

Manual control cybernetics

State-of-the-art and current trends

Mulder, Max; Pool, Daan M.; Abbink, David A.; Boer, Erwin R.; Zaal, Peter M.T.; Drop, Frank M.; El, Kasper van der; van Paassen, Marinus M.

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Manual Control Cybernetics: State-of-the-Art and Current Trends

M. Mulder, D. M. Pool, *Member, IEEE*, D. A. Abbink, *Senior Member, IEEE*, E. R. Boer, *Member, IEEE*, P. M. T. Zaal, *Member, IEEE*, F. M. Drop, *Student Member, IEEE*, K. van der El, *Student Member, IEEE*, and M. M. van Paassen, *Senior Member, IEEE*

Abstract—Manual control cybernetics aims to understand and describe how humans control vehicles and devices using mathematical models of human control dynamics. This ‘cybernetic approach’ enables objective and quantitative comparisons of human behavior, and allows a systematic optimization of human control interfaces and training associated with manual control. Current cybernetics theory is primarily based on technology and analysis methods formalized in the 1960s and has shown to be limited in its capability to capture the full breadth of human cognition and control. This paper reviews the current state-of-the-art in our knowledge of human manual control, points out the main fundamental limitations in cybernetics, and proposes a possible roadmap to advance the theory and its applications. Central in this roadmap will be a shift from the current linear time-invariant modeling approach that is only truly valid for human behavior under tightly controlled and stationary conditions, to methods that facilitate the analysis of adaptive, and possibly time-varying, human behavior in realistic control tasks. Examples of key current developments in the field of cybernetics – human use of preview, predictable discrete maneuvering, skill acquisition and training, time-varying human modeling, and neuromuscular system modeling – that contribute to this shift are presented in this paper. The new foundations for cybernetics that will emerge from these efforts will impact all domains that involve humans in manual and semi-automatic control.

Index Terms—Manual control, man-machine systems, cybernetics, dynamic behavior, modeling

I. INTRODUCTION

CYBERNETICS is a system-theoretical, model-based approach to understand and mathematically model how humans control vehicles and devices [1]–[6]. Most of current cybernetics theory has been developed in the 1960s – for 1960s technology – and has been applied in aerospace [7]–[29], automotive [30]–[46], other vehicles [47]–[52], robotics [53]–[57] and medical applications [58]–[61]. The power of cybernetics is evident from the seminal *crossover model* [2]–[4], which captures the systematic adaptation of the Human Controller (HC) to the dynamics of the controlled vehicle or device, to achieve good feedback performance and robustness which are largely invariant with the controlled system. By

revealing such key *invariants* and providing a means for *predicting* manual control performance, classical cybernetics theory has accelerated many innovations in human-machine control system design, such as in aerospace [7]–[17].

Despite its many successes, cybernetics theory has also often been shown to be limited in capturing the full breadth of human cognition and control. Modern interface technologies, such as three-dimensional visual displays [6], [62], [63] and haptic (shared) control manipulators [43]–[46], [55], [64] are rapidly expanding the way humans can interact with dynamic systems. They also dramatically expand the factors that drive human control adaptation. It is safe to say that, despite haphazard attempts to update cybernetics theory, the progress in technology has leapfrogged the classic cybernetics theory, and our current tools and models fail to completely explain and predict how humans interact with modern interfaces.

State-of-the-art cybernetics theory describes human controllers as (quasi-)linear, time-invariant (LTI) *feedback* systems [2]–[4], [65]–[77]. The most successfully applied models are those that consider human behavior in the highly-constrained *compensatory tracking* task [2], [69], without any preview of future task constraints, allowing the operator only to *react* on what happens (pure feedback). The time-invariance assumption prevents us from modeling what is a defining attribute of human controllers, namely their ability to *adapt* to changing situations, which, in the age of increasing automation, is often the only reason humans are kept in the control loop. The same theoretical constraints that prevent us from studying and understanding human learning, adaptation and the versatile set of anticipatory *feedforward* control behaviors, also prevent us to optimize current-day control interfaces in realistic tasks.

But this lack of understanding of realistic HC behavior is not our only problem, as also our methodology and tools to identify human manual control are limited to rather crude experimental techniques. We can only identify the overall, *lumped* response of a fully-trained human, based on prolonged measurements [69], [78]–[84]. This approach fuses all cognitive and physiological adaptations and averages-out all adaptation effects, preventing us from understanding design-relevant aspects of human adaptation and learning.

In the past decade, we have come to the conclusion that the intertwined *theoretical* and *methodological* limitations of the state-of-the-art in cybernetics theory have become a limiting factor in evaluating and improving our manual control interfaces. The inability to step-up from classical compensatory control to more relevant real-life tasks means that *we are*

M. Mulder, D. M. Pool, F. M. Drop, K. van der El, and M. M. van Paassen are with the section Control and Simulation, Faculty of Aerospace Engineering, Delft University of Technology, 2629 HS Delft, The Netherlands. Corresponding author: m.mulder@tudelft.nl

D. A. Abbink and E. R. Boer are with the department BioMechanical Engineering, Faculty of Mechanical, Maritime and Materials Engineering (3ME), Delft University of Technology, 2628 CD Delft, The Netherlands

P. M. T. Zaal is with the San Jose State University Research Foundation performing collaborative research at the Human Systems Integration Division of NASA Ames Research Center, Moffett Field, CA 94035, USA

currently able to model only the exception in manual control, and not the rule. We see a striking similarity to the domain of human visual perception, where in the 1950s the psychologist James J. Gibson came to the conclusion that “*the theory of visual perception is all wrong*” [85]. The theory and experiments at that time studied visual perception performance mainly through forcing human subjects to look at *static* scenes, from a fixed position. Gibson was the first to conclude that staring at static pictures is an *exceptional* case, as human visual perception is all about dynamically perceiving (and acting upon) the *dynamics of environments*, leading to the now overarching *ecological* perspective on visual perception [86].

