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Identification of the Transition from Compensatory to Feedforward Behavior in Manual Control

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***Abstract*—The human in manual control of a dynamical system can use both feedback and feedforward control strategies and will select a strategy based on performance and required effort. Literature has shown that feedforward control is used during tracking tasks in response to predictable targets. The influence of an external disturbance signal on the utilization of a feedforward control strategy has never been investigated, however. We hypothesized that the human will use a combined feedforward and feedback control strategy whenever the predictable target signal is sufficiently strong, and a predominantly feedback strategy whenever the random disturbance signal is dominant. From the data of a human-in-the-loop experiment we conclude that feedforward control is used in all the considered experimental conditions, including those where the disturbance signal is dominant and feedforward control does not deliver a marked performance advantage.**

***Index Terms*—Manual control, tracking tasks, feedforward, pursuit, precognitive control.**

I. Introduction

Behavior of the Human Controller (HC) in manual control has been investigated since the 1940s. By far, the largest portion of research was conducted on *compensatory* control behavior, which can be modeled accurately by linear *feedback* models. These compensatory models were used in, amongst others, research on flight simulator fidelity [1], bicycle operation[2], and automotive control [3]. However, as acknowledged by many [4], [5], a large portion of real-world manual control involves more complex control strategies, similar to machine world *feedforward* control.

The Successive Organization of Perception (SOP) theory, as put forth by McRuer and Krendel [6], [7], further formalized this hypothesis in the context of manual tracking tasks. The SOP hypothesizes three levels of control behavior which trade off complexity (effort) and performance.

In the first level, the *compensatory* stage, the HC achieves stable control by controlling in a closed-loop feedback fashion on the 'error' between the target and the current state of the system. Compensatory control was studied extensively for unpredictable target signals and a compensatory display [4], [8], [9]. The performance of compensatory control is limited due to a considerable time delay in the human, which requires the human to restrict his feedback gain to maintain stability. Doing so reduces the tracking performance, resulting in a trade-off between stability and performance.

In the second (*pursuit*) and third (*precognitive*) stages, the HC uses (inferred) knowledge on the target to improve performance without sacrificing closed-loop stability. In pursuit control [6], [9], [10], the *current* value of the target or system output signal is perceived and used directly in a control law. In precognitive control [11], [12], the HC bases his control action on a memorized representation of the target signal and might anticipate on its future course. We consider all control action based on the target signal (pursuit and precognitive) as forms of *feedforward* control.

A feedforward control strategy is likely to be applied in response to predictable target signals [12], [13]. This was experimentally shown for predictable sine target signals [11], and ramp target signals [14]. Ref. [14] investigated the feedforward mode as a function of the relative magnitude of the ramp target signal and a quasi-random disturbance signal. Ref. [14] expected a transition from a combined feedforward and feedback strategy for a relatively strong target signal, to a predominantly feedback strategy for a strong disturbance signal. This hypothesis was not confirmed, due to the limited range of relative magnitudes at which the experiment was performed. It is the objective of this paper to investigate this hypothesis for the entire range of relative signal magnitudes at which the analysis method, based on linear models, is reliable. This will result in clear boundary conditions on the applicability of the feedforward model proposed in Ref. [14].

II. Background

The control task that is studied is depicted in Fig. 1. It is the goal of the HC to minimize the tracking error e, defined as the difference between system output θ and target signal f_t. The performance of the HC in minimizing e is influenced by certain external factors (*task variables*) and his ability to adapt his control strategy to these factors [15].

The task variables are those elements that cannot be changed by the HC, the important being 1) the tracking display, Fig. 2, either the compensatory or pursuit display, 2) the system dynamics [9], [15], 3) the properties of the target and disturbance signals (*forcing functions*), and 4) the presence of additional cues (e.g. vestibular). The HC will adapt his control behavior depending on the aforementioned task variables, and the obtained experience with the task at hand, to optimize his tracking performance.

