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Constraints in Identification of Multi-Loop Feedforward Human Control Models

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Abstract: The human controller (HC) can greatly improve target-tracking performance by utilizing a feedforward operation on the target signal, in addition to a feedback response. System identification methods are used to determine the correct HC model structure: purely feedback or a combined feedforward/feedback model. In this paper, we investigate three central issues that complicate this objective. First, the identification method should not require prior assumptions regarding the dynamics of the feedforward and feedback components. Second, severe biases might be introduced by high levels of noise in the data measured under closed-loop conditions. To address the first two issues, we will consider two identification methods that make use of linear ARX models: the classic direct method and the two-stage indirect method of van den Hof and Schrama (1993). Third, model complexity should be considered in the selection criteria, that make an explicit trade-off between model quality and model complexity, are considered. Based on computer simulations with a HC model, we conclude that 1) the direct method provides more accurate estimates in the frequency range of interest, and 2) existing model selection criteria do not prevent false-positive feedforward identification. *Copyright* $\bigcirc 2016 IFAC$

Keywords: Cybernetics, manual control, feedforward control, parameter estimation

1. INTRODUCTION

Manual control of a vehicle often requires the human controller (HC) to steer a dynamic system along a reference trajectory, while being perturbed by disturbances. This target is often visible or to some extend known *a priori* by the HC. As a result, the HC *might* respond to the target in a feedforward fashion, but it is not known for which control tasks this is true. To obtain insight, we study the HC performing target-tracking and disturbance-rejection control tasks by means of system identification methods.

In many control tasks the path of the vehicle is perturbed by unpredictable disturbances, to which the HC can respond only with a closed-loop *feedback* control strategy. That is, the HC compensates for the 'error' between the target and the current vehicle output. The HC might use a purely feedback control strategy for target-tracking too, but could improve tracking performance considerably by utilizing an additional feedforward control strategy (Wasicko et al., 1966). It is of interest to know when the HC utilizes feedforward and when not.

System identification techniques allow us to objectively measure if and model how the HC responds to multiple sources of information. The identification of HC control dynamics, with a focus on feedforward detection and modeling, involves three important challenges.

First, most system identification methods require the user to make assumptions regarding the model structure and/or dynamics. The results of such analyses are thus dependent on the *subjective* choices of the researcher. In this paper, we will utilize black-box linear time invariant (LTI) autoregressive with exogenous input (ARX) models, that do not require any assumptions regarding model structure or parametrization.

Second, data measured in human-in-the-loop experiments involve relatively high levels of noise (Zaal et al., 2009) and measurements need to be taken under closed-loop feedback conditions. The combination of both can severely complicate identification (van den Hof and Schrama, 1998). If a closed-loop feedback path is present, noise in the output signal will appear (through the feedback path) in one or more input signals. The correlation between the input signal and the output noise can cause the estimate of the HC to be biased, in this case towards the inverse of the system dynamics. Several identification methods exist that explicitly deal with such closed-loop issues. In this paper, we will compare the indirect two-stage method of van den Hof and Schrama (1993) against the classical direct method (Ljung, 1999), that does not account for any closed-loop issues explicitly. We expect the indirect method to perform better.

Third, a model that includes a feedforward path in addition to a feedback path generally has more parameters and thus more degrees of freedom. For that reason alone the feedforward model potentially describes the data better than a purely feedback model, even if a real feedforward strategy was not present. Thus, if the 'best' model is selected based on the quality of the fit alone, a false-positive feedforward identification is possible. One, of many, methods to prevent model over-parametrization is the use of a model selection criterion, such as the Akaike Information Criterion (AIC, (Akaike, 1974)) or the Bayesian Information Criterion (BIC, (Schwarz, 1978)). These criteria explicitly take into account model complexity when selecting the 'best' model, but apply different penalties to the number of model parameters.

In this paper, we will explore these three issues through computer simulations with a fixed and known HC model, and compare the identified dynamics to the ground truth. Output noise will be present to model the human remnant. Both the direct and the indirect identification methods are applied to data generated by two different HC models, based on earlier experimental data. First, a pure feedback HC model is used to investigate false-positive feedforward identification. Second, a combined feedforward-feedback HC model is used to investigate the accuracy of the obtained estimates of the multi-loop HC model. Three metrics of model quality are considered: 1) the mean square error is used by the model selection criterion, 2) the Variance Accounted For (VAF) to assess time domain quality of fit, and 3) the absolute error in magnitude and phase as a function of frequency to assess the identifiability of specific model dynamics.

