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Using Position Dependent Damping Forces around Reaching Targets for Transporting Heavy Objects: A Fitts' Law Approach

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Abstract— **Passive assistive devices that compensate gravity can reduce human effort during transportation of heavy objects. The additional reduction of inertial forces, which are still present during deceleration when using gravity compensation, could further increase movement performance in terms of accuracy and duration. This study investigated whether position dependent damping forces (PDD) around targets could assist during planar reaching movements. The PDD damping coefficient value increased linearly from 0 Ns/m to 200 Ns/m over 18 cm (long PDD) or 9 cm (short PDD). Movement performance of reaching with both PDDs was compared against damping free baseline conditions and against constant damping (40 Ns/m). Using a Fitts' like experiment design 18 subjects performed a series of reaching movements with index of difficulty: 3.5, 4.5 and 5.5 bits, and distances 18, 23 and 28 cm for all conditions. Results show that PPD reduced (compared to baseline and constant damping) movement times by more than 30% and reduced the number of target reentries, i.e. increasing reaching accuracy, by a factor of 4. Results were inconclusive about whether the long or short PDD conditions achieved better task performance, although mean human acceleration forces were higher for the short PDD, hinting at marginally faster movements. Overall, PDD is a useful haptic force to get humans to decrease their reaching movement times while increasing their targeting accuracy.**

I. Introduction

Understanding physical interaction between humans and mechatronic devices can be useful in the field of teleoperation, rehabilitation and power augmentation robotics. Shaping the interface dynamics and reflected forces when interacting with (virtual) objects (i.e. haptics) allows for task performance optimization. For example, gravity and inertia compensation can reduce physical effort during lifting tasks, and haptic shared control can increase situational awareness and task accuracy in remote transportation tasks [1]. Although interactive robotic manipulators are extremely versatile in their applications and functionality, such as the admittance controlled devices used in industry [2], they pose an inherent safety risk during physical interaction with users. Passive systems, comprised of mechanically passive elements such as springs and dampers/brakes, could be preferred over active systems for specific tasks. Advantages of passive systems include the reduced design complexity, increased inherent safety (although energy can be stored in springs), reduced (maintenance) costs, and increased mobility due to reduced weight and power demands. Examples of passive systems are the mobile Lockheed Fortis [3] in industry, the stationary rehabilitation exoskeleton Dampace [4], and the ankle-foot exoskeleton by Collins et al. [5].

Compared to active systems, the types of forces that can be generated with purely passive systems are limited. Such limitation is partially overcome in Cobot systems by scaling and changing passive dynamical properties accordingly through continuous variable transformers [6], [7].

We propose a system inspired by the Cobot systems, but for reaching-like tasks. Controlled damping forces around a reaching target (position dependent damping, or PDD) will be used to optimize a person's motion during human-machine cooperative tasks of picking and placing of heavy objects. The term 'controlled' implies the use of a physical passive element of which its dissipative properties are varied, e.g. by controlled disk brakes or varying a moment arm of a dashpot damper. The term 'optimize' implies that movements become faster and easier to perform with higher accuracy and subjective likability. A potential industrial application of PDD would be assisting cooperative transportation of heavy objects with a passive gravity compensation mechanism to a target location by a human operator, where the target is determined by range finding sensors. The PDD could then be used for faster and more accurate placement of heavy objects by the human operator.

In this study we investigated how PDD changes the human's reaching strategy and performance in terms of reaching time, accuracy and applied force during Fitts-like [8], [9] reaching tasks. Additionally, we evaluated whether Fitts' law still holds during reaching with PDD. We hypothesize that humans optimize their motions to be energy efficient [10] and will use the PDD to help them brake the reaching movement and improve reaching accuracy and therefore movement performance.

II. Background

Modeling human reaching is challenging due to nonlinear arm and muscle dynamics, high muscle redundancy and the required optimal integration of both visual and proprioceptive information [11], [12]. Fitts proposed a simple linear relationship that models speed-accuracy trade-offs in

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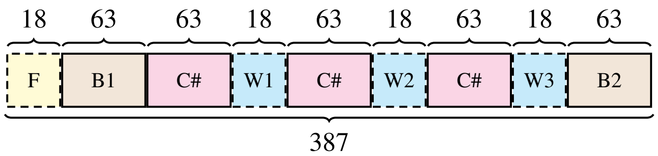

Fig. 1: Trial blocks presented to the subject. Numbers above the blocks indicate number of trial repetitions. F: Familiarization; B1: Baseline1 condition (nondamping); C1, C2 and C3: Damping condition 1–3 with specific PDD; W1, W2 and W3: Washout phase 1–3 without damping; B2: Baseline2 condition (nondamping). Dashed outlines indicate these blocks are not used for data analysis.

rapid, aimed two-way tapping [8] or one-way reaching [9] movements:

$$MT = a + b \cdot ID. \tag{1}$$

This relationship describes the movement time (MT) as a function of Index of Difficulty (ID) and two empirical coefficients a and b, which are dependent on environment properties. In [13] it is proposed to use the Shannon formulation of the ID (in bits) as a function of reaching distance D and target size/diameter W around that target:

$$ID = \log_2 \left(\frac{D}{W} + 1 \right), \tag{2}$$

which we will use in the remainder of this work.