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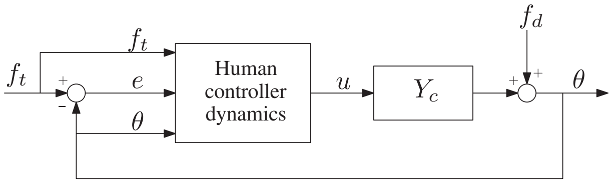
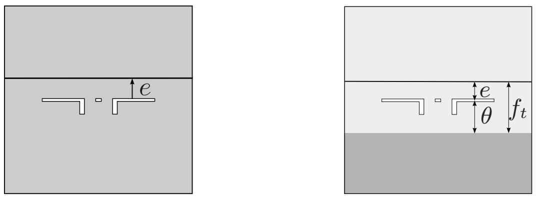


Fig. 1. The control task studied in this paper. The HC can use f_t, the system state θ and the error e to generate the control signal u. Control signal u drives the linear dynamical system Y_c, which is perturbed by disturbance signal f_d.



(a) Compensatory display, presenting only the tracking error e.

(b) Pursuit display, showing input f_t, output θ, and error e.

Fig. 2. Compensatory and pursuit displays for aircraft pitch control.

A. Compensatory control

The HC will adapt a *compensatory* control strategy, controlling in a feedback fashion on the tracking error, Fig. 3, in situations where the forcing functions are unpredictable and a compensatory display is used. In such situations, the HC cannot directly perceive f_t, nor can he infer the current or future value of f_t due to its unpredictability and can thus only respond to e. Using this strategy the HC can achieve stable control and reasonable performance.

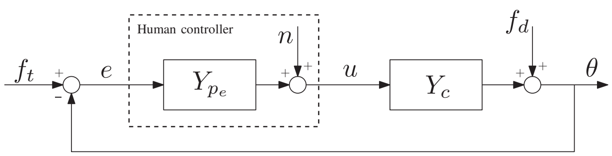


Fig. 3. Single-loop compensatory model. The HC only perceives the error e or is assumed to respond only to the error, even if other signals are available from the display or from cognition.

Compensatory control was studied extensively in the 1960s, resulting in the formulation of the Crossover Model (CM) and its derivatives: the Extended Crossover Model and the Precision Model [8]. The CM states that the HC adapts his behavior to the system dynamics, such that the combined dynamics approximate a single integrator and a time delay around the crossover frequency, ω_c, see Eq 1.

$$Y_{p_e}(s) \cdot Y_c(s) = \frac{\omega_c e^{-\tau_p s}}{s} \tag{1}$$

From Eq. 1 one can find that a higher ω_c will result in a higher performance. To prevent instabillity the controller will maintain a certain phase margin, φ_m, which is dependent on ω_c and the time delay τ_p through the following relation [8]:

$$\varphi_m = \pi/2 - \tau_p \omega_c \tag{2}$$

From Eq. 1 and Eq. 2 one can easily verify that a lower limit on φ_m and a given time delay pose an upper limit on the crossover frequency ω_c and thus on performance. A further performance improvement requires the use of more advanced control strategies.

B. Feedforward pursuit control

If the current value of f_t can be perceived from the display or is otherwise known to the HC, a *feedforward* pursuit control strategy can be selected. During feedforward control, the HC employs a direct control operation on f_t, Fig. 4, similar to feedforward control schemes in automatic controllers. This can result in a performance increase in the tracking of f_t, without affecting the closed loop stability.

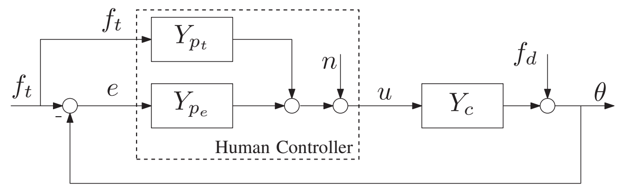


Fig. 4. Linear model of feedforward pursuit behavior. Signal n indicates remnant, accounting for non-linearities present in the HC.