We strongly believe that cybernetics theory should step up from studying merely the exception in manual control – compensatory behavior – to the rule. Relevant control tasks have *preview* of the future constraints and in many cases not only allow, but actually *require* human adaptation. A targeted research effort is needed to radically advance our theory, our models, our tools. We must address some fundamental research questions on human manual control. Examples are: 1) How do humans use preview of future task constraints? 2) What are the factors and mechanisms that drive adaptation, and which invariants in adaptation exist? 3) To what extent are measured human adaptations caused by physiological (e.g., neuromuscular) rather than cognitive adaptations? 4) What are the temporal scales of human adaptation and learning in changing situations? 5) What novel control theories and system identification techniques exist that could allow us to study time-varying and possibly non-linear manual control?

With this paper we aim to provide an overview of the field of manual control cybernetics, elaborate on its fundamental problems, provide a way forward, and show some of the latest results in extending theory and applications. The paper is structured as follows. In Section II we attempt to briefly summarize the state-of-the-art; for some earlier summaries one is referred to [2]–[4], [74], [76]. A roadmap to systematically address the fundamental challenges is provided in Section III. A number of key theoretical and methodological innovations that follow from this roadmap will be discussed in Section IV. Three novel applications of cybernetics theory, in haptic feedback design, multi-modal simulator fidelity evaluations, and transfer-of-training studies are summarized in Section V. The paper will end with a conclusions section.

The paper’s scope is intentionally kept limited, by mainly focusing on classical control-theoretic frequency-domain approaches to modeling human control dynamics, and only occasionally referring to other modeling perspectives that have emerged in the past decades, such as those originating from optimal, robust or satisfying control theory, and time-domain analysis. In our experience, it is mostly this first class of *physical* models that has prevailed, also because – the perhaps in principle more generic and certainly intellectually appealing – *optimal* human control models [87]–[89] have shown to be over-parameterized [90] meaning that they cannot be validated experimentally. Further note that, in our discussion of innovations and applications, we focus primarily on the ongoing activities in our labs, as modernizing cybernetics *theory* is one of our key objectives.

II. STATE-OF-THE-ART

A. Successive Organization of Perception

In 1960, Krendel and McRuer [68] first introduced the Successive Organization of Perception (SOP) hierarchy for human manual control. The SOP postulates a framework describing the development of skill-based manual control behavior, in three stages: compensatory, pursuit and precognitive control, see Fig. 1 for schematic representations. Depending on the defining features of the control task, such as the display format and the applied forcing functions, and training, human operators may apply compensatory, pursuit, or precognitive control strategies, or could be switching between any combination of these levels [68], [71]. The next subsections discuss the three SOP levels in more detail.

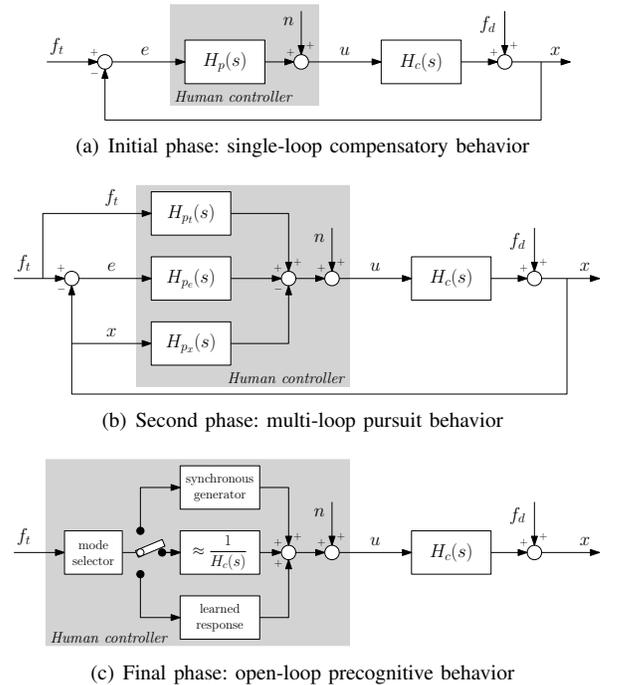


Fig. 1. Schematic representations of the three stages of control behavior described in the Successive Organization of Perception (SOP), initially described in [68], later adapted in [71]. These figures are reproduced, with minor modifications, from [71].

B. Compensatory Tracking

In the compensatory stage, see Fig. 1(a), the human controller (HC) acts solely on the error e between the reference and the system output [67]. The HC responds only to the error, either because it is the only perceivable signal, or because the HC chooses to act on the error only. Compensatory control has been studied extensively for control tasks where the HC could only perceive the error, and all forcing functions were unpredictable [2], [52], [65], [69], [79], [80]. Reasons for retaining a compensatory organization in situations where more signals can be perceived are: 1) a lack of experience, the HC has not yet learned sufficiently to progress to the pursuit or precognitive stages, 2) the HC is under stress, causing him/her to ‘revert’ to a compensatory organization, or 3) a pursuit