The paper is structured as follows. First, the targettracking and disturbance-rejection control task is introduced in Section 2 followed by a description of the HC model. Then, the two identification methods and model selection criteria are discussed in Section 3. The computer simulation details are described in Section 4 followed by the results in Section 5. The paper ends with conclusions and recommendations for future work.

2. CONTROL TASK AND HC MODEL

2.1 Control Task

This paper focuses on the identification of human control behavior in a combined target-tracking and disturbancerejection task, with a predictable target signal and an unpredictable disturbance signal, see Fig. 1. The HC perceives the target signal f_t , the system output θ perturbed by f_d and the tracking error $e = f_t - \theta$ from a pursuit display (Wasicko et al., 1966). The HC generates a control signal u to steer the system with dynamics Y_c such that θ accurately follows f_t , thereby minimizing e. An example is an aircraft pitch attitude tracking task where f_t is the intended pitch attitude and θ the actual pitch attitude.



Fig. 1. Control scheme studied here.

The target signal to be tracked is composed of constant acceleration-deceleration parabola segments, see Fig. 2, representative for a realistic control task. Each parabola segment consists of a constant acceleration phase, directly followed by a constant deceleration phase, of identical duration and magnitude. The parabola segments resemble a rapid change in pitch attitude, performed in minimum time within the pitch acceleration limits of the aircraft. The unpredictable disturbance signal f_d consists of a sum of ten sines, with the lowest frequency at 0.23 rad/s and the highest frequency at 17.33 rad/s, and is identical to the one used in (Drop et al., 2013).



Fig. 2. Control task target and disturbance signals. Note that f_d is scaled by 300% for clarity in this plot.

The system dynamics Y_c are second-order dynamics:

$$Y_c(s) = \frac{K_c \omega_b}{s \left(s + \omega_b\right)},\tag{1}$$

with $K_c = 2.75$ and $\omega_b = 2$. Dynamics of this form can represent a wide array of vehicle dynamics.

2.2 HC Model

Highly predictable target signals such as the parabola signal considered here might invoke feedforward control behavior in the HC, in addition to a closed-loop feedback component, see the HC model in Fig. 3 (Drop et al., 2013; Laurense et al., 2015). The ideal feedforward response is equal to the inverse of Y_c , such that $u(s) = f_t(s)/Y_c(s)$ and subsequently $\theta(s) = Y_c(s) \cdot f_t(s) / Y_c(s) = f_t(s)$, which results in e = 0. A feedback component is still necessary even if the HC were able to perform perfect feedforward control on f_t , to attenuate the disturbances by f_d .



Fig. 3. HC model block diagram.

The feedforward path Y_{p_t} is modeled according to the *Inverse Feedforward Model* of (Laurense et al., 2015):

$$Y_{p_t}(s) = K_{p_t} \frac{1}{Y_c(s)} \frac{1}{(T_I s + 1)^2} e^{-s\tau_{p_t}},$$
(2)

where the gain K_{p_t} , the second-order filter parametrized by T_I and the feedforward time delay τ_{p_t} are included to model imperfections in the human feedforward control. The feedback path Y_{p_e} is described as:

$$Y_{p_e}(s) = K_{p_e}(T_L s + 1)e^{-s\tau_{p_e}},$$
(3)

with K_{p_e} the feedback gain, T_L the lead time and τ_{p_e} the feedback path time delay (McRuer and Jex, 1967).

The neuromuscular system (NMS) is described by:

$$Y_{nms}(s) = \frac{\omega_{nms}^2}{s^2 + 2\zeta_{nms}\omega_{nms}s + \omega_{nms}^2},\tag{4}$$

with ω_{nms} and ζ_{nms} the natural frequency and damping, respectively (McRuer et al., 1968).