As can be verified from Fig. 4, the ideal feedforward control law is equal to the inverse system dynamics: [9]

$$Y_{p_{t_{\text{Ideal}}}}(s) = \frac{u(s)}{f_t(s)} = \frac{1}{Y_c(s)} \Rightarrow u(s) = \frac{1}{Y_c(s)} f_t(s). \tag{3}$$

The system output θ is then found to be:

$$\theta(s) = Y_c(s) \cdot u(s) = Y_c(s) \cdot \frac{1}{Y_c(s)} \cdot f_t(s) = f_t(s). \tag{4}$$

That is, output θ is exactly equal to the target signal f_t, yielding zero tracking error.

The improvement in tracking due to a feedforward path might decrease, or even become zero, if a time delay appears in the feedforward path. Since humans always have a considerable time delay in their compensatory control action, it is likely they have a similar time delay in a feedforward path. This time delay can be reduced (effectively) if the human is able to exploit predictable elements of the target signal, as is done in the *precognitive* control mode.

C. Precognitive control

Given extensive experience with the control task, the HC might attain the highest level of manual control behavior as defined in the SOP: *precognitive* control [11], [12]. Precognitive control inputs originate from cognitive knowledge of the current or *future* value of the forcing functions. The control inputs might also be memorized motor commands triggered by a recognized event or pattern in one of the forcing functions. Usually, precognitive control is described as a purely open-loop mode, but might also exist in conjunction with feedback control [12].

It is hypothesized that a precognitive mode might even occur with a compensatory display and difficult dynamics, given extensive experience and sufficiently predictable forcing functions. That is, the use of a compensatory display does not guarantee compensatory behavior in the HC.

III. Transfer function models

In this paper we investigate the hypothesized transition from compensatory behavior to feedforward behavior, as a function of the relative magnitude of the predictable target signal (consisting of ramps) and the unpredictable (quasi-random multi-sine) disturbance signal. The system dynamics of interest is a single integrator, $Y_c(s) = K_c/s$. We will perform a number of analyses by means of two linear transfer function models, which model the hypothesized compensatory and feedforward control strategies.

A. Compensatory model

The model representing compensatory behavior is based on the Simplified Precision Model [8] as appropriate for control of single integrator dynamics. In this paper, it is referred to as the Basic Compensatory Model (BCM) to be consistent with Ref. [14]. The model structure of Fig. 3 applies, with Y_{p_e} defined as:

$$Y_{p_e}^{\mathrm{BCM}}(s) = K_{p_e} e^{-\tau_p s} Y_{nms}(s) \tag{5}$$

It consists of an equalization gain K_{p_e}, a time delay and a neuromuscular system (NMS) dynamics model $Y_{nms}(s)$. Y_{nms} is a mass-spring-damper-system with natural frequency ω_{nms} and damping coefficient ζ_{nms}.

B. Feedforward model

The model representing feedforward behavior (FFM) has a combined feedback and feedforward structure, as shown in Fig. 5.

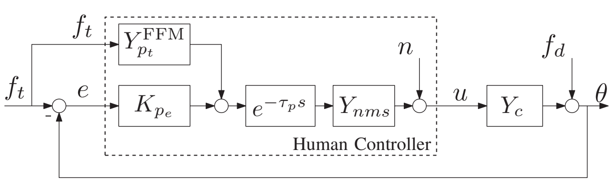


Fig. 5. Model structure of the feedforward model (FFM).

The feedback path is essentially identical to the BCM, although the exact model structure is slightly different. The feedback path consists of the same elements, but the contribution of the feedforward path is added halfway, before the time delay and the neuromuscular system.

The feedforward path transfer function is based on inverse system dynamics and given as:

$$Y_{p_t}^{\mathrm{FFM}}(s) = K_{p_t} \frac{1}{Y_c(s)} \frac{1}{T_I s + 1}. \tag{6}$$

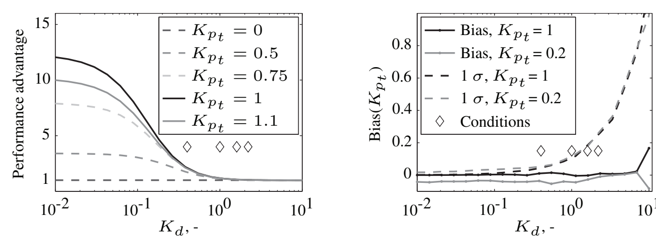
The last fraction, a low pass filter, is required for numerical simulation of the inverse system dynamics, which are a differentiator ($1/Y_c(s) = 1/(K_c/s) = s/K_c$). The value of T_I is fixed to 0.2 s. The gain K_{p_t} is the only free parameter in the feedforward path and directly affects the amount of feedforward action in the model. Note that the FFM reduces to the BCM if K_{p_t} is set to zero.