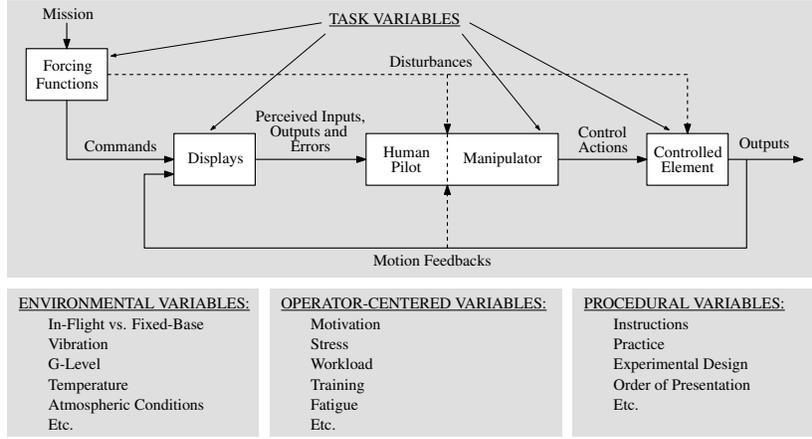


Fig. 2. The variables that affect a closed-loop human controlled system, reproduced from [2].

or precognitive organization is not beneficial for improving performance [68], [75].

Pioneering research into human tracking behavior by Tustin [65] and Elkind [66], [91] led to a comprehensive framework for the analysis and modeling of compensatory control behavior in the 1960s [2]–[4], [67]–[69]. Much of our current knowledge stems from these investigations into human dynamics during *single-loop* compensatory tracking tasks [2], [66], [69]. This research also showed the complexity of studying the human controller, due to her or his capacity to adapt to a myriad of task, environmental, operator-centered, and procedural variables, as summarized in a comprehensive overview compiled by McRuer and Jex [2], see Fig. 2.

For the most basic SOP level of compensatory control, the well-known *crossover model* given by (1), in combination with the *verbal adjustment rules* of [2], accurately describes a crucial invariant of HC behavior in the systematic HC adaptation to some of the key task variables: the controlled system dynamics (H_c) and the bandwidth of the applied forcing function spectra:

$$H_p(j\omega)H_c(j\omega) = \frac{\omega_c}{j\omega} e^{-j\omega\tau_e} \quad (1)$$

To induce a compensatory control organization, and thus force the HC into a mode where she or he cannot anticipate on what comes next, the applied forcing functions must be random-appearing [2], [66], [67], [69]. Typically, this is achieved by using *quasi-random multisine signals*, sums of a sufficient number of individual sinusoids that span the frequency range of interest [69], [92], [93]. Not only do such multisine forcing functions force compensatory control, they also facilitate the straightforward identification of frequency-domain describing functions of human dynamics in compensatory tracking tasks [69], [78], [80]. Using the quasi-linear model assumption, the linear, time-invariant (LTI) part of the HC can then be modeled. The remainder, called ‘remnant’, is usually neglected, despite attempts to provide some rationale for the remnant component as well [2], [94], [95].

Even though a number of different LTI models for compensatory HC dynamics have been proposed [15], [21], perhaps the most-used is the *precision model*, which is given by (2)

in a form that, compared to its definition in [69], omits the indifference threshold describing function.

$$H_p(j\omega) = K_p \underbrace{\left(\frac{T_L j\omega + 1}{T_I j\omega + 1} \right)}_{\text{equalization}} \underbrace{\left(\frac{T_K j\omega + 1}{T'_K j\omega + 1} \right)}_{\text{low-freq. lag-lead}} \underbrace{e^{-j\omega\tau}}_{\text{delay}} \times \underbrace{\left[\frac{1}{(T_N j\omega + 1) \left(\left[\frac{j\omega}{\omega_{nm}} \right]^2 + \frac{2\zeta_{nm} j\omega}{\omega_{nm}} + 1 \right)} \right]}_{\text{neuromuscular dynamics, } H_{nm}} \quad (2)$$

In this model, the main adaptation of the HC dynamics H_p to the dynamics of the controlled system H_c is captured by the *equalization* term of the model. Depending on what type of equalization is required to satisfy (1) for a given H_c , the lead-lag equalization form of (2) may reduce to a pure lead, a pure lag, or a pure gain [69]. Furthermore, the precision model includes an additional low-frequency lag-lead term, for capturing low-frequency phase equalization found in describing function data [2], [69]. Finally, the model includes terms that account for characteristic HC limitations in a *delay* term $e^{-j\omega\tau}$ and the *neuromuscular* actuation dynamics. In more recent applications of the precision model, the low-frequency lag-lead is often omitted and neuromuscular dynamics are simplified to the second-order term only [12], [25], [27], [92], while extended equalization was proposed for control of systems with underdamped modes [27].

Theories and models for compensatory tracking have been extended to *multi- or multiple loop* control tasks. Here, a distinction is often made between control of 1) multiple nested loops (e.g., aircraft pitch and altitude) [2], [32], [71], [73], [96], 2) multiple (coupled) parallel loops (e.g., aircraft pitch and roll) [2], [70], [73], [77], [79], [97]–[99], and 3) a single-loop task with a single controlled variable, but with a multi-loop HC feedback organization (e.g., multimodal visual/vestibular feedback) [21], [25], [100]. Multi-loop scenarios typically result in elaborate and often over-determined HC models, requiring extended identification and modeling methods to separate the different HC responses [79], [81]–

[83]. It is safe to say that current-day cybernetics theory and methods, predominantly deal with *single-loop* compensatory tracking. Only for this extremely simple task do we have accepted, universal models, such as the crossover and precision models, that allow us to *predict* how a (well-trained) HC adapts to task variable settings.