Few studies investigated validity of Fitts' law in dissipative environments. In [14], [15] it was shown that moving underwater (a dissipative, but highly inertial environment) can be described by Fitts' law with minor modification. Further studies [16]–[18] investigated the influence of constant friction and damping on the movement times. They found that for small masses (below 2 kg) a friction force could reduce reaching times and increase accuracy in a Fitts type targeting tasks.

In contrast to the aforementioned studies, we are interested in moving heavy masses (12.5 kg, motivated by the industrial application) and in *position dependent* damping forces around the reaching target, instead of constant damping or friction forces.

III. Methods

A. Experimental Conditions

In this experiment we compared three damping conditions (C1, C2 and C3) where subjects performed reaching tasks with different damping forces. These conditions were also compared to two baseline conditions (B1 and B2) without any damping forces during the reaching task. These baselines were used to observe possible overall performance improvements during the complete experiment.

During reaching tasks in conditions C1, C2 and C3, subjects would feel different viscous damping forces F_d (in N):

$$F_d = -b(x)v, \tag{3}$$

where $b(x)$ (in Ns/m) is a damping coefficient (d.c.), possibly dependent on position x (in m) for PDD, v (in m/s) is the instantaneous velocity of the moved manipulandum. The minus sign in (3) shows that this force opposes the motion

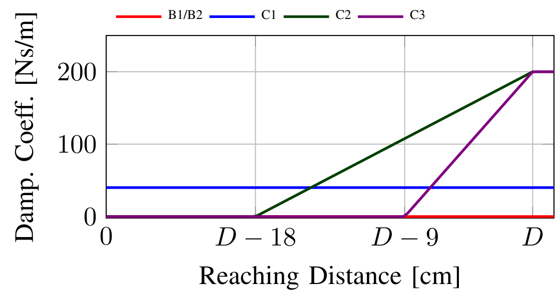

Fig. 2: Damping coefficients for each condition. Conditions B1 and B2 have zero damping coefficient. Condition C1 has a constant coefficient of 40 Ns/m. Conditions C2 and C3 increase linearly towards the target point from 0 Ns/m to 200 Ns/m.

TABLE I: Used distances (D in cm), and index of difficulty (ID in bits) result in nine combinations of target size (W in cm) per frame.

	ID [bits]		
D [cm]	3.5	4.5	5.5
18	1.75	0.83	0.41
23	2.23	1.06	0.52
28	2.71	1.29	0.63

and makes the dynamical system passive. The d.c. was dependent on conditions as shown in Fig. 2. Baselines B1 and B2 had zero d.c. Condition C1 had constant d.c. of 40 Ns/m. Conditions C2 and C3 had 0 Ns/m d.c. at the start of the movement, ramping up linearly to 200 Ns/m over a distance of 18 cm (C2) or 9 cm (C3) from the target at D. The d.c. was never lower than 0 Ns/m, nor higher than 200 Ns/m. Familiarization (F) and washouts (W1, W2 and W3) had zero d.c.

B. Experimental Protocol

After a detailed explanation of the purpose and procedure of the experiment, subjects performed a total of 378 reaching movements (i.e. trials) with a haptic manipulandum (see Sec. III-E). Of these trials, 315 were grouped over the 5 conditions, and 63 trials were used for familiarization or washout. First, 18 familiarization trials (F) were performed. Subsequently, all subjects performed the baseline1 (B1) of 63 trials without any damping forces. After B1, subjects performed, in random order, three conditions C1, C2 and

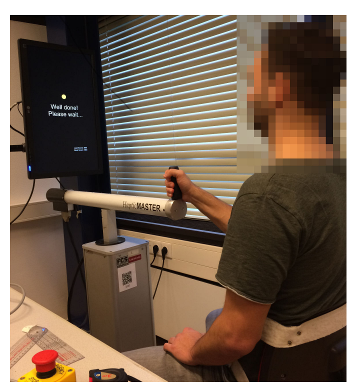

Fig. 3: A subject uses the Moog HapticMaster to move a cursor to a target shown on screen, while experiencing different kinds of damping forces.

C3, each of 63 trials. Between each condition, 18 washout trials (W1, W2 and W3) were performed to reduce learning carryover from one condition to the next. After W3, subjects performed a second baseline (B2) of 63 trials.

Target reaching distance D was chosen to lie within the reachable workspace of the human arm and the used manipulandum, and to have a large spread, with reasonable target sizes. The chosen ID values were based on the fact that below ID=3.5 movements are ballistic and possibly without visual feedback, although literature disagrees on whether this happens at this ID value. Above ID=5.5 the ID makes the targets too small to assume Fitts' law is valid for this experiment when showing the target on screen [19], [20]. We chose three different ID values (3.5, 4.5 and 5.5 bits) to be able to better observe linearity when fitting the data with (1).

