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Analysis of Human Skill Development in Manual Ramp-Tracking Tasks

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Abstract: Human modelling approaches are typically limited to feedback-only, compensatory tracking tasks. Advances in system identification techniques allow us to consider more realistic tasks that involve feedforward and even precognitive control. In this paper we study the human development of a feedforward control response while learning to accurately follow a ramp-shaped target signal in the presence of a disturbance acting on the controlled element. An experiment was conducted in which two groups of eight subjects each tracked ramps of different steepnesses in a random or ordered fashion. In addition, ordered runs were followed by a 'surprise' run with a random ramp steepness. Results show that operators learn rapidly, continue to learn during the entire experiment, and can adapt very quickly to surprise situations. Experiments involving learning operators are challenging, as it is difficult to balance-out all experimental conditions and control for inevitable differences between (groups of) subjects.

Keywords: cybernetics, manual control, skill, learning, modeling

1. INTRODUCTION

Models of human control behaviour have existed since the 1960s (Krendel and McRuer, 1960; Wasicko et al., 1966; McRuer and Jex, 1967). Research focused on compensatory tracking, where the human controller (HC) operates a dynamic system, the controlled element (CE), based on the visually presented tracking error between a quasi-random target signal and the system output. The human operator then behaves as a *feedback*-only controller which can be accurately modelled and predicted using the crossover model (McRuer and Jex, 1967).

In many real-life tasks, such as driving or flying, the target or 'reference' signal is directly observable and its future to some extent predictable, allowing the HC to activate a versatile *feedforward* control loop. This is characterized in the Successive Organization of Perception (SOP) theory (Krendel and McRuer, 1960), where humans can progress from feedback-only compensatory control (level 1) to feedback-feedforward pursuit control (level 2) to possibly 'open loop' (feedforward-only), *precognitive* control (level 3), depending on the HC experience (McRuer and Jex, 1967). Despite their paramount importance in everyday manual control, these higher levels received only little attention in the literature (Mulder et al., 2018).

Empirical evidence for human feedforward control has been found in pursuit tracking, and tasks with predictable target signals (Wasicko et al., 1966; Magdaleno et al., 1969; Hess, 1981; Yamashita, 1990; Drop et al., 2016). Fairly recently, it was found that a combined feedback-feedforward model accurately describes observed HC behaviour on higher SOP levels. In these tasks the HC was instructed to accurately follow a deterministic, predictable ramp-shaped target signal, with a pursuit display. The feedforward path was found to approximate the inverse of the CE dynamics, for a range of target and disturbance signal amplitude variations (Drop et al., 2013) for all common CE dynamics (Laurense et al., 2015). and becoming stronger when learning advanced (Zhang et al., 2017).

In this paper, we aim to study the adaptation of human controllers while learning how to perform a ramp-tracking task, using the SOP as a theoretical basis. An experiment will be presented where subjects performed a combined ramp-tracking disturbance-rejection task, with single integrator (SI) dynamics, while manipulating the steepness of the ramp target signal. The experiment had two parts, one in which the subject performed the same steepness condition in ten consecutive runs, the 'ordered' session, the other in which a different steepness condition was performed each run, the 'random' session. In addition, after each ordered session a 'surprise' run was done with a different ramp steepness. The HC control models will be identified using data from single runs, using averaged data, and data from small time intervals *within* a run.

The paper is structured as follows: Section 2 summarizes previous research on ramp-tracking tasks. The experiment is described in Section 3, its results are discussed in Section 4, and conclusions are drawn in Section 5.

2. BACKGROUND

2.1 Successive Organization of Perception

Krendel and McRuer proposed the Successive Organization of Perception (SOP) scheme to characterize HC control strategies (Krendel and McRuer, 1960). It has three levels, see Fig. 1: compensatory, pursuit and precognitive

