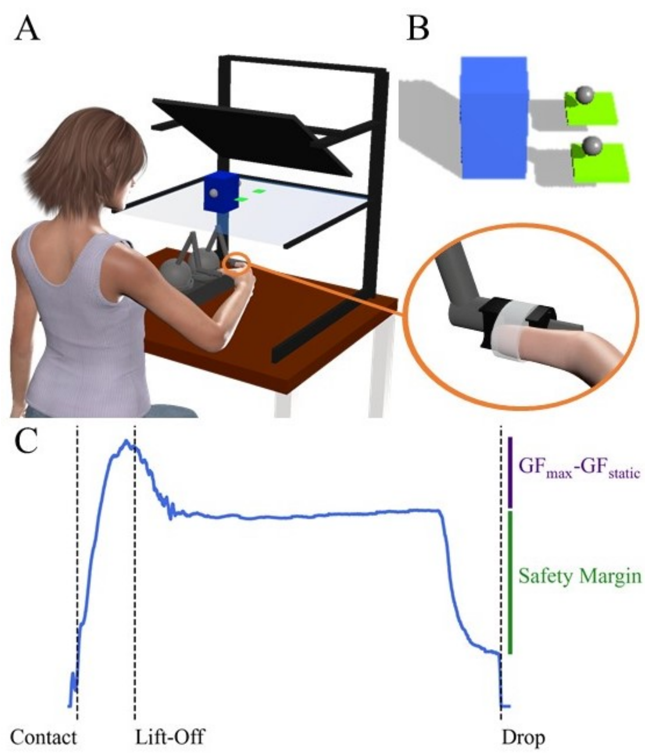

Fig. 1. Experimental Setup. A) Two haptic robots are connected to the participant's index and thumb, while a monitor and mirror system occlude the participant's view of their hand and show visual feedback of the scene. B) Zoomed in screenshot of the virtual environment, including the blue object participants lifted, the gray spheres representing index and thumb, and green squares indicating the correct starting position for each digit. C) Typical grip force trace for one participant with vertical lines indicating the time point at which both digits were in contact with the object, object lift-off, and object drop. Green and purple bars indicate the safety margin and difference between maximum and static grip force, respectively.

A. Participants

A total of ten right-handed [6] volunteers (3 women, 7 men), aged 28 years (SD=2.6) took part in the experiment.

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All individuals reported to have normal or corrected to normal vision, no neurological disorders, and to be free of acute upper limb injuries. Participants provided written informed consent before participation. The study was approved by the institutional ethics committee of the Technical University of Munich.

B. Experimental Setup

We used a custom-built setup consisting of two haptic robots (Phantom Touch, 3D Systems, Rock Hill, USA) that provided position and force feedback, and a monitor that provided visual feedback via a mirror system. The mirror system was placed in such a way that direct visual feedback of the hand was prevented. Participants were seated in a chair with the index and thumb of the right hand connected to the robots' end-effectors with a custom, 3d-printed thimble and rigid medical tape (see Fig. 1A). Participants viewed a virtual environment, programmed using CHAI3D [7] and Open Dynamics Engine libraries [8]. In this virtual environment, the fingers' positions were visualized by two dark gray spheres, that were used to interact with different objects placed in the scene (see Fig. 1). Positions and forces in the virtual environment were sampled at 500Hz.

C. Experimental Procedure

Participants were instructed to lift and hold a virtual object, using their index and thumb and the haptic robots. Participants were instructed to move at a natural speed. The object's size was 5x5x7cm, the object stiffness was 450 N/m and the coefficient of friction was 1. The virtual object was represented as a rigid object with uniform mass distribution and its movement was not constrained.

At the beginning of each trial, two red squares appeared, marking the starting positions for each cursor, which turned green when the cursors were placed on them (see also Fig. 1B). After 0.5 seconds an auditory cue indicated the start of a trial. Participants were instructed to grip and lift and hold the object to a target height of 7cm, at which the object's color changed to green. After holding the object for 3 seconds, a second auditory cue, and a color change to red indicated the end of the trial and participants were instructed to slowly let the object slip from their fingers. The object was then replaced to the original position and participants returned to the starting position for the next trial.