Combinations of three values for D and three values for ID give nine values for W according to (2), as shown in Table I. These nine combinations, which together we call a 'frame', were presented in random order. Washout and familiarization blocks consisted of two frames, while the five conditions consisted of seven frames.

C. Subject Instruction

Subjects were instructed to move a cursor (which was set to emulate 12.5 kg, unknown to the subject) from a starting position to a target position in front of them using a manipulandum (see Sec. III-E). This reaching motion was done at shoulder height, in front of the sternum while moving straight forward.

The cursor and target were represented as a yellow and magenta circle respectively on a computer screen. The subjects had to perform the task as fast and accurately as possible and stay for 500 ms (dwell time) inside the target. Subjects were motivated to improve their reaching time by an on-screen score that was calculated from the movement time and ID.

At the start of a trial, the text 'Go!' would appear on screen after a random amount of time. This strategy was chosen to avoid anticipation of this starting event. After seeing this phrase, the subject would be able to move the handle to the target on screen. If the subject would push the handle before the starting event, the screen would turn red, the manipulandum would not move, and the random count-down would restart. After the subject stayed in the target for the required dwell time, the manipulandum would automatically move back to a fixed 'home' position and stay there until the start of the next trial.

Subjects were told when a wash-out or change of condition would happen, and they could take breaks before washouts and after B1.

D. Participants

A total of 18 age matched healthy right-handed male subjects aged 24.4±2.8 (mean±sd) years of age participated in this study. They were unaware of the aim of the experiment.

The Ethics Committee of the Vrije Universiteit of Amsterdam approved the study design, protocols and procedures, and informed consent was obtained from each subject.

E. Set-up

The used experimental set-up is shown in Fig. 3. Subjects were fixated in a chair by velcro straps to avoid compensatory trunk and shoulder movements. The one dimensional reaching movements are made on a Moog HapticMaster: an admittance controlled haptic device to emulate inertia and damping forces [21]. A computer monitor at a distance of approximately 1.5 meters from the subject showed the cursor, a target and instructive or motivational text (e.g. 'Please Wait'). The image size on screen was scaled to match the real-world movement distances and target sizes. The HapticMaster communicated with a Windows 10 operated laptop, over TCP/IP at a sample frequency between 800 Hz and 1000 Hz. This communication was used to set damper parameters and log relevant data. This software, which included the visualization, was created in Visual Studio C$^{\#}$ 2013 Community (Microsoft, 2013).

The positioning of the subject was defined such that for the largest D, the elbow extension was at most 140°. This avoided the use of the singularity of the arm to stop the reaching motion.

Safety of the subjects was guaranteed by proper positioning of the device such that they could never be hit or obstructed by it. Subjects could let go off the handle at any time. The device was equipped with an emergency stop button that could be pressed by either the researcher or the subject.

F. Performance Metrics and Data Analysis

Movement performance was evaluated in terms of movement time (MT), mean human acceleration force during a trial, mean human deceleration force during a trial, and mean damper force during a trial. The MT was determined a posteriori by 1) taking as the start of the movement the time instant when the subject would move faster than 2% of his maximal velocity during that trial (to remove reaction time offset) [22], [23], 2) removing the dwell time of 500 ms at the end of the movement time [24], [25].

Task accuracy was determined by counting the number of times the cursor reentered the target before the trial was accepted. A value higher than zero indicated that the cursor had exited the target and had to be moved back.

Since we are interested in steady-state performance only, we analyzed the last 27 trials (the last three frames) per condition. We ignore the first 36 trials, and assumed it would take that long to reach a performance plateau. This assumption was based on a pilot study performed with 12 subjects. Additionally, this assumption has been validated in the current study, as shown in Fig. 7.

Statistical analyses were performed between conditions, for each ID, and to determine whether a performance plateau was reached. Measurement data was fitted to Fitts' law (1) and (2) for each condition, using a linear least squares

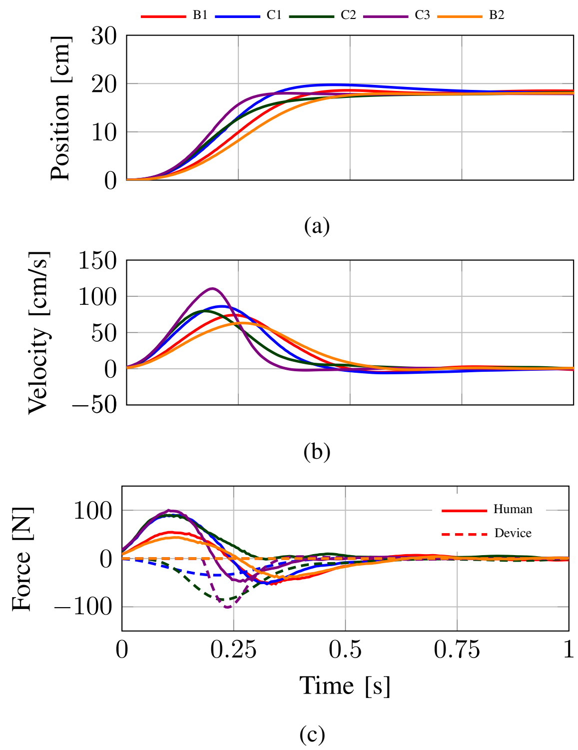

Fig. 4: Typical reaching movements from a single subject, moving to a target at D=18 cm, with ID=5.5 bits, within the last frame of all conditions. a) Position b) Velocity c) Force data from the human (solid) and the damper (dashed).

method. Familiarization and washout blocks were not analyzed.