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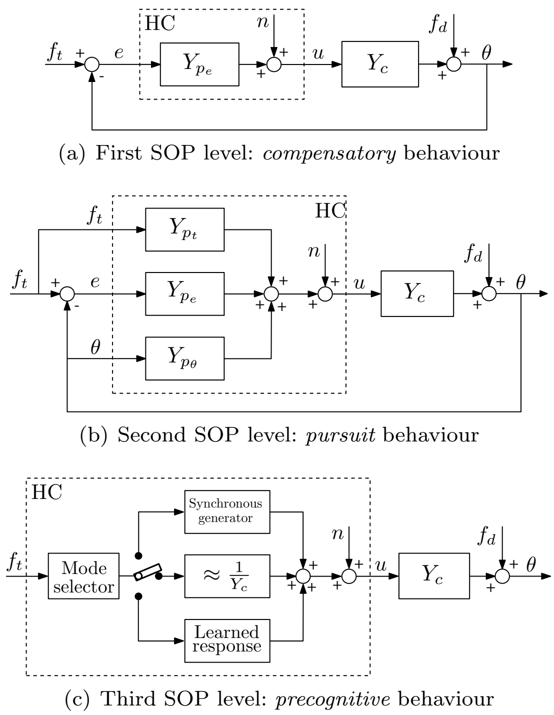
control. The level at which the HC can exercise control depends on the task variables: the type of visual display, the CE dynamics Y_c and the characteristics of the target f_t and disturbance f_d signals acting on the closed loop. Effects of these task variables on HC tracking behaviour have been extensively studied (Wasicko et al., 1966; McRuer and Jex, 1967); here, we will also investigate an operator-centered variable, namely the *level of experience*.

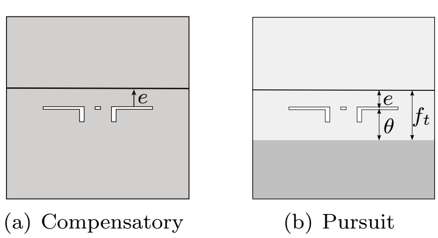


(a) First SOP level: *compensatory* behaviour

(b) Second SOP level: *pursuit* behaviour

(c) Third SOP level: *precognitive* behaviour

Fig. 1. Successive Organization of Perception (SOP).



(a) Compensatory (b) Pursuit

Fig. 2. Example of a compensatory and a pursuit display for a pitch tracking task, with the tracking error e, the target f_t and the output θ indicated.

At the lowest SOP level the HC is shown a compensatory display, Fig. 2(a), and minimizes the error e between an *unpredictable* target reference f_t and the controlled element output θ. *Compensatory* HC behaviour can be predicted well with McRuer's crossover model (McRuer and Jex, 1967) which describes the HC as a feedback-only servo-controller, Y_{p_e} in Fig. 1.

When using a pursuit display, Fig. 2(b), or when the target signal has characteristics that allow the HC to predict its (near) future values, the HC can move on to the second SOP level, *pursuit* control. Here, the HC can be described as a multi-loop controller acting on error e, target signal f_t and CE state θ. Wasicko et al. (1966) showed that (because $e = f_t - \theta$) a HC model with two inputs can fully capture the observed behaviour. Drop et al. (2013) reported that a combined feedback-feedforward model, with Y_{p_e} the HC feedback response on e and with Y_{p_t} the HC feedforward response on f_t can accurately describe HC behaviour.

At the third level, *precognitive* control, three possible 'open-loop' control modes are defined. The HC is assumed to adopt one of these modes when becoming very experienced with the task. Ideally, the HC FF response would be a perfectly timed and scaled response to an expected feature in the target, requiring a perfect inversion of the CE dynamics. For some types of (easy) controlled elements and (predictable) target signals humans can indeed be trained to the precognitive control level, e.g., in tracking sinusoids (Yamashita, 1990; Drop et al., 2016).

To limit the degrees of freedom, in this paper we only consider the control of a single integrator CE with a pursuit display, and focus on investigating the adaptation in the HC feedback and feedforward paths when learning to perform a ramp-tracking task. Besides the ramp-shaped target signal f_t, our analysis requires the insertion of a second signal into the closed loop, an unpredictable disturbance f_d, to identify the HC behaviour, Fig. 1. This means that the HC continuously needs to compensate for effects of f_d acting on the controlled element, and the observed HC behaviour will here never be *purely* open loop.

2.2 HC model and identification

We use the pursuit HC model of Fig. 1(b), without the state feedback, $Y_{p_\theta} = 0$. We expect the HC open loop, precognitive response to the target ramps to become apparent in the feedforward (FF) path Y_{p_t}, the response to f_t. This is equivalent to considering Fig. 1(c) with the 'Mode Selector' set to $\approx 1/Y_c$, but with an additional feedback loop Y_{p_e} to compensate for f_d and remaining errors in responding 'open loop' to f_t. The third component of the control signal u is the remnant n, which reflects the control input that is not linearly related to the input of the HC model (McRuer and Jex, 1967).