C. Pursuit Tracking

In the pursuit stage, see Fig. 1(b), the HC utilizes a combination of at least two of the following control strategies: 1) a feedforward response (H_{p_t}) on the target f_t [101], [102], 2) a compensatory feedback response (H_{p_e}) on the error e as in compensatory tracking [101], and 3) a feedback response (H_{p_x}) on the system output x [101]–[103]. The theoretically optimal pure feedforward control law approximates the inverse system dynamics, i.e., $H_{p_t} \approx 1/H_c$ [101], [104], while feedback of the system output x is useful for mechanizing a stabilizing “inner” control loop, mostly for tasks with sluggish system dynamics [101]. Key is, however, that a “pursuit” organization of HC behavior is not adopted in all tasks where the feedbacks to support it are available [75], [101], [105]. The opposite holds as well: a pursuit (or even precognitive, see Section II-D) strategy may be developed even in a compensatory tracking task – so, if *no* additional feedbacks are available – for example when forcing functions are predictable.

Many studies report improved task performance when HCs reach the pursuit stage [101], [105]–[109]. As proposed in [101], the underlying change in HC control behavior can be detected from the ‘*effective open-loop describing function*’ – i.e., the describing function from the tracking error e to the system output x – which shows strongly reduced low-frequency phase lag in pursuit [75], [101]. While helpful for detection, the effective open-loop lumps together all control dynamics and thus does neither reveal the true adopted HC control organization, nor the separate contribution of each feedforward or feedback response (e.g., H_{p_t} , H_{p_e} , and H_{p_x}).

Compared to the modeling of HC behavior in compensatory tasks, pursuit tracking tasks have received meager attention [75], [101], [102]. The main reason is that the multi-loop control behavior in pursuit (see Fig. 1(b)), makes its modeling significantly more complicated [75], [101]. In pursuit tasks, HCs may choose to mechanize feedforward and/or feedback control responses driven by the f_t , e , and x signals, see Fig. 1(b). However, as $e = f_t - x$, only two of the three possible HC responses are independent, resulting in an inherently overdetermined model structure. For modeling pursuit control, model structures that include H_{p_t} and H_{p_e} [2], [101], [102], [110], H_{p_e} and H_{p_x} , or H_{p_t} and H_{p_x} [111] have all been proposed and applied. Furthermore, from an identification perspective, the pursuit task requires *two* independent forcing function signals (f_t and f_d in Fig. 1(b)) to separately estimate the *two* independent describing functions [79], [81] and model both using LTI model structures. Up until quite recently, this has almost never been tried [104], [111].

What is stated for pursuit control, is even more true when the HC has *preview* on the future task constraints, like the future trajectory of the target signal [112]. With the direct

capacity for overcoming inherent HC control delays, preview almost invariably results in improved task performance far exceeding that of pursuit [80], [89], [113], [114]. In essence, in tasks with preview, HCs adopt a pursuit control organization with a strong feedforward H_{p_t} response driven by the *future* target signal. From sampling and cueing theories, it is known that HCs become almost optimal samplers with preview [89], and that HCs’ *internal representation* [115] of task variables greatly improves. The human response to preview is a convolved and very likely *time-varying* weighing of this future information [112], which cannot be directly measured, as an infinite number of different weighing mechanisms theoretically yield the same control response. Even more than for pure pursuit, the difficulty for preview control lies in the fact that, when preview information becomes available, a multitude of control strategies become possible [111], [112].

When considering realistic manual control tasks, it is difficult to think of tasks that better resemble pure compensatory tracking than pursuit or preview tracking. Therefore, there is a strong need for *universal* models for HC pursuit and preview control, similar to those that are available for compensatory control. Given the increased degrees-of-freedom in HC adaptation, developing such universal models and sets of “adjustment rules” for pursuit and preview control is extremely challenging. Still, a firm grasp of how humans control in pursuit or preview is one of the main crucial elements that is missing in the current cybernetics state-of-the-art.

D. Precognitive Control

In the precognitive stage, see Fig. 1(c), the HC is assumed to have complete knowledge of the target signal and to generate a control input that results in perfect target tracking [72], [108], [116]. In the precognitive phase, HCs may develop purely open-loop control responses based on a fully-developed internal representation of task demands, such as dominant frequency components and the controlled system dynamics [68], [71]. The HC does not actively rely on *any* feedback, at least not for a particular time interval [71].

When the SOP was postulated, the hypothesized precognitive level was not yet fully supported, mainly because direct identification of human feedforward responses was lacking [68]. Still, a broad collection of empirical observations and recent data support the SOP’s precognitive phase. For example, numerous studies report notably improved tracking performance when following ‘predictable’ target signals, in comparison with ‘unpredictable’ signals [72], [106], [108], [117]–[120], even for signals with equivalent frequency content and bandwidth. Further evidence for the development of a precognitive control mode has been found with observed response time delays and phase lags that are smaller than a ‘normal’ human reaction time [108], [121]. Finally, studies involving temporal occlusion [116], where HCs tracked a sum-of-two-sines target signal for a certain time, after which the display was switched off, also report reasonably accurate continued tracking of predictable, repetitive signals only. Though lacking a formal definition of subjective predictability and empirical evidence for its limits, these observations provide indirect evidence for a precognitive strategy.

To conclude, ample indirect and mostly qualitative evidence of a precognitive level of manual control exists. Still, in most cases the evidence is thin, with possible alternative explanations that do not require the existence of a true precognitive control strategy (e.g., strongly adapted feedback control). Except for a rudimentary understanding and proposed cybernetic models for the (partially) precognitive feedforward control in ramp tracking tasks [104], [122], [123], we still lack a structured, systematic understanding of the final level of the SOP, as would be relevant to real world applications.