As the data for all metrics was not normally distributed, the most appropriate statistical test was a Friedman test with a post-hoc Wilcoxon signed-rank test with Bonferroni correction on the significance threshold for 10 pair-wise comparisons.

IV. Results

A. Typical Movement Profiles

Figure 4 shows typical reaching movements from a single subject, moving to a target at D=18 cm, with ID=5.5 bits, within the last frame of all conditions. It is noted that all damping conditions (C1, C2 and C3) have a steeper slope (i.e. higher velocity) than the baselines (B1 and B2). Furthermore, for baseline movements the human force profile is very symmetrical, although this is not the case for the damping conditions (especially not for C2).

TABLE II: Regression parameters. Coefficient r_m is the regression coefficient for taking the mean MT per subject for that ID and condition. Coefficient r_a is the regression coefficient for taking all MT from a subject for that ID and condition.

	a [s]	b [s/bits]	r_m	r_a
B1	-0.3180	0.2686	0.8882	0.6218
C1	-0.0952	0.1858	0.8644	0.5979
C2	-0.1938	0.1730	0.8636	0.6299
C3	-0.1881	0.1599	0.8753	0.5460
B2	-0.3498	0.2568	0.8961	0.6304

B. Relationship between ID and MT

The ID and MT showed a linear relationship for all conditions (see Table II and Fig. 5). Using only the mean value per subject (averaging 9 movements per ID per condition into 1 value) resulted in regression coefficient r_m around 0.875. Taking all 9 values per subject, per ID, per condition lead to the same intercept and slope (a and b in (1)) but lower regression coefficient r_a around 0.55.

C. Within Subject Comparisons

1) Movement Times: For *all* ID values, there was a significant change in movement time between condition, ($p < 0.0005$, nDOF=4, $\chi^2_{ID=3.5} = 48.44$, $\chi^2_{ID=4.5} = 50.04$, $\chi^2_{ID=5.5} = 57.47$). Post-hoc analysis (see Fig. 6a–c) showed that for ID=3.5 the mean MT was significantly different for all conditions except for B1-B2, B1-C1 and C1-B2. For ID=4.5 the mean MT was significantly different for all conditions except for B1-B2, C2-C3 and C1-B2. For ID=5.5 the mean MT was significantly different for all conditions, except B1-B2 and C2-C3.

To investigate learning effects, we also took the mean MT per frame, resulting in 7 values per condition, and averaged over these means for 18 subjects. This gave an overall 'learning curve', as shown in Fig. 7. For all conditions the MT did not change significantly in the last three frames. This result validates the assumption that a performance plateau was reached in the last 27 trials.

2) Forces: Mean human acceleration forces, and human and device deceleration forces are shown in Fig. 6d–f. For *all* ID values, there was a significant change in mean human acceleration force from the subject between conditions, ($p < 0.0005$, nDOF=4, $\chi^2_{ID=3.5} = 48.22$, $\chi^2_{ID=4.5} = 53.29$, $\chi^2_{ID=5.5} = 55.47$). Mean human acceleration force was not significantly different (n.s.d) between C1-C3 and C2-C3 for all IDs, and n.s.d. for C1-C2 for ID=3.5 bits. For *all* ID values, there was a significant change in mean human deceleration force from the subject versus condition, ($p < 0.0005$, nDOF=4, $\chi^2_{ID=3.5} = 61.387$, $\chi^2_{ID=4.5} = 56.22$, $\chi^2_{ID=5.5} = 55.42$). Mean human deceleration force was n.s.d. for B1-C3 and C1-C3 for all IDs, and n.s.d. for B1-C1 for ID=4.5 and 5.5 bits. For *all* ID values, there was a significant change in maximal deceleration force form the device versus condition, ($p < 0.0005$, nDOF=4, $\chi^2_{ID=3.5} = 28.78$, $\chi^2_{ID=4.5} = 29.78$, $\chi^2_{ID=5.5} = 32.44$). Post-hoc analysis showed that all damping conditions had significantly different mean damping forces.

3) Reaching Accuracy: For *all* ID values, there was a significant change in reaching accuracy between conditions, ($p < 0.0005$, nDOF=4, $\chi^2_{ID=3.5} = 51$, $\chi^2_{ID=4.5} = 55.52$, $\chi^2_{ID=5.5} = 57.47$). Post-hoc analysis showed that for all IDs there was no significant difference (n.s.d.) between C2-C3 and between B1-B2. For ID=4.5 there was n.s.d. between C1-C3 and for ID=3.5 there was n.s.d. between C1-B2. For ID=3.5 and ID=4.5 there was n.s.d. between B1-C2. All other pairwise comparisons were significantly different, $p \leq 0.001$.