With an SI controlled element, Y_{p_e} is given by:

$$Y_{p_e}(s) = K_{p_e} e^{-s\tau_{p_e}} Y_{nms}(s), \tag{1}$$

with K_{p_e} and τ_{p_e} the gain and effective time delay of the feedback response, and Y_{nms} the neuromuscular (NMS) dynamics, modeled by a second order system.

The FF dynamics Y_{p_t} are given by (Laurense et al., 2015):

$$Y_{p_t}(s) = K_{p_t} \frac{s}{K_c} \frac{1}{(1 + T_{I_t} s)} e^{-s\tau_{p_t}} Y_{nms}(s), \tag{2}$$

with K_{p_t} and τ_{p_t} the gain and effective time delay of the feedforward response. In (2) we see the inversion of the SI dynamics (s/K_c term). A lag term (time constant T_{I_t}) is included to model the imperfect HC response to the discrete onset and ending of the ramp segments (Drop et al., 2013; Laurense et al., 2015).

2.3 Ramp tracking tasks

Ramp signals Ramp-like target signals are representative for a variety of discrete flight and driving maneuvers and have been used extensively in previous research (Pool et al., 2010; Drop et al., 2013; Laurense et al., 2015). In the ramp-tracking task, the target line on the pursuit display starts and stops moving at instances not communicated to the HC, i.e., no preview is available. Their movement has a constant velocity q that is typically used for all ramps occuring in a run, see Fig. 3; higher q's yield steeper ramps.

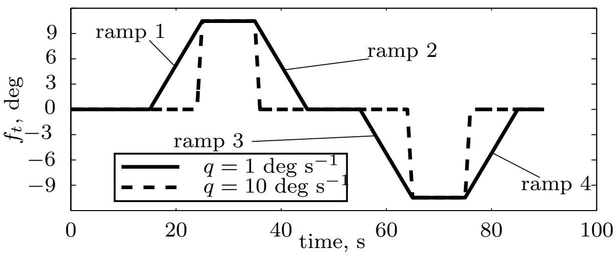


Fig. 3. Typical ramp-like target signal definition.

Phases in ramp tracking In the HC response to a ramp signal we hypothesize three phases, similar as McRuer et al. (1968), see Fig. 4. First, in the *delay phase* (I) the

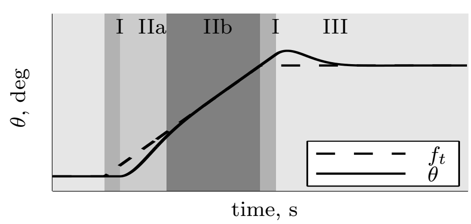


Fig. 4. Definition of ramp response phases.

HC is unaware of the onset of the ramp and is suddenly confronted with an error which rises with ramp steepness q. In the *rapid response phase* (IIa) the HC quickly reacts to the growing error, possibly in an open-loop fashion. In the *ramp-tracking phase* (IIb) the HC aims to match the velocity of the system to the ramp. It is during this phase that we hypothesize that the HC has 'recognized' the signal as a ramp with steepness q and tries to predict the remainder of the ramp. In phase III the compensatory path will again dominate; we focus on phases IIa and IIb as here we expect most of the feedforward activity.

Previous experiments Pool et al. (2010) used time-domain identification to parameterize a combined feedback-feedforward HC model for ramp tracking. A strong FF response could be identified only, however, when the disturbance f_d was small. Drop et al. (2013) investigated the presence of the HC FF response as a function of a Steepness to Disturbance Ratio, SDR $= q/K_d$, with q the ramp steepness and K_d the disturbance signal scale factor. Their analysis showed that the FF path is more beneficial and increases in strength relative to the feedback path for higher SDR values.

These experiments confirmed that human controllers, with predictable target signals on a pursuit display, perform at a higher SOP level than compensatory tracking. These also showed the promising applicability of time domain identification methods, which will be applied here.

3. EXPERIMENT

Rationale A target-following disturbance-rejection task was done, with four ramp steepness conditions: q=0 (no ramps), 2, 4 and 6 deg/s. To study skill *development*, the experiment had two Sessions. In each Session, eight subjects performed the same condition in ten consecutive runs, the 'ordered' part, the other eight subjects performed a different condition every run, the 'random' part. Then, we could investigate control adaptations from Session 1 to Session 2, to study the overall learning process, but also how this process depends on a situation where subjects know *exactly* what to expect in the next run, versus one where each run may have a different ramp target.