E. Neuromuscular Dynamics

Cybernetic theory emphasizes how control inputs to the plant result from visual and vestibular cues. But McRuer [124] already stated in 1966 that neuromuscular actuation properties are “*an essential element in the operators dynamic characteristics*”. He recognized that the neuromuscular system (NMS) constitutes an inner loop that not only translates desired control inputs to realized control inputs, but that can also provide very fast reflexive feedback to forces on the control device, even instantaneous responses from (co)contracted muscles and passive limb dynamics. Although subsequent work also took into account this ability of the neuromuscular system to provide force feedback [2], [87], [124], [125], this detail has been neglected in later cybernetic studies. Often, the neuromuscular system is viewed as a physical limitation, to account for the fact that physical properties of our body coupled to the control interface inherently limit the bandwidth of HC control inputs. This limitation shows up in HC describing functions as a distinctive peak around 2-4 Hz, with an ensuing decay.

Mathematical models of NMS dynamics were developed in parallel to HC models [2], [87], [124], [125], see also (2). In HC models, the combined manipulator and NMS dynamics are typically accounted for with a single, lumped, low-order model; generally an underdamped second- or third-order low-pass transfer function [2], [124]. That no separate gain is modeled, indicates the assumption that the NMS is fully adapted to the control device dynamics [19], [126], [127], and also avoids over-parameterization. The estimated parameters of the cut-off filter have been shown to vary as a function of manipulator characteristics [127], [128], the controlled system dynamics [111], [123], and the presence of motion feedback [25]–[27]. Simplification of the neuromuscular system as a ‘physical limitation’ described by a filter is valid for applications where the operator controls a system where the control device receives no force feedback about plant states. Such applications include fly-by-wire aircraft, rate-controlled systems, or uni-directional telemanipulation.

For other control tasks, force feedback on the control interface is essential for human operator performance. For instance, during driving, forces and movements at the tires are physically coupled to forces and movements at the steering wheel, allowing the neuromuscular system to respond to force perturbations from wind gusts or road properties – before these perturbations change vehicle states enough to be observable by visual or vestibular cues. The neuromuscular system then acts as an inner-loop, responding to forces very quickly (through

reflexive feedback) or even instantaneously (through limb inertia and visco-elasticity of co-contracted muscles). Frequency response functions (FRFs) of the NMS can be estimated as “*admittance*”, a measure of the allowed limb displacement due to an applied force [129]. HCs can adapt the admittance of their NMS – i.e., how “stiff” or “compliant” their response to forces is – which affects control performance in car driving [40], [45], aircraft control [24], and the impact of biodynamic effects in moving environments [130], [131].

Proposed models to describe NMS contributions to operator control dynamics are based on theory about muscle and arm dynamics [19]. Functional mathematical models typically describe overall endpoint admittance by separating manipulator dynamics from neuromuscular dynamics, which comprise passive limb dynamics (inertia, visco-elastic properties of ligaments and (co)contracted muscles), reflex dynamics (position and velocity feedback from muscle spindles and force feedback from Golgi tendon organs) as well as their interaction through cognitive processing [24], [132].

Clearly the NMS can increase or decrease admittance through many mechanisms, whose interactions are complex to determine. This means that NMS model structures are per definition over-determined, making the parameters difficult to extract from physical measurements. Regardless, the NMS needs to be taken into account, to avoid attributing its contribution to visual or vestibular control activity.

III. NOVEL FRAMEWORK FOR CYBERNETICS

The cybernetics overview of the previous section clearly showed that our knowledge and methods mostly cover highly-constrained tasks – mainly compensatory tracking – that are quite far from typical real-world manual control scenarios. In this section we propose a five-step framework [84] to increase our understanding of the *learning and adaptive human controller*, see Fig. 3. It consists of five “steps”, each describing a major extension of our knowledge of human control, that will take the field of manual control cybernetics from its current state-of-the-art (shown with the gray shaded area in Fig. 3) to the level required for applications to real-world optimization of human control interfaces and training.

Central in the framework is the concept of Internal Representation (IR) [115] that, as shown with the purple blocks in Fig. 3, is developed and refined during learning, when the HC is exposed to the task constraints. For manual control, primarily the task variables of Fig. 2 characterize the task, especially key task variables such as the plant dynamics (P) and the statistical properties of the target and disturbance signals (T and D). Our premise is that it is the IR, the quality of which increases with exposure and experience, that is the critical driver behind human control adaptations. The IR enables HCs to evolve through the different phases of the SOP and thereby develop an optimal combination of feedforward (FF) and feedback (FB) control to satisfy task constraints.

The following subsections describe the different fundamental steps of the proposed framework of Fig. 3 in more detail.