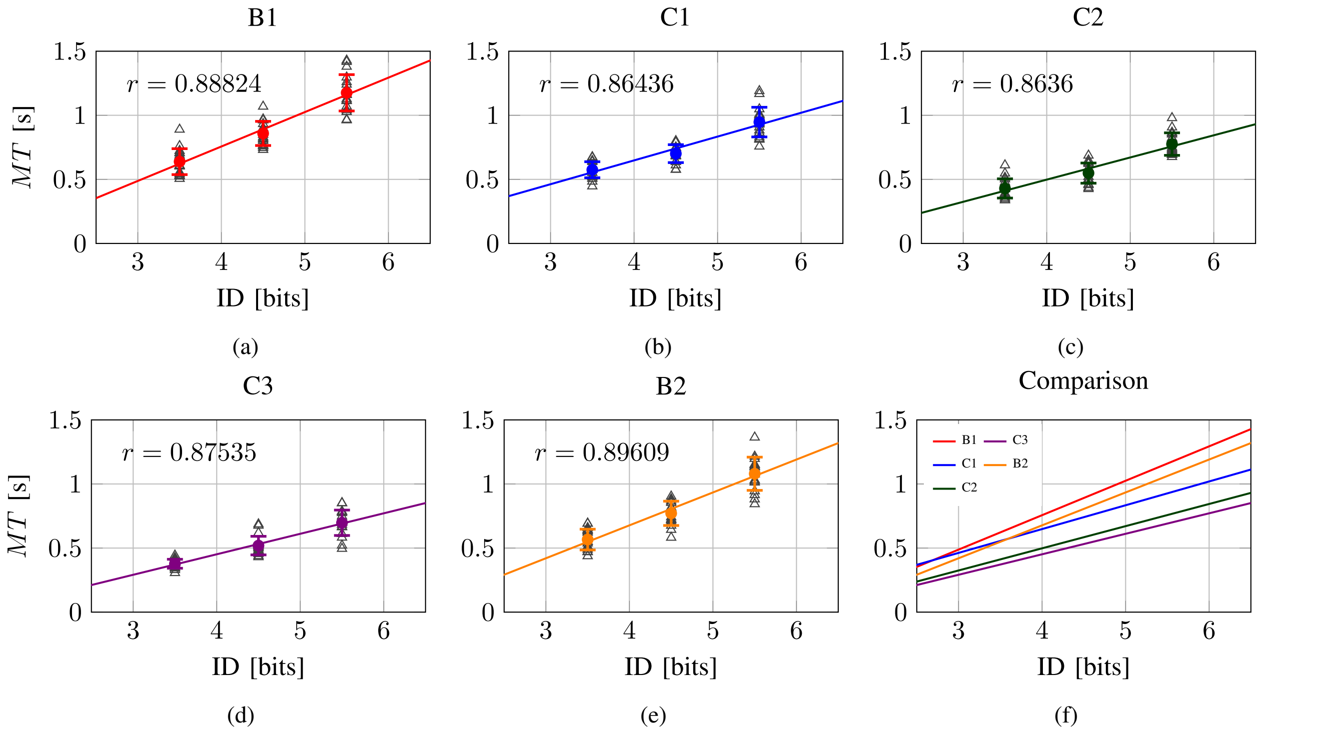

Fig. 5: Linear regression of ID in bits versus movement time MT in s. a–e) Regression of conditions B1, C1, C2, C3 and B2. The mean per subject for that ID and condition are shown as grey triangles. The mean over all 18 subjects is shown as a solid circle. The error bars indicate 1 standard deviation from the mean in both directions. f) Comparison of regressions for all conditions, showing lower slope (b) and overall lower MT for conditions C2 and C3, compared to the other conditions.