Independent Variables The two independent variables were the target signal ramp steepness q (4 levels) and the order of conditions (2 levels: ordered and random).

Participants, Instructions Sixteen subjects participated, all males, students or staff of TU Delft and experienced in tracking tasks. Two groups of 8 subjects were comprised: Group A first performed the ordered session, then the random session; Group B did it the other way around. Subjects were instructed to minimize the pitch tracking error e on the pursuit display.

Controlled Element Single integrator dynamics were used: $Y_c = K_c/s$, with gain $K_c = 1.0$ (Drop et al., 2013), such that subjects would never reach the maximum deflection limits of the stick and were still able to provide fine, accurate control inputs.

Forcing Functions For each run, the target signal had 8 identical ramps (3 seconds each) constructed with the four levels of ramp steepness q, see Fig. 5. Note that in the first condition, q=0 deg/s, our subjects essentially performed a disturbance-rejection task ($f_t = 0$).

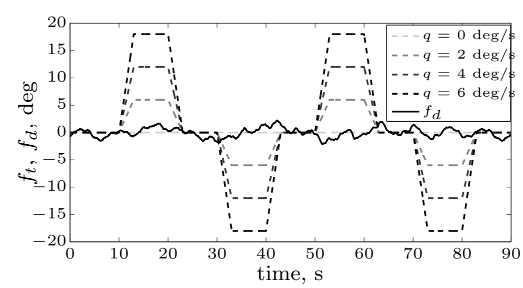
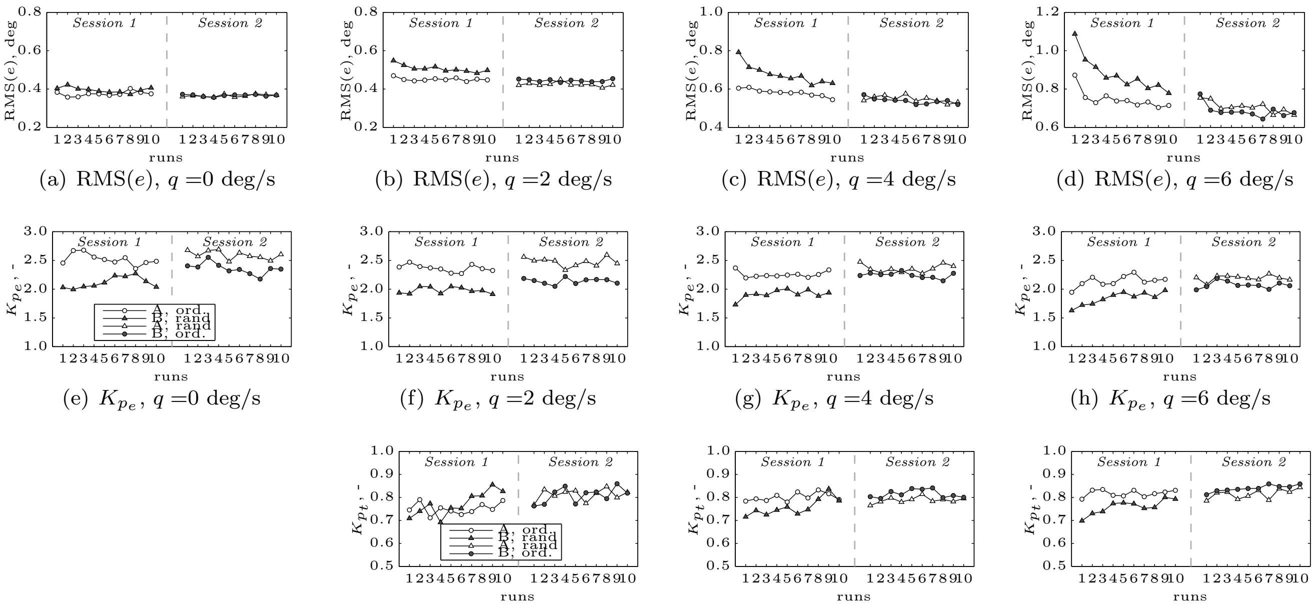


Fig. 5. Target and disturbance forcing function time traces.