The FFM contains one time delay affecting both the feedforward and feedback responses, for two reasons. Ref. [14] has shown that a separate feedforward time delay cannot be reliably estimated in conditions where the disturbance signal is relatively large, as is the case in this study. Secondly, in conditions where it was possible to reliably estimate a separate time delay, the numerical value was highly similar to the compensatory time delay.

C. Performance comparison in simulation

The relative performance advantage of the FFM over the BCM provides a measure of the likelihood which control strategy is selected by the HC, as a function of the relative magnitude of f_t and f_d. The relative magnitude is varied by keeping the magnitude of f_t fixed and varying the magnitude of f_d by multiplying a baseline disturbance signal by gain K_d. The steepness of the ramps in f_t was 1 deg/s, as in the experiment. During the simulations, parameter K_{p_e} was set to 2.5, τ_p to 0.2 s, ω_{nms} to 12 rad/s, and ζ_{nms} to 0.2, resulting in ω_c = 2.6 rad/s, based on the results of Ref [14].

The performance advantage is defined as the ratio between the variance of the error signals of the BCM and FFM, that is, $\sigma^2_{e_{\mathrm{BCM}}}/\sigma^2_{e_{\mathrm{FFM}}}$. The results of the analysis are given in Fig. 6(a), demonstrating that $K_{p_t} = 1$ results in the highest performance advantage, as one might expect from Eqs. 3 and 4.



(a) Performance advantage of the FFM over the BCM.

(b) Parameter estimation bias of the K_{p_t} parameter.

Fig. 6. Simulation analyses results. The four disturbance levels of the experiment are marked with a diamond marker.

The performance advantage resulting from the adoption of feedforward is very large for $K_d < 1$, but negligibly small for $K_d > 1$, and we thus hypothesize that the HC will use a predominantly compensatory control strategy for $K_d > 1$. Controlling only on e would result in a lower workload than controlling on both f_t and e, yielding the same performance.

D. Identification limit of feedforward behavior

The relative contribution of the feedforward path to the measured control signal u will decrease as the relative magnitude of f_d becomes larger, making it more difficult to reliably identify feedforward action from remnant (noise and non-linearities in the HC) affected data. Ultimately, there is a ‘feedforward identification limit’ on K_d, above which it is impossible to reliably identify feedforward behavior. We investigate this limit by means of simulations.

The response of the FFM was simulated for different values of K_d and a constant f_t. Human remnant was simulated as in Ref. [16] and contributed 15% to the variance of the control signal. The model parameter values were then estimated from the simulated data using the same Maximum Likelihood Estimation (MLE) method as applied to the experimental data [16]. The 'estimation bias' is defined as the difference between the estimated value and the simulated value. The simulation was performed for two values of K_{p_t} (0.2 and 1) to test the sensitivity of the method for the value of K_{p_t}.

Fig. 6(b) shows the mean of the bias in K_{p_t} and one standard deviation over 200 simulation results. The results are essentially the same for both tested values of K_{p_t}: the bias in K_{p_t} remains close to zero, but the variance grows exponentially. This demonstrates that the method is equally capable of identifying feedforward action when it is truely present (K_{p_t} = 1) as identifying the lack of feedforward action if its contribution is truely small (K_{p_t} = 0.2). At $K_d = 2.5$, one standard deviation of the bias distribution is approximately 20% of the simulated value of K_{p_t}, meaning there is a 30% chance that the estimated value of K_{p_t} of a set of data is more than 20% from its real value. We therefore consider $K_d = 2.5$ to be the 'feedforward identification limit'.