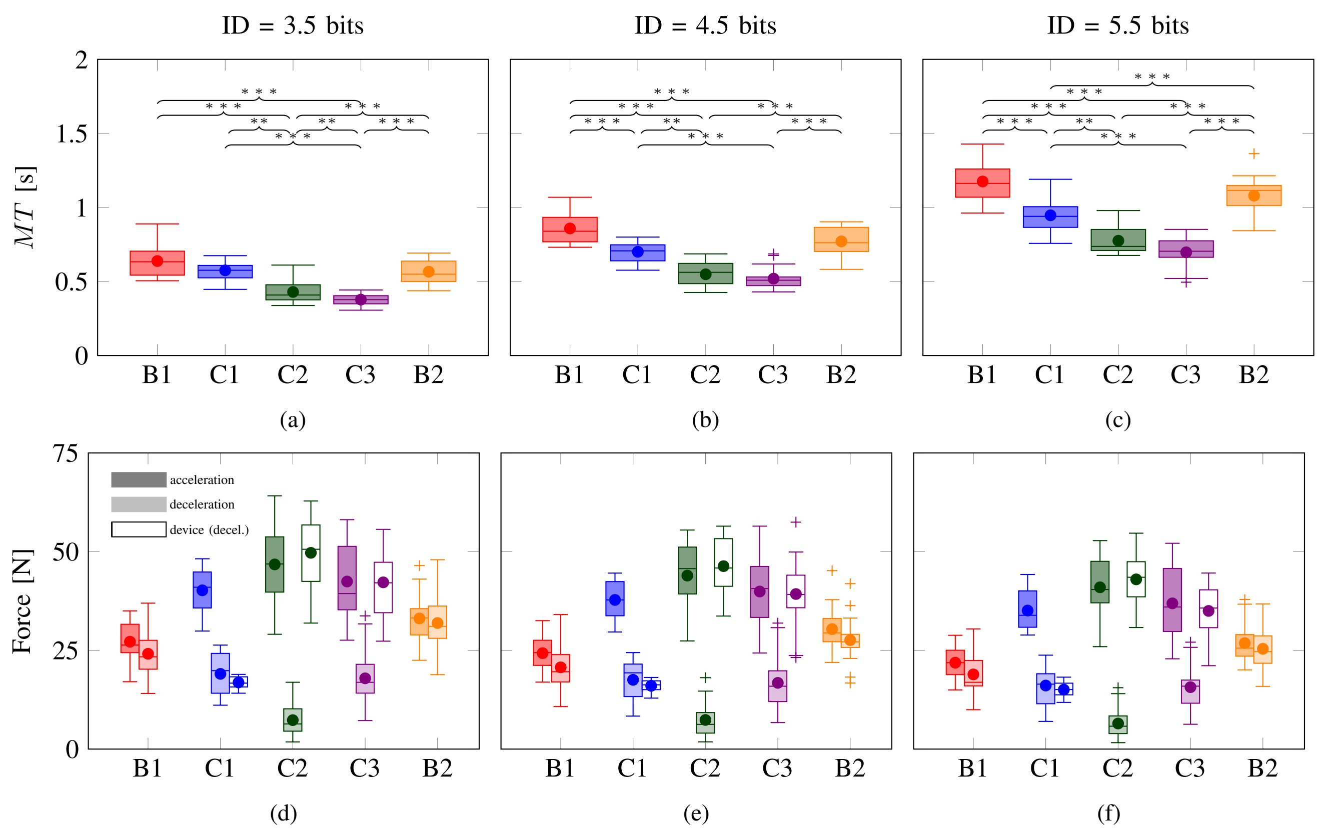

Fig. 6: Movement statistics. a–c) Movement Time MT. Statistical differences are only investigated between conditions and not between ID. Note that: $^{(**)}p \leq 0.001$, $^{(***)}p \leq 0.0005$, and corrected significance threshold $\alpha = 0.005$. d–f) Modulus of mean acceleration force (left) and mean deceleration force (light colored, center) and mean device deceleration force (filled white, right) during a trial. For B1 and B2, there was no damper force from the device.

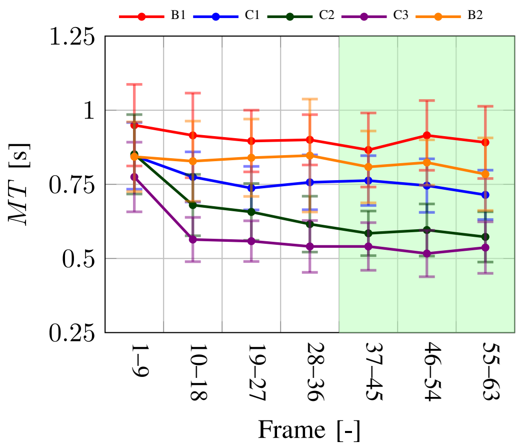

Fig. 7: Learning curves showing the mean MT per frame. The shaded green area highlights the last three frames that are taken for data analysis. A performance plateau is assumed to be reached in the last three frames.

For ID=3.5 the PDD C2 and C3 had an average of 0.04 target reentries, versus 0.40 for B1 and B2 and 0.29 for C1. For ID=4.5 the PDD C2 and C3 had an average of 0.19 target reentries, versus 0.69 for B1 and B2 and 0.48 for C1. For ID=5.5 the PDD C2 and C3 had an average of 0.42 extra target reentries, versus 1.3 for B1 and B2 and 0.9 for C1.

V. Discussion

A. Metric Comparisons

Using PDD to move 12.5 kg objects reduced movement times for almost all IDs by almost 40%, compared to nondamping baselines. Constant damping also reduced reaching times, as expected from results presented in [16]–[18], albeit not as much as PDD did. PDD also improved reaching accuracy. Subjects required fewer target reentries during PDD conditions than during baseline and constant damping conditions, with a reduction factor of almost 4. PDD also resulted in a lower spread in movement times, compared to baselines and constant damping, resulting in a more consistent motion. Acceleration forces are higher for PDD than for constant damping and nondamping baselines, although human deceleration forces become lower.