To make sure that subjects could not predict the start of the first ramp, a random time τ, varying between 0 and 5 s was added to the 90 s measurement time. Furthermore, to prevent subjects to use the property that ramps stop on the horizon, the target signal was off-set by a random number between 0.1 and 1 degrees each run.

The disturbance signal f_d was defined as a multisine, with gain 0.4, similar as done by Drop et al. (2013).

Dependent Measures We focus on just a few measures: (i) tracking performance, i.e., the RMS tracking error RMS(e), and (ii) the HC model parameters representing the gains in the feedback K_{p_e} and FF K_{p_t} channels. The HC model will be fit to the measurements using MLE identification (Zaal et al., 2009). For the q=0 condition only the feedback parameters will be estimated, as this is essentially a disturbance-rejection compensatory tracking



(a) RMS(e), q =0 deg/s (b) RMS(e), q =2 deg/s (c) RMS(e), q =4 deg/s (d) RMS(e), q =6 deg/s

(e) K_{p_e}, q =0 deg/s (f) K_{p_e}, q =2 deg/s (g) K_{p_e}, q =4 deg/s (h) K_{p_e}, q =6 deg/s

(i) K_{p_t}, q =2 deg/s (j) K_{p_t}, q =4 deg/s (k) K_{p_t}, q =6 deg/s

Fig. 6. RMS error (top row), error feedback response gain (center) and feedforward response gain (bottom); data are shown for both sessions and groups. Group A (ordered session first) is shown in white symbols, Group B (random session first) is shown in colored symbols. Circles and triangles represent ordered and random session data, respectively.

task where the HC will not be able to develop a FF response. The model will be fitted on data of entire runs and on data *per ramp*.

Data Analysis Data are analyzed in three ways. First, we consider the data *per run*, to see how humans learn to control the ramps in either the ordered or random condition. Second, we consider the data *averaged over the last five runs*, the common approach to measuring human performance. Third, we consider the surprise run, for which we will also study the data *per ramp*.

Hypotheses First, we grouped our subjects such that both groups were assumed to perform about the same, our first hypothesis (H.I). Second, we hypothesize that in the ordered session, human control behavior develops more towards the highest level, precognitive control, because after a few runs subjects are familiar with and can anticipate for the ramp steepness (H.II). Third, we hypothesize the effects of the surprise run to be largest in the first ramps of the surprise runs (H.III), as we expect our subjects to have ‘perfectly tuned’ their response to the repeated ramp conditions in the ordered session.

4. RESULTS AND DISCUSSION

4.1 Data per run

Fig. 6 shows the performance RMS(e) and the HC model feedback gain K_{p_e} and FF gain K_{p_t}, for all ten runs in the first and second sessions. To compute or estimate each variable, the entire run (i.e., all 8 ramps) was used.

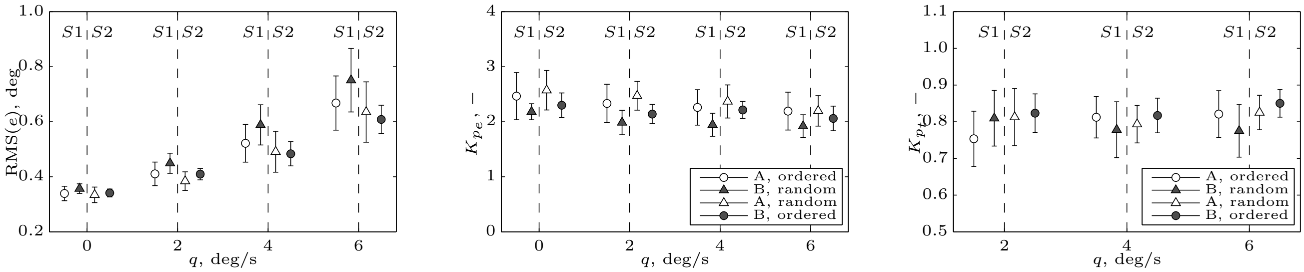
Tracking performance Figs. 6(a)-6(d) show that performance worsens when ramps come into play, and for steeper ramps. It improves rapidly in the first runs, and continues to improve especially for the more difficult conditions. That is, the learning curve becomes less steep towards the end of the experiment, but its gradient is still non-zero for the harder runs ($q = 4, 6$ deg/s).