This analysis shows that the relative contribution of feedforward decreases for larger disturbance gains. This might also have an effect on the behavior of the HC. A relatively small feedforward imput might be more difficult to generate precisely while compensating for large errors due to large disturbances, than while compensating for small errors. This is another reason to expect the HC to use a predominantly compensatory control strategy for K_d larger than 1.

IV. Experiment

To validate the theoretical concepts concerning the identification of changes in control behavior, a human-in-the-loop experiment was conducted.

A. Method

1) Apparatus: The (pitch axis) tracking task was presented on a pursuit display, Fig. 2(b). The display update rate was 100 Hz and the time delay of image presentation was measured during the experiment to be approximately 15 ms on average. No motion cues were available. Subject used the fore/aft axis of an electrical helicopter cyclic stick (Wittenstein Aerocontroller) to give control inputs. Subjects experienced a stiffness of 117 N rad^{-1}, a damping ratio of 0.3 and a mass of 0.8 N s^2 rad^{-1}, at the hand contact point located 65 cm above the point of rotation. The lateral axis of the stick was locked.

2) Controlled element dynamics: Single integrator dynamics were considered: $Y_c = K_c/s$, with K_c equal to 1. The display gain was 16 pixels (or 4.4 mm) per degree pitch.

3) Independent variables and forcing functions: The independent variables were the occurrence of ramps in f_t and the gain K_d on the disturbance signal. Target signal f_t either contained a number of ramps with steepness 1 deg/s (R1) or was equal to zero for the entire measurement time (R0). Four levels of K_d were tested: 0.4, 1.0, 1.6 and 2.2, designated D40, D100, D160 and D220, respectively. The resulting f_t and f_d signals are shown in Fig. 7. Each level of K_d was tested for both f_t signals, resulting in eight conditions.

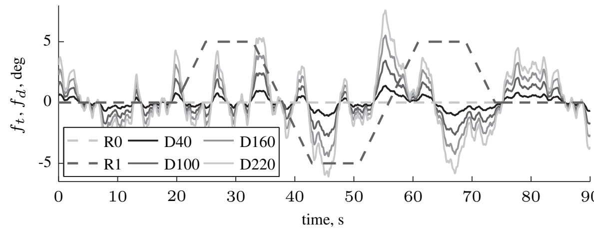


Fig. 7. Forcing functions f_t (Rx) and f_d (Dx).

During the R0 conditions the task reduced to a pure disturbance-rejection task. These conditions were added to verify the variations in the compensatory control behavior as a function of K_d.

The disturbance signal f_d was a multi-sine signal, consisting of ten sets of adjacent frequency components. The phases of the sinusoids were chosen such that the signal appeared random. It was identical to the signal used in Ref. [17] and [14].

4) Subjects and instructions: Eight subjects, all males, aged 25-31 years, were instructed to minimize the tracking error e. After each run the subjects were informed of their tracking score.

5) Procedure: Subjects performed the eight conditions in two sessions of four conditions each. On average, each session took 1.5 hours. Conditions were randomized over subjects using a balanced Latin square design.

The individual tracking runs lasted 90 seconds, of which the last 81.92 seconds were used as the measurement data. When subject proficiency in performing a particular condition had reached an asymptote, five repetitions were collected as the measurement data. The time traces of e, u and θ were recorded. The five time traces were averaged to reduce effects of remnant, resulting in one time trace for each subject for each condition. The averaged time traces were used to calculate the dependent measures.

B. Dependent measures

1) Non-parametric measures: The frequency response functions of the subjects were calculated from the measured signals for the R0 conditions by means of Fourier coefficients. This metric allows for a direct comparison of the subject behavior between conditions from raw data, without assuming a particular model structure.

2) Parametric measures: The BCM and FFM models were fit to the data with a time-domain Maximum Likelihood Estimation (MLE) method [16], resulting in model parameter estimates from which changes in behavior become evident. The quality of the model fits is expressed by the Variance

Accounted For (VAF):

$$\text{VAF} = \left(1 - \frac{\sum_{k=0}^{N} |u(k) - \hat{u}(k)|^2}{\sum_{k=0}^{N} u(k)^2}\right), \tag{7}$$

In Eq. 7, $\hat{u}$ is the modeled and u the measured control signal.