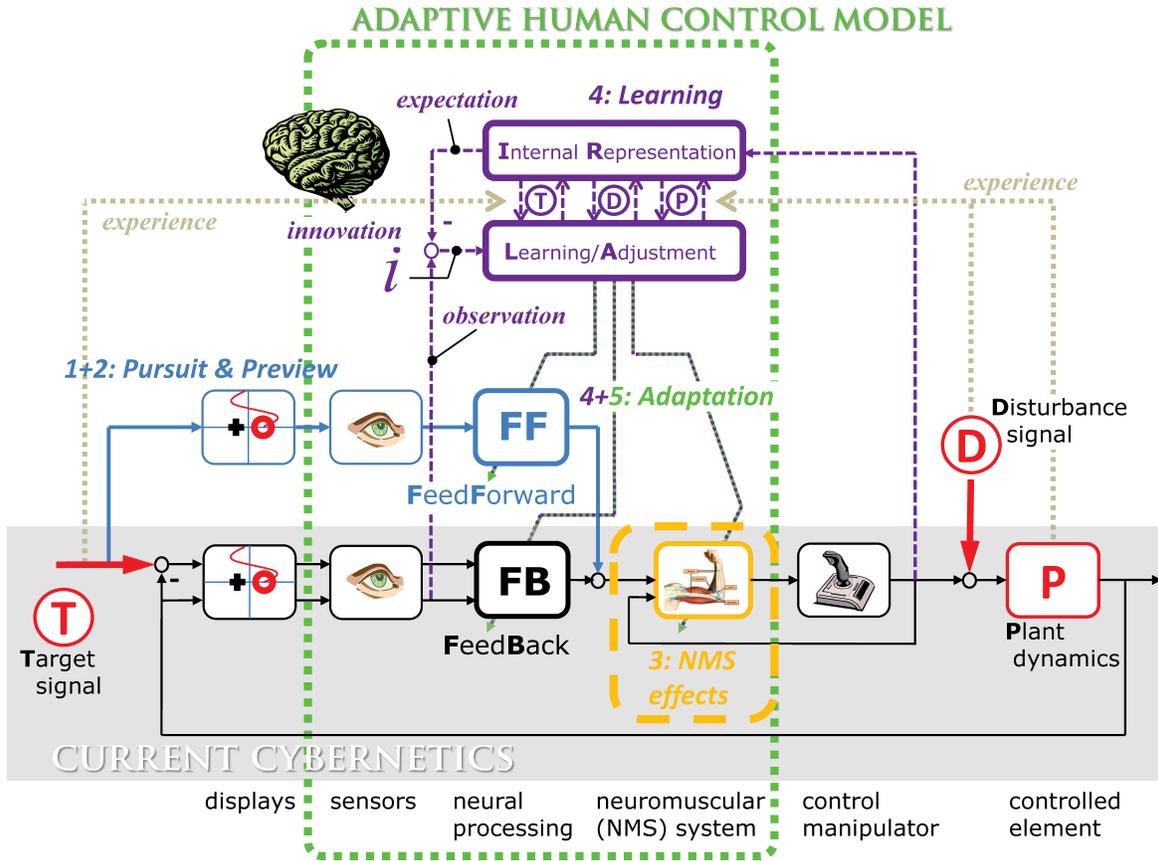


Fig. 3. A proposed framework for understanding the learning and adaptive human controller, reproduced from [84].

A. Steps 1 + 2: Understanding Pursuit and Preview

The first two steps to update our theory, see Fig. 3, focus on developing validated and practical models and analysis methods for HC control at the *pursuit* level (Step 1), as well as for human *preview* control (Step 2). While often seen as separate levels of HC behavior, pursuit can be viewed as an extreme (zero preview) case of preview control. Furthermore, both pursuit and preview are characterized by a strong *feedforward* component [75], [111], [112]. Hence, in our view, Steps 1 and 2 will be studied in unison. Similar to the crossover model for compensatory tracking [2], [68], there is a need for a *universal model* for pursuit and preview control, with an extensive set – in fact a much more extensive set given the additional degrees-of-freedom in HC adaptation – of *adjustment rules* for the key HC control responses and parameters.

Developing this added understanding and modeling “toolkit” will require a significant amount of new experimental HC data, where human control is measured with a wide variation in critical task variables, such as plant dynamics (e.g., linear vs. non-linear), target and disturbance signal properties (e.g., spectrum, stochastic properties, predictability), and display and preview settings. Experiments can be preceded by a theoretical analysis and computer simulations, e.g., through assuming optimal control [87], [89], to explore the parameter sensitivities and theoretically optimal information-weighting strategies for human control in pursuit and preview tasks.

Steps 1 and 2 are required to ensure the applicability of cybernetic models for the design of manual control interfaces to support HCs in realistic, real-life control tasks, where our current lack of understanding of how HCs actually control leads to sub-optimal support systems. For example, this is evident in the haptic shared control systems [44] that are currently being developed to support car drivers, whose control is strongly based on both visual preview of the road ahead and a neuromuscular response to the guidance forces [43], [45].

B. Step 3: Isolating Neuromuscular Adaptations

The study of human control dynamics relies heavily on their identification from measurements of HC “inputs” and “outputs”, inherently resulting in a “lumped” insight into all effects of HC adaptation to various task variables. Isolating NMS contributions from the lumped adaptive HC data is essential to lift the “blurring” effects of different parallel modes of HC behavior. Also during learning, the HC dynamics change not only due to “higher-level” cognitive adaptations, as described in the SOP, but also due to “lower-level” underlying physical adaptations in the neuromuscular system [133].

Motor control literature has shown the synergy between improving internal models for limb movement and accompanying reduction in co-contraction of relevant muscles [134], which may also occur during driving: during repeated lane-changes performance increases, while muscle co-contraction reduces [39]. Hence, to understand the learning and adaptive nature of

HCs, we need to study the synergy between low-level NMS adaptations and higher-level learning, see Fig. 3. That is: how is the IR learned, and how does it drive adaptation of the HC’s feedback, feedforward, and NMS dynamics?

This requires better understanding of the (time-varying) nature of NMS adaptations in manual control and which NMS parameters change the most, both captured in models of the adapting HC dynamics – at “higher-level” and “lower-level”. Essential here is to improve our measurement techniques, to obtain more accurate and less intrusive estimates of the time-varying NMS settings, for instance by taking additional non-intrusive *grip force* measurements that are often related to NMS admittance settings [135].