When considering the $q = 0$ condition, purely disturbance rejection, we see that our subjects rapidly show a more or less constant performance, with Group A slightly better in Session 1, a performance difference which disappears in the second session. From this we can safely say that, at least for this condition, our two groups of subjects had – on average – comparable tracking skills, supporting H.I.

Considering the $q = 2$ deg/s condition, Fig. 6(b), we see that Group A, starting with the ordered runs, performs better than Group B, who started with the random runs [2]. In Session 2 the performance of both groups improves, where Group A continues to become better trackers in the random session, and Group B stablizes to the performance of Group A in Session 1 while tracking the ordered runs. Tentatively, the ordered runs help subjects to increase their skills very rapidly, and when then confronted with the random runs, they are able to keep up with this performance and even slightly improve further.

Regarding the $q = 4$ and $q = 6$ deg/s conditions, Fig. 6(c)-6(d) reveal that here a similar benefit exists for learning with ordered ramp conditions (Group A in Session 1), but tracking performance of Group B in Session 2, i.e., moving to the ordered conditions while coming from the random ones, improves quite remarkably, even outperforming subjects in Group A. This will be elaborated on further below.

[2] Note that here the runs were not performed in a sequential 1-2-3-... way, but were all taken from randomized conditions. I.e., although run 2 was done after run 1, there was at least one other run (different q) in between.



(a) RMS(e) (b) K_{p_e} (c) K_{p_t}

Fig. 7. RMS error (top), error feedback response gain (center) and feedforward response gain (bottom); data are averaged over last five runs per session.

HC feedback gain Figs. 6(e)-6(h) show estimates of the feedback gain K_{p_e}, and reveal that for all runs and sessions these gains were markedly lower for Group B compared to Group A. Only for the more difficult conditions ($q = 6$ deg/s) we see some evidence of a learning curve (increasing gain towards the end), but overall learning effects are small. Note that the feedback path operates on the disturbance signal f_d, which is the same for all runs, and on what is left after the feedforward operation on f_t. Apparently, Group A subjects were better 'disturbance-rejectors', and/or Group B subjects were slightly better at following the ramp targets.

When regarding ordering effects, it is clear that for Group B the ordered runs led to markedly higher feedback gains as the random runs, which could be attributed to the ordering effect, but may also have had a strong component from a continuing learning effect, as for all groups the gains were higher in Session 2 as compared to Session 1.

Overall, our subjects continued to improve throughout the experiment, and whereas performance more or less stabilizes towards the end, the HC model parameters still show slight changes towards improvement.

HC feedforward gain The feedforward gains K_{p_t}, Figs. 6(i)-6(k), slowly creep towards a higher value (ideally: $K_{p_t} = 1.0$) towards the end of the experiment. Gains are higher for the steeper ramps ($q = 4$, $q = 6$ deg/s), confirming the SDR analysis of Drop et al. (2013) as steeper ramps have a higher SDR value with a constant disturbance signal power. Especially for the steeper ramps the increase in feedforward gain for Group B in Session 2 is substantial. That is, when confronted with a randomized ramp signal to be tracked, gains are more or less constant and lower with respect to the case the ramp conditions are ordered. Subjects rapidly increase their feedforward gains when they see that the ramps are identical every run. The subjects who go from the ordered runs towards the random runs (Group A) appear to slightly *lower* their gains, especially for the two more difficult ramp conditions.

4.2 Data averaged over last five runs

Fig. 7 shows the RMS(e) and the HC model feedback gain K_{p_e} and FF gain K_{p_t}, when *averaging over the last five runs* in the two sessions. This is what is commonly being done in cybernetics-studies, averaging-out learning and adaptation effects (Mulder et al., 2018).

Performance Fig. 7(a) shows the averaged RMS(e) for the two groups in the two sessions. Performance for Group A is slightly better than Group B in the disturbance-rejection task ($q = 0$), but differences are very small. Performance is, on average, better in the second session, which makes sense as our subjects continued to learn and improve. Clearly, in Session 1 the performance in the ordered runs is better, whereas in Session 2 the performance becomes more or less the same for both groups. When moving from the random session to the ordered session, Group B in Session 2, led to quite a substantial performance improvement, especially for the steeper ramps ($q = 4, 6$ deg/s).