Before the beginning of the experiment, 20 familiarization trials were performed in which each of four object weights was presented for five trials in a randomized order. After the familiarization trials, participants performed the full experiment which consisted of four blocks of 30 trials each. Within each block participants lifted identical objects, however, between blocks the object weight was changed. The presented weights were 86g, 136g, 186g, and 236g. The order of the blocks of different weights were presented in a pseudorandomized order counterbalanced across participants.

D. Data Analysis

Grip force and load force were calculated for each finger from the forces produced by the haptic robots and the object orientation in the virtual environment; where the grip force (GF) is the normal component of digit force with respect to the object's surface and the load force (LF) is the digit force component in line with the orientation of the object. Each of these signals was then filtered with a 10th order zero-phase butterworth filter with a cutoff frequency of 20Hz.

Using these data we then detected the maximum overall GF (GF_{max}) and LF (LF_{max}), the maximum GF ($GF_{max,bl}$) and LF before liftoff ($LF_{max,bl}$), and the static GF. Liftoff was defined as the time at which the object's position on the z-axis was greater than 3mm. The static GF was defined as the mean GF between liftoff+750ms and the time at which the object was dropped-750ms.

From these values we determined further combined variables, the safety margin defined as the difference between the static GF and the minimum GF required to not drop the object, and the difference between the GF_{max} and the static GF. Further, we calculated the ratio of $GF_{max,bl}$ divided by $LF_{max,bl}$. When comparing safety margin and the difference between GF_{static} and GF_{min} across blocks, values were normalized to the mass of the object in a block.

III. Results

Participants were expected to scale their grip forces to the object's mass. Further we expected to observe a trial-by-trial adaptation of all metrics. Across all participants, 26 trials from a total of 1200 trials had to be excluded from analysis as participants dropped the object during the hold phase. The number of rejected trials never exceeded two trials per block per participant.

A. Adaptation to Object Mass

Across participants and object masses, we observed a clear scaling of static grip forces (see Fig. 2). Despite some inter-participant variability, we could observe that all participants adapted their static GF to the object's mass (see Fig.2A). Further variability was observed within blocks for some participants, which may be introduced due to the individual order of blocks. However, the general effect was consistent and the variability disappeared when pooling data across all participants.

On average, the participants used a static GF of 3.49±0.06N, 4.03±0.05N, 4.37N±0.07N and 5.13N±0.07N for the four objects (sorted lightest to heaviest, reported values are mean and standard error of the mean) (see Fig. 2B). We fitted a linear function to the averaged data across participants (see Fig. 2B), the parameters of the fit ($y = mx + b$) were: $m = 1.07$, $b = 2.57$, $r^2 = 0.9772$.

B. Trial-by-trial adaptation

The object mass was unknown in the first trial within each block. Therefore, participants had to adapt to the new mass on a trial-by-trial basis. Across metrics, a clear adaptation occurred within the initial trials (see Fig. 3).

The ratio of $GF_{max,bl}$ and $LF_{max,bl}$ indicates the adaptation of predictive control based on previous trials as these parameters are not yet influenced by somatosensory feedback