Human nonlinearities and output noise are modeled by the remnant signal n, which is modeled as white noise filtered by (Zaal et al., 2009):

$$Y_n(s) = \frac{K_n \omega_n^3}{\left(s^2 + 2\zeta_n \omega_n s + \omega_n^2\right) \left(s + \omega_n\right)},\tag{5}$$

with $\omega_n = 12.7$ rad/s and $\zeta_n = 0.26$ (Zaal et al., 2009). K_n was chosen such that $\sigma_n^2/\sigma_u^2 = 0.15$ in a disturbancerejection only tracking task ($f_t = 0$) and f_d as in Fig. 2.

3. IDENTIFICATION METHODS

3.1 ARX model estimation

Both the direct and indirect HC identification methods considered in this paper utilize multi-input-single-output (MISO) ARX models for identification (Ljung, 1999), see Fig. 4. Signals i_1 and i_2 are the two input signals, and ois the output signal to be modeled. The input and output signals last 81.92 s and are sampled at 25 Hz, such that each signal consists of 2048 samples. The subscript m used throughout this section denotes signals measured under closed-loop conditions, either from computer simulations (here) or from a human-in-the-loop experiment.

$$i_{1} (k - n_{k_{1}}) \rightarrow \boxed{B_{1} (q; n_{b_{1}}) / A (q; n_{a})} \xrightarrow{\downarrow} \underbrace{\frac{1}{A(q; n_{a})}}_{+} i_{2} (k - n_{k_{2}}) \rightarrow \boxed{B_{2} (q; n_{b_{2}}) / A (q; n_{a})} \xrightarrow{\downarrow} o(k)$$

Fig. 4. Generic ARX model structure.

The ARX model is described by the discrete-time difference equation in (6), with k the discrete time samples:

$$\begin{aligned}
A(q; n_a)o(k) &= B_1(q; n_{b_1})i_1(k - n_{k_1}) + \\
B_2(q; n_{b_2})i_2(k - n_{k_2}) + \epsilon(k)
\end{aligned} (6)$$

Here, ϵ is a white noise signal and q is the discrete time shift operator. Polynomials A, B_1 , and B_2 are defined as:

$$A(q; n_a) = 1 + a_1 q^{-1} + \ldots + a_{n_a} q^{-n_a}$$

$$B_1(q; n_{b_1}) = b_{1,1} + b_{1,2} q^{-1} + \ldots + b_{1,n_{b_1}} q^{(-n_{b_1}+1)} \qquad (7)$$

$$B_2(q; n_{b_2}) = b_{2,1} + b_{2,2} q^{-1} + \ldots + b_{2,n_{b_2}} q^{(-n_{b_2}+1)}$$

Each ARX model is defined by three model orders: the number of parameters in the A polynomial n_a , the B_1 polynomial n_{b_1} , and the B_2 polynomial n_{b_2} . For each of the two input signals a delay parameter also needs to be set: n_{k_1} , and n_{k_2} . The model orders and delay parameters are not known a priori; in both methods many candidate

models are evaluated and the best model is chosen by means of a model selection criterion.

The ARX models are estimated on a *subset* of the available time traces: the *estimation* data set, ranging from $k_{e,s}$ to $k_{e,e}$, such that $N_e = k_{e,e} - k_{e,s} + 1$ samples are used to fit the models. After estimation, each ARX model is evaluated by *simulating* the input signals through the estimated ARX model over all samples to obtain \hat{o} : the modeled estimate of the true output signal o. The model quality is calculated over a *subset* of the available time traces: the *validation* data set, ranging from $k_{v,s}$ to $k_{v,e}$:

$$V = \frac{1}{N_v} \sum_{k=k_{v,s}}^{k_{v,e}} \left(\hat{o}_m(k) - o(k)\right)^2, \qquad (8)$$

with $N_v = k_{v,e} - k_{v,s} + 1$ the number of samples used to measure model quality.

In all identification steps of the direct and indirect methods, the target signal f_t is shifted forward in time by 1 s, to account for possible *anticipatory* feedforward control, i.e., negative HC delays in the feedforward response. To obtain the true time delay in the path associated with f_t , one should substract 25 samples from the estimated $n_{k_{f_t}}$.