C. Step 4: Understanding Learning

Although closely related, we distinguish between *learning* (Step 4) and *adaptation* (Step 5) as follows. Learning involves how the novice human controller matures, for a *fixed* set of task variables, to an expert controller, establishing the best compromise between control effort and control performance. Adaptation is seen as the process where a HC, proficient in the manual control of the whole set of task variables under investigation, switches from one control strategy to another when one (or more) of the task variables *change*. Generally speaking, training a learning HC to full proficiency is a comparatively slow process when compared to the often rapid HC adaptation response to a change in task variables.

An understanding of learning of the human controller can, in our view, best be gained from investigating how the HC’s internal representation (IR) of the task *develops over time*. Fig. 3 illustrates that the IR evolves during learning, perhaps even from scratch with novice controllers. The IR is used by the brain to adapt the feedback and feedforward control mechanisms and NMS dynamics (the purple parts in this figure) to balance control effort and performance.

Where the majority of our current knowledge of cybernetics is based on the control behavior of well-trained subjects under steady-state task conditions, elucidating human control *learning* requires a completely different approach: monitoring the progress during the full learning curve, observing novice HCs become expert controllers. This requires dedicated experiments, which explicitly focus on training HCs, covering a wide variety of *constant* tasks and task variables. This gives insight into how IRs evolve in relation to specific task characteristics and how HCs develop proficient control skills to deal with combinations of different task variables.

Such data would facilitate “probing” the quality of the evolving IR, to observe the extent to which novice controllers, while gaining experience, develop an accurate IR of the task constraints, to become experts. Of special interest for understanding HCs’ learning are the possible limitations in the evolving IR and especially the *temporal scale* of learning for different key task variable combinations. The capability to peek into the what is currently a “black box” of human learning, and quantify the dynamics of experience, may have great impact in all domains where humans are trained to manually control dynamic systems.

D. Step 5: Understanding Adaptation

When task variables – which represent “situations” from a control-theoretical perspective – change during manual control, proficient human controllers may detect these changes because their *expectation* obtained from the IR (see Fig. 3) does not match their *observation*. The plant will respond to the control commands in a different way than expected, with the expectation driven by the IR, resulting in an *innovation* (the large i in Fig. 3). This mismatch then triggers cognitive adaptations in the HC’s feedback and feedforward control dynamics, as well as physiological changes in the NMS, as indicated with the purple parts of Fig. 3.

When studying human control adaptation, intriguing questions include what external factors drive the IR adaptation, to what extent do controllers detect these changes, and how exactly the IR in turn drives the various adaptive parts of human control behavior. Hence, we need experiments that include systematic *explicit time variations* in task settings, to gain full insight into *whether*, to *what extent*, and *how fast*, HCs and their IRs adapt to such changes. Of special interest would be ‘hysteresis’-effects that may occur when humans adapt, back and forth, to varying task parameters.

Steps 4 and 5 both entail the development of a completely new theoretical framework for cybernetics, within which human *adaptive* control capabilities can be interpreted and predicted. A truly focused analysis of adaptive human control not only requires focused experimentation, but also significant methodological advances. Most notably, we need an ability to explicitly capture the time-varying nature of human controllers, perhaps even in real-time. The main thrust forward towards understanding HC learning and adaptation would be to move to *intrinsically time-varying manual control identification and modeling*, for which novel excitation techniques and test signals – with the lowest possible level of intrusiveness – are definitely needed, to ensure the most reliable results.

IV. CURRENT INNOVATIONS

Here we present three examples of current investigations that contribute to the roadmap discussed above, which all highlight the combination of theoretical and methodological advances that is required. Examples include human preview control, feedforward control with predictable target signals, and time-varying behavior.

A. Manual Control with Preview

There is a need for a *universal* model for HC preview control, together with a set of *adjustment rules* for HC adaptation in preview tasks. Many HC preview control models have been proposed (e.g., [20], [30], [31], [33]–[38], [41], [113]), mostly based upon the pioneering work of Sheridan [112]. None of these preview models has been widely accepted, mainly because the enormous variation in control organization HCs can adopt in preview tasks is still poorly understood. Even in constrained laboratory tracking tasks determining these characteristics is difficult, as preview information allows HCs to adopt separate responses to any part of the previewed target trajectory ahead (H_{pt}), the controlled element output