C. Hypotheses

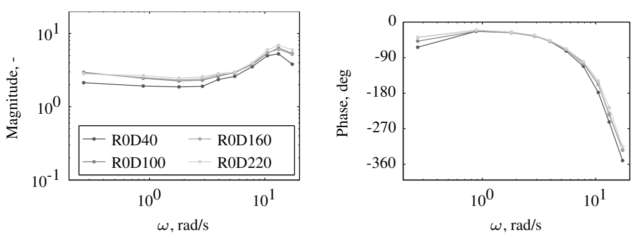
As found in the analysis of Sec. III-C the performance advantage of a feedforward strategy is negligibly small for $K_d > 1$. Hence, we hypothesize that our subjects will use a feedforward control strategy only for conditions with $K_d \leq 1$ and a predominantly compensatory strategy for $K_d > 1$.

More specifically, we expect 1) the VAF of the BCM to be significantly lower than the VAF of the FFM, for $K_d \leq 1$, and that 2) the value of feedforward path gain K_{p_t} decreases significantly for $K_d > 1$, indicating that subjects are utilizing their feedforward path less. Ultimately, we expect K_{p_t} to become zero, meaning no feedforward behavior is present.

V. Results

A. Disturbance-rejection only conditions (R0)

The Frequency Response Functions (FRF) obtained by means of Fourier Coefficients for R0 conditions are shown in Fig. 8. Most notably, the shape of the FRFs are highly similar for all conditions, i.e., a constant magnitude at lower frequencies, a NMS resonance peak at higher frequencies and an exponentially increasing phase lag. Comparing the conditions in more detail, the FRF of condition R0D40 is lower in magnitude and has a slightly larger phase lag than the other three conditions. The NMS peak appears at a slightly lower frequency, also causing the larger phase difference at higher frequencies.



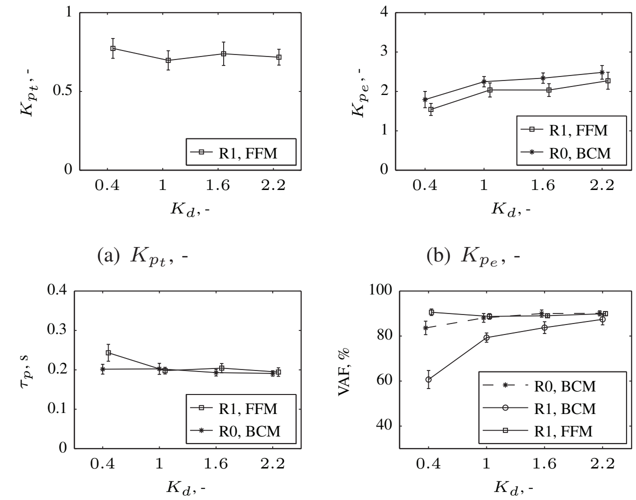
(a) Magnitude. (b) Phase.

Fig. 8. Estimated FRFs of Y_{p_e}, averaged over all subjects.

B. Transfer function model fits (R0 and R1)

The BCM was fit to all conditions, the FFM only to the R1 conditions. The resulting VAF and identified model parameters values are shown in Fig. 9.

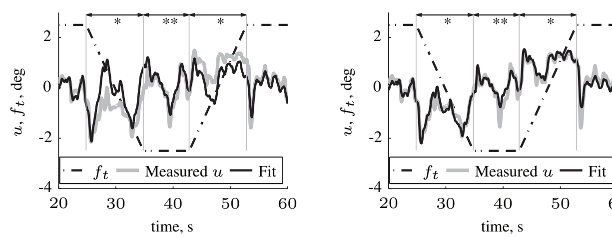
The VAF of the model fits show that 1) the BCM obtained good fits to all R0 conditions, 2) the FFM obtained good fits to all R1 conditions, and 3) the BCM only obtained good fits to R1 conditions for $K_d \geq 1.0$. The VAF of the BCM fits to the R1 conditions are significantly lower than the VAF of the FFM fits to the R1 conditions, including condition R1D220 (numerical difference only 2.5%).