3.2 Indirect two-stage method

The indirect two-stage method of (van den Hof and Schrama, 1993) involves two identification steps. In stage 1, a high-order model is used to obtain an accurate, noisefree estimate e_r of the tracking signal e_m for use in stage 2. The forcing functions f_t and f_d are used as inputs i_1 and i_2 , respectively, and the tracking error signal e_m as output o. Thus, in stage 1 all inputs are uncorrelated with the output noise and closed-loop effects do not play a role.

It was found that in stage 1 one cannot use just *any* highorder ARX model, because not all model order and delay parameter combinations result in a stable ARX model. Therefore, a range of ARX model orders is considered, see Table 1, and the 'best' model is the one with minimum V. In stage 1, $k_{e,s} = 1$, $k_{e,e} = 2048$, $k_{v,s} = 1$, and $k_{v,e} = 2048$, i.e., all data is used for both estimation and validation.

In stage 2, a direct estimation is performed with $i_1 = f_t$, $i_2 = e_r$, and $o = u_m$. Here, the input signal e_r is not correlated with output noise in u_m and closed-loop effects should *not* play a role. In stage 2, $k_{e,s} = 129$, $k_{e,e} = 1088$, $k_{v,s} = 1089$, and $k_{v,e} = 2048$.

The range of evaluated model orders and delay parameters is given in Table 1. Bounds of stage 1 and 2 were chosen such that the selected model orders did not 'hit' these bounds with a margin of at least 2. For stage 1, however, it was not possible to choose the bounds of n_{bf_t} following this rule, because model selection is based on V only. It was found that the lowest V is always obtained by the model with the maximum value of n_{bf_t} . Therefore, a very large value (25) was chosen as upper bound of n_{bf_t} .

3.3 Direct method

The direct method involves one identification step only, with $i_1 = f_t$, $i_2 = e_m$, and $o = u_m$. The direct method does not explicitly deal with closed-loop effects, and assumes

Table 1. ARX model order ranges.

	n_a	$n_{b_{f_t}}$	n_{b_e}	$n_{k_{f_t}}$	n_{k_e}
Indirect stage 1	[110]	[025]	[010]	[15]	[15]
Direct and indi-	[17]	[07]	[07]	[150]	[110]
rect stage 2					

that measurements were in fact taken in an open-loop experiment. Each ARX model is fit on the data from $k_{e,s} = 129$ to $k_{e,e} = 1088$, to be consistent with the indirect method. Model quality is evaluated over the data from $k_{v,s} = 1089$ to $k_{v,e} = 2048$.

The large range of evaluated $n_{k_{ft}}$ delay parameters in the direct method and in step 2 of the indirect method, see Table 1, is a result of shifting the target signal forward in time to account for anticipatory feedforward control.

3.4 Model selection

A model selection criterion is used to select the 'best' model from the set of considered models. Model selection criteria (MSC) make a trade off between model quality measured by V, and model complexity measured by the number of model parameters d, penalized by a factor W:

$$MSC = \log V + Wd \tag{9}$$

For the AIC $W_{\text{AIC}} = 2/N_f$, and for the BIC $W_{\text{BIC}} = \log(N_f)/N_f$. Here, we will present results as a function of W to investigate the effect of utilizing a particular criterion or penalty value on model quality and complexity. The number of parameters d is the sum of n_a , $n_{b_{f_t}}$, and n_{b_e} , plus the total number of delays in the model, which is equal to the number of responses with $n_b > 0$.

4. COMPUTER SIMULATIONS

Computer simulations are performed utilizing the HC model of Section 2.2 with two sets of model parameter values, referred to here as 'models', see Table 2. First, the purely feedback model (FB) is used to investigate false-positive feedforward identification. The feedforward gain K_{p_t} is set to zero; only feedback control is present. Second, simulations with the feedforward model (FF) with parameter values representative for this control task (Laurense et al., 2015) are performed to investigate the methods' ability to identify the feedforward-feedback multi-loop model structure and dynamics. The feedforward gain K_{p_t} is set to 0.8, which is a 'conservative' value: a slightly larger value, closer to the ideal value of 1, was estimated from experimental data (Drop et al., 2013; Laurense et al., 2015). For both models, $\omega_{nms} = 10.1$ rad/s and $\zeta_{nms} = 0.35$.

Table 2. Model parameters values.