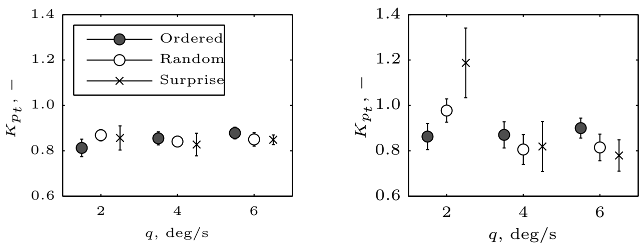
HC feedback gain Fig. 7(b) shows the averaged K_{p_e} gains, again showing higher gains for Group A in almost all conditions. Gains slightly increase when moving from the ordered to the random runs (Group A), and more markedly increase when moving from the random to the ordered runs (Group B). Our subjects were clearly adapting and learning to the very end of the experiment, but changes in the feedback gain are on average very small.

HC feedforward gain The averaged feedforward gains K_{p_t} are shown in Fig. 7(c). Here we see that the gains slightly increase towards the end of the experiment no matter what groups we consider, indicating learning. When considering Group A (ordered runs first) the feedforward gain increases for the steeper ramps, reported in (Drop et al., 2013). Moving to Session 2 (random runs), the gains either increase ($q = 2$) or remain the same. Feedforward gains for group B are smaller for the steeper runs in the first, random, session, but then steeply increase when moving towards the second session. It is clear that this group benefits the most in the second session, especially for the steeper and more difficult ramps. These results support H.II: ordered conditions yield stronger feedforward control.

4.3 Behavioral Changes in Surprise Runs

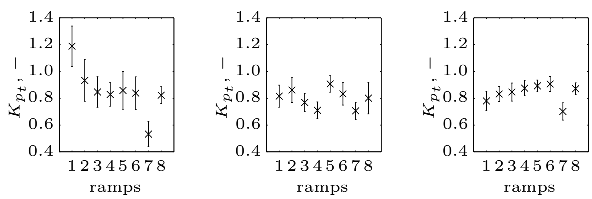
The surprise runs suddenly exposed subjects to a different ramp steepness when they had fully adapted their response characteristics to the ramp signal steepness of the ordered block. Data were averaged over the final five runs.

Fig. 8 shows the estimates of K_{p_t}, comparing the gains applied in the surprise runs to the averages of the gains applied in the ordered and random sessions, using the full



(a) full run data (b) first ramp data

Fig. 8. Means, 95% conf. intervals of K_{p_t} estimates.



(a) q=2 (b) q=4 (c) q=6

Fig. 9. Mean, 95% conf. intervals of K_{p_t} parameter estimates, surprise run.

run data (left) or using only the data corresponding to the first ramp (right). Clearly, the differences are much larger in the latter case. For each ramp steepness, subjects adjust their gain towards the gain used in the random sessions.

Fig. 9 shows how K_{p_t} (averaged over all subjects) progresses throughout the surprise run. Subjects adapt quickly, within the first four to five ramps towards the value used in the random session, supporting H.III. For the surprise run with steepness q=2 deg/s the feedforward gain is initially too high (> 1.0) as subjects were experiencing either a q=4 or q=6 deg/s condition in the previous ten consecutive runs (requiring a high gain), but quickly reduce their gain after the first ramps. The opposite is true for the q=6 deg/s condition where K_{p_t} is initially too low, as subjects were experiencing either a q=2 or 4 deg/s condition in the previous ten ordered runs (requiring a lower gain), and quickly increase their gain. For the surprise run with steepness 4 deg/s, the gain shows more variations around an average value, which is likely the result of averaging, since for this surprise run the previous runs either had a lower (q=2) or a higher ramp steepness (q=6). The lower value of K_{p_t} in the seventh ramp is an artifact, caused by the disturbance signal f_d, which at that time coincidentally moved the system in the right direction, requiring a smaller gain.

5. CONCLUSIONS

We investigated human control behavior in ramp tracking tasks, and assessed manual control skill development using a combined feedback/feedforward model. Results show that: 1) as hypothesized, ordered runs lead to higher feedforward gains, 2) training with random runs and then moving to ordered runs yields the strongest performance benefits, and 3) HCs adapt very quickly to a change in ramp steepness. In addition, our data show that HCs continue to learn throughout the experiment, but the extent to which they do that depends on the individual subject. To balance-out these individual learning trajectories, a large number of subjects is mandatory.

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