(a) K_{p_t}, - (b) K_{p_e}, - (c) τ_p, s (d) VAF, %.

Fig. 9. Identified transfer function model parameter values and VAF.

Typical fits of the BCM and FFM to the data of condition R1D40 are shown in Fig. 10. The BCM delivers a good fit during 'hold segments' (marked **), but not during 'ramp segments' (marked *). The FFM provides a good fit for *all* segments. Apparently, the subjects were not controlling solely on the error, but also used f_t in their control strategy during the ramp segments. The identified model parameters of the BCM fits to the R1 conditions are not shown, because of the modeling discrepancy during the ramp segments.



(a) BCM. (b) FFM.

Fig. 10. Typical model fits on condition R1D40. f_t is scaled by 50%.

The identified value of K_{p_t}, Fig. 9(a), is approximately constant for all R1 conditions and approximately equal to 0.7. The compensatory gain K_{p_e}, Fig. 9(b), was estimated higher by the BCM in the R0 conditions than by the FFM in the R1 conditions ($F_{1,7} = 226.4$, $p < 0.001$). Also, K_{p_e} is significantly larger for larger disturbances ($F_{3,21} = 6.24$, $p < 0.01$). The time delay τ_p, Fig. 9(c), was estimated around 200 ms for all conditions, which is a value commonly found for single integrator dynamics. The neuromuscular system parameters ω_{nms} and ζ_{nms}, not shown, were constant across all conditions and both models.

VI. Discussion

An experiment was performed in which the relative strength of the quasi-random disturbance signal was varied with respect to the strength of the predictable target signal. The R0 conditions were added to check that the subjects did not change their strategy due to the variation in K_d alone. The FRFs of the subjects revealed that behavior was constant, but that the subjects tuned their response considerably in the R0D40 condition. A likely explanation is that the very small disturbance resulted in relatively large errors in the perception of the tracking error e, especially at higher frequencies, that the subjects were forced to lower their crossover frequency, to maintain adequate performance. This 'tuning' likely also took place in the R1D40 condition, but since the fitted transfer-function models have enough freedom in their parameters, the results of the R1 conditions are mutually comparable.

Contrary to what we hypothesized, the identified parameter values of K_{p_t} did not decrease for $K_d > 1.0$, but remained constant consistently accross all subjects. This shows that subjects maintained their feedforward control strategy, even though it delivers no performance advantage. Apparently, our hypothesis that maintaining a feedforward path increases workload and is therefore 'switched off' when it is not useful, was incorrect. A possible explanation is that although there is no performance gain, there is also no performance penalty in using a feedforward strategy for larger disturbances. The human might therefore favor the use of one and the same strategy, rather than constantly adapting to a new condition.

We therefore conclude that a feedforward path is necessary for modelling the measured behavior in all conditions, since the VAF of the FFM fit is always significantly better than that of the corresponding fit of the BCM and because the value of K_{p_t} remains high. The results for condition R1D220, however, show that the additional feedforward path adds only a very small amount of describing power to the model (2.5%), whilst adding considerable complexity.

The necessity of modeling the feedforward path in offline simulations will depend on the purpose of the simulations. A conservative performance estimate of the HC can be obtained simply by neglecting the feedforward path. When the highest degree of model fidelity is required, the feedforward path should be included, at the expense of model complexity.

VII. Conclusions

This paper investigated the hypothesized transition from a feedforward to a compensatory control strategy in a tracking task, as a function of the relative magnitude of the quasi-random disturbance signal to the magnitude of the predictable target signal. Contrary to what was hypothesized, we found that the subjects adopted a combined feedforward and compensatory control strategy for all conditions, including those where the additional effort of utilizing feedforward does not improve performance. That is, the subjects utilized the same strategy for all conditions and no transition point where human operators revert to purely compensatory behavior was identified. It is therefore important that future studies focus on feedforward behavior. In particular, the dependency of feedforward behavior on the system dynamics and the type of target signals is considered relevant, since the dynamics and target signal used in this study represent only a small portion of real-life control tasks.

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