	K_{p_t}	T_I	τ_{p_t}	K_{p_e}	T_L	τ_{p_e}	RMS(e)
	-	\mathbf{s}	s	-	\mathbf{s}	s	deg
FB	0	-	-	0.75	0.4	0.24	2.43
\mathbf{FF}	0.8	0.25	0.35	0.75	0.4	0.24	1.22

The RMS(e) reflects the performance level of each model for this control task, see Table 2. The RMS(e) of the FF model is around 50% of the FB model, illustrating the potential performance improvement of utilizing feedforward control (Wasicko et al., 1966; Drop et al., 2013). Each model is simulated for fifty different realizations of the signal n. Both identification methods are applied to each realization.

5. RESULTS

5.1 Model fit quality

The model fit quality of the selected models is assessed here by means of the Variance Accounted For (VAF):

$$\text{VAF} = \left(1 - \frac{\sum_{k=k_{e_s}}^{k_{e_e}} (u_m(k) - \hat{u}_m(k))^2}{\sum_{k=k_{e_s}}^{k_{e_e}} \hat{u}_m(k)^2}\right) \times 100\% \quad (10)$$

Note that the VAF is different from V, but more intuitive to interpret.

Fig. 5(a) depicts the VAF obtained for all models with both methods, averaged over all remnant realizations, as a function of W. Errorbars depict one standard deviation. For W < 0.1 the VAF is approximately constant and close to 98% for all conditions, which illustrates that the models obtained from both methods describe the data very well. The VAF is always higher for the direct method (D) than for the indirect method (I), for both models.



Fig. 5. Model fit quality as a function of W. Vertical dashed lines mark the value of W for AIC and BIC.

Fig. 5(b) shows the VAF for much larger values of W; note the ordinate axis scaling. The VAF reduces dramatically for W > 0.5, albeit at different values for different conditions, suggesting that model complexity was penalized too much and important dynamics were left out.

5.2 False-positives and false-negatives

Fig. 6 shows the number of parameters in the feedforward path $n_{b_{f_t}}$ of the selected ARX models, averaged over all remnant realizations, as a function of W. To describe the low-frequency feedforward response (the inverse of Y_c , which is equal to a differentiator) $n_{b_{f_t}}$ should be ≥ 2 .

For the FB model $n_{b_{f_t}}$ should be 0; any non-zero result is a false-positive feedforward identification. For the direct method, false-positives are found up to $W < 1.2 \times 10^{-2}$, but for the indirect method up to a much higher value: 3.7×10^{-2} . The penalty that would be imposed by both the AIC and BIC is too small to prevent false-positives, and thus both model selection criteria are unsuited.

For the FF model $\bar{n}_{b_{f_t}} \geq 2$ up to $W < 2.6 \times 10^{-1}$ for both the direct and indirect method. $\bar{n}_{b_{f_t}}$ rapidly decreases to zero for larger values of W, these are false-negative results:



Fig. 6. $\bar{n}_{b_{f_{\star}}}$ as a function of W.

feedforward is present in the true model, but not in the identified model.

5.3 Frequency response of identified models

Fig. 7 shows the frequency responses of the identified models for all remnant realizations, selected for $W = W_{\rm BIC}$, compared to the true FB dynamics. Vertical dashed lines mark the lowest and highest frequency component in f_d , outside this region inaccurate estimates are expected.



Fig. 7. Bode plot of the feedforward and feedback paths of the selected models for the FB model, $W = W_{\text{BIC}}$.

Fig. 7(a) shows the *false-positive* feedforward results, compared to the true feedforward response of FF, but with $K_{p_t} = 0.2$. The magnitude response of these false-positives resemble the FF feedforward dynamics very well, albeit with a rather small static gain. This nevertheless increases the likelihood of falsely interpreting such results as a 'real' feedforward identification. The phase response is 180 degrees different from the FF feedforward dynamics, by which false-positive results could be recognized. Note, however, that this statement relies on knowledge of the true model, which is not known for a real human controller.

The identified feedback dynamics, see Fig. 7(b), resemble the true FB dynamics very well. At higher frequencies, some responses rapidly increase in magnitude to fit the noise. Surprisingly, also models identified by the indirect method suffer from this effect.