B. Movement Strategies

Movement profiles for baseline movements mostly resemble minimum-jerk trajectories with bell-shaped velocity profiles. These reaching movement trajectories have smooth accelerations and decelerations minimize endpoint error in the presence of signal-dependent noise [26]. The addition of PDD makes the velocity profile asymmetrical, with higher average human acceleration forces (increase of almost 100%) in the acceleration phase of the movement, compared to baselines.

Human information processing proceeds by a series of essentially independent steps. In [27] it is suggested that two separate controlling processes are involved during reaching; first an acceleration phase and afterwards a fine-tuning phase. This could explain why PDD is successful in increasing accuracy (or for the same accuracy in reducing movement time), since it assists during the fine-tuning phase. This could also explain that constant damping hinders the acceleration phase, making C1 reaching times almost 30% slower than C2 and C3. For increasing ID, both acceleration and deceleration forces seem to decrease for all conditions. Possibly, a more cautious strategy is adopted when targets appear far away or are of smaller sizes.

To reduce reaching times with a passive system, higher forces are required for faster accelerations and decelerations. Since faster movements will have a higher mean and peak velocity, the expended net energy by the subject to perform this movement has increased. Condition C2 has the highest average acceleration forces (energy added) and lowest deceleration forces (energy extracted) by the subjects, out of all conditions. The energy added during condition C3 seems lower than for C2, and more energy is extracted by the subject. However, movement times were not significantly different between C2 and C3 for higher IDs.

C. Fitts' Law

Fitts' law seems to hold for PDD, when comparing regression coefficients with baseline. The found regression coefficients are slightly lower when compared to literature (0.875 versus 0.95). In literature, different methods for determining the movement time in Fitts-like experiments are used; button pushes, tapping, the application of pressure on a surface or the usage of dwell time are common options. Compared to tapping and pressing, the usage of dwell time might have increased the timing spread, and therefore might have reduced the regression coefficient.

PDD and constant damping have faster movement times than no-damping baselines. The decrease in MT between B1 and B2 conditions was minimal and not significant, from which we conclude no overall significant effect of learning over the complete experiment. For baseline and damper conditions the regression only differs in intercept a (in s) and not in slope. The slope (b in s/bits) of Fitts' law is reciprocally related to the index of performance, or information transmission rate, during the reaching motion. For both baselines (B1 and B2) the slope is the same. The slope is also the same for all three damping conditions (C1, C2 and C3), but lower than baseline. From an information theoretical perspective, it is tempting to state that with any damping force more information was transferred per unit time to the subject to perform the motion. As discussed in [13], the fundamental interpretation of this information channel is not straightforward for human reaching. Future work will focus on investigating why this grouping in slope occurs.

D. Position Dependency of the Damping Coefficient

In this experiment, the d.c. was either constant (C1), or linearly increasing from different distances (C2 and C3). We picked the linearly increasing d.c., starting at different locations, to be able to control the influence of starting location (onset).

Different 'shapes' other than linear could have been used with later onset, monotonically increasing nonlinear, steeper and possibly exponential increase. If we would have used an exponentially increasing d.c., we cannot investigate the influence of onset versus shape; since it behaves like a d.c. that is zero over a long range and suddenly increases rapidly. Furthermore, a linearly increasing d.c. answers the current research questions properly.

From experience we know that rapidly increasing d.c. shapes work well, but too high gradient and too high value (e.g. a brick wall effect) reduces subjective likability. Optimizing the shape of the d.c. is an aspect we will look into in future work.

VI. Conclusion

Results show that PPD reduced (compared to baseline and constant damping) movement times by more than 30% and reduced the number of target reentries, i.e. increasing reaching accuracy, by a factor of 4. The results are inconclusive about whether the 18 cm ramp (C2) or 9 cm ramp (C3) in damping coefficient performs better in terms of accuracy and movement time. Force profiles hint at a marginally lower energy expenditure from the subjects in condition C2 than in C3. Both strategies exploit high accelerations during the acceleration phase, and assisted deceleration of the movement to reduce overall reaching time. Results indicate that PDD is a useful haptic force to get humans to decrease their reaching movement times, while increasing their targeting accuracy.

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References

[1] J. van Oosterhout, J. G. Wildenbeest, H. Boessenkool, C. J. Heemskerk, M. R. de Baar, F. C. van der Helm, and D. A. Abbink, "Haptic shared control in tele-manipulation: Effects of inaccuracies in guidance on task execution," *Haptics, IEEE Transactions on*, vol. 8, no. 2, pp. 164–175, 2015.

[2] A. Lecours, B. Mayer-St-Onge, and C. Gosselin, "Variable admittance control of a four-degree-of-freedom intelligent assist device," in *Robotics and Automation (ICRA), 2012 IEEE International Conference on*. IEEE, 2012, pp. 3903–3908.

[3] Lockheed Martin, "FORTIS Exoskeleton," http://www.lockheedmartin.com/us/products/exoskeleton/FORTIS.html, 2016, [Online; accessed 1-March-2016].