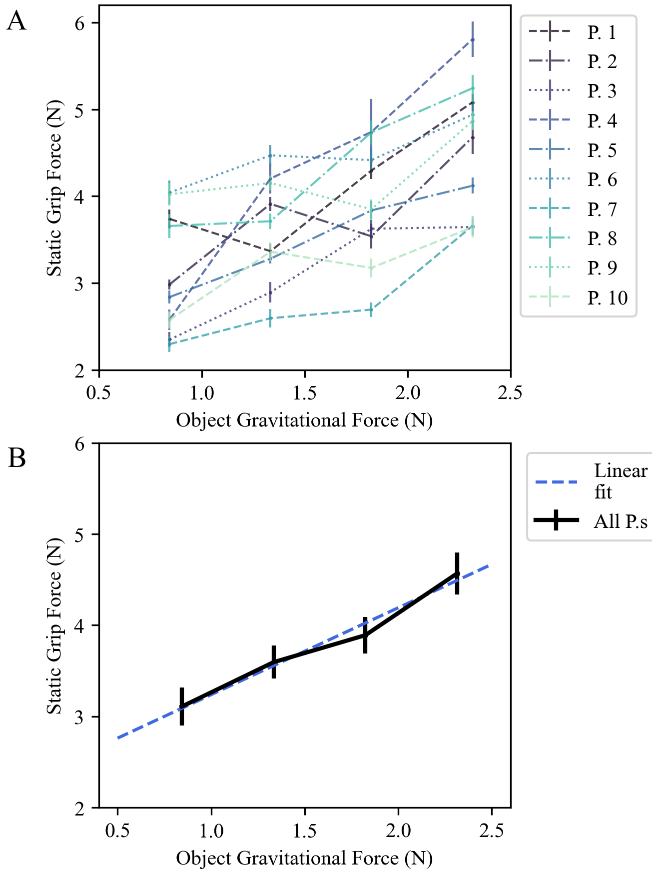

Fig. 2. Average static grip forces for all participants for all object masses. A) Data points show the mean, error bars show the standard error of the mean for all trials within a block for each participant. Each participant shows increasing static GF with increasing object mass. B) The black trace shows averaged data across all participants. The data points represent the mean, error bars the standard error of the mean across participants. The dashed blue line shows a linear fit ($y = mx + b$) to the mean data across all participants. Average static grip forces steadily increase with increasing object mass.

in the current trial. Therefore, it should decrease with adaptation across a block of trials. Averaged across participants and blocks, the values of this ratio show a clear adaptation from 2.87±0.02 (Mean±SEM) in Trial 1 to 2.56±0.02 in Trial 8 (see Fig. 3A). Afterwards, the values oscillate around this value from trial to trial, but remain below the initial value ($\min_{t9:t30}$=2.35±0.02, $\max_{t9:t30}$=2.68±0.07).

The difference between GF_{max} and static GF indicates how well the participants' prediction (GF_{max}) of the object mass matches the true object mass as estimated after an online correction process and reflected in the static GF. Therefore, we expected a decrease of this metric as the predicted mass converges to the true mass across each block of trials. As shown in Fig. 3B we observed an adaptation of this difference from 93.30±2.04% of the object's gravitational force in Trial 1 to 68.61±0.67% in Trial 5. After Trial 5, there are trial-by-trial oscillations of the metric between 54.13% and 81.37%, however, the values remain stably below the initial values. The oscillations are likely to

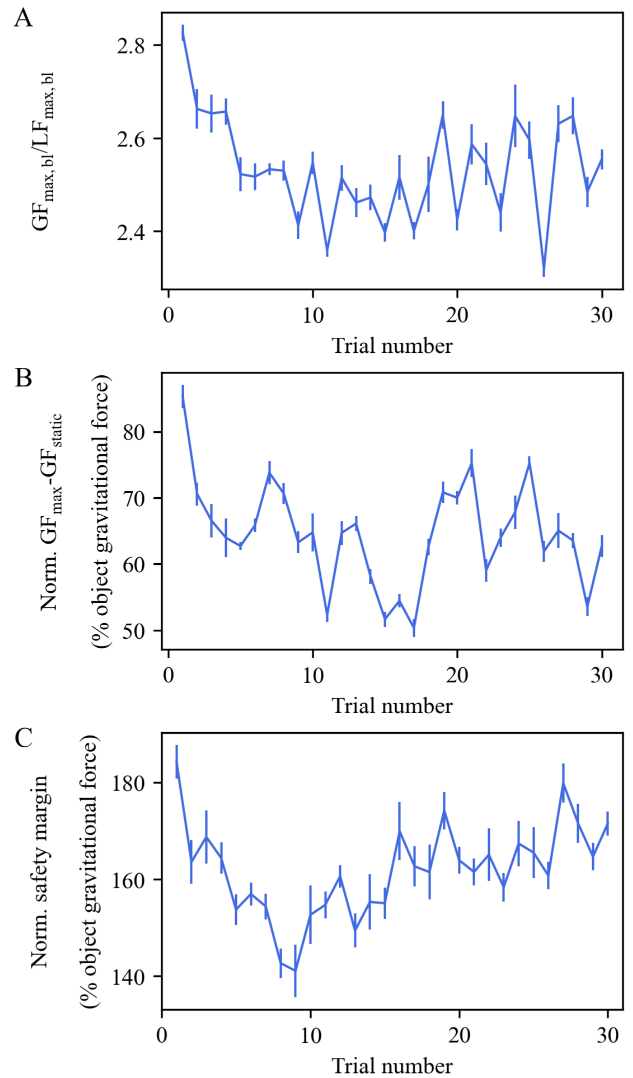

Fig. 3. Trial-by-trial adaptation metrics across all participants normalized to object mass. A) Trial-by-trial adaptation of ratio between $GF_{max,bl}$ and $LF_{max,bl}$ across all participants and blocks. B) Trial-by-trial adaptation of difference between initial maximum and static GF across all participants and blocks. Difference is normalized to object gravitational force. C) Trial-by-trial adaptation of safety margin across all participants and blocks. Safety margin is normalized to object gravitational force. All three metrics show a decrease across the initial 5-9 trials.

stem from the low number of participants and are expected to even out with more participants.