Fig. 8(a) shows that for the FF model, the identified feedforward dynamics resemble the true FF dynamics very well for $\omega < 3$ rad/s. Above 3 rad/s the identified responses



Fig. 8. Bode plot of the feedforward and feedback paths of the selected models for the FF model, $W = W_{\text{BIC}}$.

show a neuromuscular peak, although these dynamics are not present in the true model's feedforward path. The apparent identification of NMS dynamics is caused by the denominator polynomial A, that is shared by the feedforward and feedback paths (see Fig. 4). The identified feedback dynamics of the FF model, see Fig. 8(b), are very similar to the true dynamics.

5.4 False-negative feedforward results

Upon closer inspection of Fig. 5(b) and Fig. 6 for the FF model, it becomes clear that for 0.4 < W < 1 models without a feedforward path are selected, that nevertheless provide a VAF similar to the VAF of models with a feedforward path (selected for W < 0.1). Fig. 9 reveals that models selected for 0.4 < W < 1 contain a feedback path that partly describes the feedforward dynamics. That is, the feedback dynamics are a leaky integrator at low frequencies, whereas the true feedback dynamics are a gain at low frequencies. This leaky integrator integrates the steady-state tracking error during the parabola segments, thereby generating a control signal that is similar to the real control signal (Drop et al., 2013).



Fig. 9. Bode plot of the feedback path of the selected ARX models for the FF model, W = 0.47.

To conclude, models exist with very different dynamics from the true dynamics that nevertheless describe the data with high accuracy. This clearly demonstrates the importance of choosing the correct value for W when analyzing experimental human-in-the-loop data for which the true model is *not* known.

5.5 Comparison between direct and indirect methods

To compare the direct and indirect methods, we compute two error metrics between the identified dynamics and the true dynamics. The absolute error in magnitude $\varepsilon_{\text{magnitude}}$ and the absolute error in phase $\varepsilon_{\text{phase}}$ is calculated as:

$$\varepsilon_{\text{magnitude}}(j\omega) = ||Y_p^{\text{best}}(j\omega)| - |Y_p^{\text{hyp}}(j\omega)||$$
(11)

$$\varepsilon_{\text{phase}}(j\omega) = |\angle Y_p^{\text{best}}(j\omega) - \angle Y_p^{\text{hyp}}(j\omega)|$$
 (12)

Fig. 10 shows the mean and maximum values of these metrics, taken over all 50 realizations, for the FF model. Fig. 10(a) shows that the direct method provides a better estimate of the true feedforward dynamics than the indirect method, for $\omega < 8$ rad/s. For instance, at low frequencies the error averaged over all remnant realizations in both magnitude and phase is smaller; and the maximum error is smaller too. Both methods perform worse at higher frequencies than at low frequencies, caused by the appearance of a neuromuscular peak in the ARX model which is not present in the true model. The indirect method provides a slightly smaller error at certain higher frequencies.



Fig. 10. The average and maximum error in magnitude and phase between the estimated and true dynamics for $W = W_{\text{BIC}}$.

Fig. 10(b) shows that the direct method also provides a smaller average error for the feedback dynamics for $\omega < 7$ rad/s for the FF model. The same is true for the feedback dynamics of the FB model (not shown).

Note that for $W = W_{\text{BIC}}$ the models identified by the indirect method are generally more complex than those identified by the direct methods, see Fig. 6. Hence, one would expect the results of the indirect method to be more accurate, but the opposite is true.

6. CONCLUSIONS

This paper evaluated a direct and an indirect identification method for identifying the feedforward and feedback control dynamics of the HC from closed-loop measurements. The 'best' of all possible models was chosen by means of a model selection criterion that makes an explicit trade-off between model quality and model complexity.

We conclude that 1) both methods identify models with dynamics similar to the true dynamics, but that 2) the direct method provides more accurate estimates in the frequency range of interest. We demonstrated the occurence of false-positive and false-negative results, and conclude that 3) the AIC and BIC model selection criteria do *not* prevent false-positive feedforward identification.

We suggest two methods, to be investigated further in future research, to deal with the issue of possible falsepositive results. First, the correct value of the model complexity penalty parameter is obtained from computer simulations for which the true model is known and highly similar to the expected HC control dynamics. Second, the identification results of experimental human-in-the-loop data will be analyzed as a function of the model complexity penalty parameter, to make the model selection more insightful and objective to the reader.

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