[4] A. H. Stienen, E. E. Hekman, F. C. Van der Helm, G. B. Prange, M. J. Jannink, A. M. Aalsma, and H. Van der Kooij, "Dampace: dynamic force-coordination trainer for the upper extremities," in *Rehabilitation Robotics, 2007. ICORR 2007. IEEE 10th International Conference on*. IEEE, 2007, pp. 820–826.

[5] S. H. Collins, M. B. Wiggin, and G. S. Sawicki, "Reducing the energy cost of human walking using an unpowered exoskeleton," *Nature*, vol. 522, no. 7555, pp. 212–215, 2015.

[6] E. L. Faulring, J. E. Colgate, and M. A. Peshkin, "A high performance 6-dof haptic cobot," in *Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference on*, vol. 2. IEEE, 2004, pp. 1980–1985.

[7] E. L. Faulring, K. M. Lynch, J. E. Colgate, and M. A. Peshkin, "Haptic display of constrained dynamic systems via admittance displays," *Robotics, IEEE Transactions on*, vol. 23, no. 1, pp. 101–111, 2007.

[8] P. M. Fitts, "The information capacity of the human motor system in controlling the amplitude of movement." *Journal of experimental psychology*, vol. 47, no. 6, p. 381, 1954.

[9] P. M. Fitts and J. R. Peterson, "Information capacity of discrete motor responses." *Journal of experimental psychology*, vol. 67, no. 2, p. 103, 1964.

[10] E. Todorov, "Optimality principles in sensorimotor control," *Nature neuroscience*, vol. 7, no. 9, pp. 907–915, 2004.

[11] P.-M. Bernier, R. Chua, C. Bard, and I. M. Franks, "Updating of an internal model without proprioception: a deafferentation study," *Neuroreport*, vol. 17, no. 13, pp. 1421–1425, 2006.

[12] D. W. F. Etienne Burdet and T. E. Milner, *Human Robotics*. The MIT Press, 2006.

[13] R. W. Soukoreff and I. S. MacKenzie, "Towards a standard for pointing device evaluation, perspectives on 27 years of Fitts' law research in HCI," *International journal of human-computer studies*, vol. 61, no. 6, pp. 751–789, 2004.

[14] R. Kerr, "Movement time in an underwater environment," *Journal of Motor Behavior*, vol. 5, no. 3, pp. 175–178, 1973.

[15] ——, "Diving, adaptation, and Fitts law," *Journal of Motor Behavior*, vol. 10, no. 4, pp. 255–260, 1978.

[16] C. Richard and M. Cutkosky, "The effects of real and computer generated friction on human performance in a targeting task," in *Proceedings of the ASME Dynamic Systems and Control Division*, vol. 69, 2000, p. 2.

[17] P. Berkelman and J. Ma, "Effects of friction parameters on completion times for sustained planar positioning tasks with a haptic interface," in *Intelligent Robots and Systems, 2006 IEEE/RSJ International Conference on*. IEEE, 2006, pp. 1115–1120.

[18] K. Crommentuijn and D. J. Hermes, "The effect of coulomb friction in a haptic interface on positioning performance," in *Haptics: Generating and Perceiving Tangible Sensations*. Springer, 2010, pp. 398–405.

[19] O. Chapuis and P. Dragicevic, "Small targets: why are they so difficult to acquire," Laboratoire de Recherche en Informatique, Tech. Rep., 2008.

[20] ——, "Effects of motor scale, visual scale, and quantization on small target acquisition difficulty," *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 18, no. 3, p. 13, 2011.

[21] R. Q. Van der Linde, P. Lammertse, E. Frederiksen, and B. Ruiter, "The hapticmaster, a new high-performance haptic interface," in *Proc. Eurohaptics*, 2002, pp. 1–5.

[22] R. Sainburg and D. Kalakanis, "Differences in control of limb dynamics during dominant and nondominant arm reaching," *Journal of neurophysiology*, vol. 83, no. 5, pp. 2661–2675, 2000.

[23] C. M. Glazebrook, D. Kiernan, T. N. Welsh, and L. Tremblay, "How one breaks fittss law and gets away with it: Moving further and faster involves more efficient online control," *Human movement science*, vol. 39, pp. 163–176, 2015.

[24] C. Ware and H. H. Mikaelian, "An evaluation of an eye tracker as a device for computer input," in *ACM SIGCHI Bulletin*, vol. 17, no. SI. ACM, 1987, pp. 183–188.

[25] J. P. Hansen, A. S. Johansen, D. W. Hansen, K. Itoh, and S. Mashino, "Command without a click: Dwell time typing by mouse and gaze selections," in *Proceedings of Human-Computer Interaction–INTERACT*, 2003, pp. 121–128.

[26] H. Miyamoto, E. Nakano, D. M. Wolpert, and M. Kawato, "TOPS (Task Optimization in the Presence of Signal-Dependent Noise) model," *Systems and Computers in Japan*, vol. 35, no. 11, pp. 48–58, 2004.

[27] A. Welford, A. Norris, and N. Shock, "Speed and accuracy of movement and their changes with age," *Acta psychologica*, vol. 30, pp. 3–15, 1969.