The safety margin indicates the GF participants employ on top of the minimum GF necessary to not let the object slip. Therefore, a high safety margin indicates a high uncertainty about the object properties. We expected a reduction of the safety margin across a block. Participants reduced the safety margin from 218.45±3.87% of the object's gravitational force in Trial 1 to 170.02±6.01% in Trial 9. Between Trial 10 and 15 these values remained stable within a range of 179±3.96% and 192.16±2.57%. From Trial 16, however, we could observe an increase to a maximum 213.91±4.48% in Trial 27 which came close to the initial values observed in Trial 1. While this increase was substantial, it remained stable within the last 15 trials.

IV. Discussion

The static GF generated in the virtual environment, showed that participants adapted to the object's mass in each block. Furthermore, trial-by-trial changes in the ratio of $GF_{max,bl}$ and $LF_{max,bl}$, the difference between the maximum GF and static GF and the safety margin, indicated an adaptation to the object's properties across each block of conditions.

A. Adaptation to Object Mass

As indicated by the safety margin, forces are considerably higher than those required to hold the object without letting it slip. This increase in grip force could be explained by the reduced feedback compared to real-life object manipulation, as well as the nature of the virtual object. In the virtual setup, participants are lacking tactile feedback from the fingertips that signals object contact and small slips that could be corrected to avoid object release. Reduction of tactile information through anesthesia [9] or even thin film covering of the fingertips [10] leads to a general increase of grip forces and higher safety margins.

Previous work reported lower static GF for grasping objects of similar mass with full feedback, but higher static GF for grasping objects of similar mass with local anaesthetic block of the digital nerve blocking participants' cutaneous feedback [5]. This observation is consistent when comparing the linear regression across the averaged static GF with similar measures in previous work [5]. Despite the non-existent cutaneous feedback of the object in our setup, participants were able to reduce their static grip forces to a lower value while maintaining a steady grip.

Another reason for higher grip forces are inherent technical limitations of the setup. The simulated manipulated object is not rigid, but soft. A lower object stiffness leads to an increase in grip forces.

While these factors explain the increase in GF, it is still noticeable that the simulated GF in some trials exceeded the maximum force generated by the haptic robots ($>$3.3N per robot). Therefore, in some cases participants experienced lower forces than those we recorded from the simulation. Despite this flaw, participants showed GF profiles similar to those recorded in real-life object manipulation (see Fig. 1C), therefore, the setup is valid as long as the simulated forces to not exceed the real forces by a substantial value.

B. Trial-by-trial adaptation

Within the first ten trials a clear adaptation is visible in each metric. While adaptation of the difference between maximum and static GF was comparatively fast (five trials), adaptation of $GF_{max,bl}/LF_{max,bl}$ ratio and the safety margin took longer (eight and nine trials, respectively). This is a considerably higher number than reported in similar studies using real-life objects, where one-trial learning is reported (e.g. [11]). One reason for this increased adaptation time could be the lacking familiarity with the virtual setup, therefore, when designing future studies, a high number of familiarization trials and an increased number of trials in comparison to similar studies in real-life settings should be applied.

Finally, while trial-by-trial adaptation was steady for two metrics, the average safety margin showed an increase from Trial 15. This could be attributed to fatigue [12] in later trials in a block, as previously reported in similar studies (e.g. [13]). Therefore, while increasing the number of trials within a block care must be taken to include sufficient time for resting between experimental conditions.

C. Summary

In this article, we showed that participants exhibit motor behaviour comparable to that grasping real-life objects. We demonstrated that participants (A) applied static grip forces according to the object mass and (B) adapted to new properties on a trial-by-trial basis. While the resulting GF and trial-by-trial adaptation were not identical to real-life experiments, the observed trends were equivalent. These insights will help us in designing future experiments according to the specific observations made in this study.

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