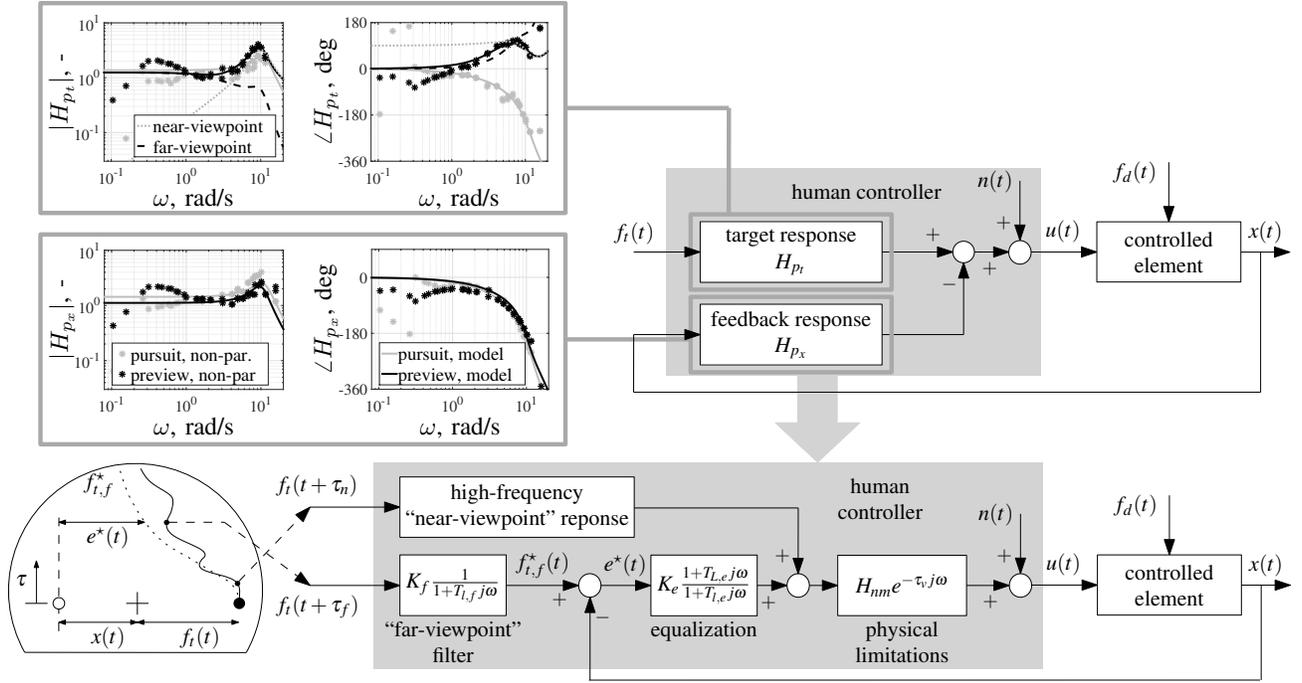


Fig. 4. Illustration of the approach to derive the human controller model for preview tracking tasks in [111]. Based on non-parametric estimates (top left) of the human’s target and feedback response dynamics (top right), the inputs, control organization, and control dynamics of the human controller model were obtained (bottom).

(H_{p_x}), and the error (H_{p_e}), see Fig. 1(b). Therefore, single-loop system identification techniques, which enabled the development of models for compensatory tasks (see Section II), no longer suffice. Moreover, it is impossible to independently identify all three control responses, H_{p_t} , H_{p_x} , and H_{p_e} , due to the interdependence between the three input signals ($e = f_t - x$) [101].

Recently the HC’s control dynamics in tracking tasks with preview were estimated non-parametrically with multi-loop system identification techniques [111]. Conditions included both zero-preview pursuit tracking tasks, and tasks with 1 s preview. Only the H_{p_t} and H_{p_x} dynamics were estimated, which are thus contaminated by the HC’s response to the current error H_{p_e} , if such a response is actually present [111]. Results from [111] are reproduced in Fig. 4. Based on the non-parametric estimates of the HC dynamics (black and gray markers in the Bode plots of Fig. 4), separate models for H_{p_t} and H_{p_x} were formulated, after which the model was restructured into the more intuitive form shown at the bottom of Fig. 4. This model is the first that is based on objective multi-loop measurements of HC’s input-output relation, without any *a priori* assumptions on the HC dynamics.

The novel model provides a new view on preview tracking behavior. Two distinctly different responses are initiated: a *near-viewpoint* response with respect to a point on the target τ_n s ahead (typically 0.1-0.9 s), and a *far-viewpoint* response with the target τ_f s ahead as input (typically 0.6-2 s). HCs track low frequencies in the target signal (up to about 6-10 rad/s) predominantly with the far-viewpoint response, which is a combined *feedback/feedforward* control mechanism on the

pursuit level of the SOP. The near-viewpoint response – an *open-loop* control mechanism – is more effective at higher frequencies. Note that the far-viewpoint response is the HC’s main control mechanism in preview tasks, while the near-viewpoint response is an optional additive response that can be used to further improve high-frequency target-tracking [114].

The far-viewpoint “filter” provides a pre-shaped input to an error feedback response, which is equivalent to the error response in compensatory tracking tasks [2], see (2). However, instead of responding to the current error e , the error e^* in preview tasks is an internal (non-physical), time-advanced error, based on the difference between the (possibly smoothed and scaled) far-viewpoint and the controlled element output. The far-viewpoint response includes a low-pass, or smoothing filter $1/(1 + T_{l,f} j \omega)$, with a bandwidth determined by the time constant $T_{l,f}$ (typically 0-1 s), to capture only the target’s low frequencies. The far-viewpoint gain K_f (typically 0.5-1.2) reflects how aggressive the HC tracks the target: $K_f = 0$ indicates that the HC completely ignores the target to focus purely on stabilizing the controlled element. Note that, when $K_f = 1$, and $\tau_f = T_{l,f} = 0$ s, the internally calculated error e^* equals the actual error e , and the far-viewpoint response equals the *precision model* for compensatory tracking [69].

A large benefit of this novel model is that its parameters have an intuitive physical interpretation, which can 1) provide unique insights into possible invariants of HC behavior, and 2) allow for predicting HC behavior. Working towards a *universal* model for preview control tasks, current research focuses on quantifying a set of *adjustment rules* for preview control, including HC adaptation to controlled element dynamics [114],

preview time, and target signal characteristics (e.g., bandwidth). Furthermore, our knowledge of human use of preview information must be extended from tracking to more realistic control tasks with preview, like car driving. Therefore, current work also investigates how HC preview control is affected by linear perspective [136] and inner feedback-loop closures due to the presence of inertial motion and a visual flow field.

B. Feedforward on Predictable Target Signals

In situations where the HC does *not* have preview information on the target, he/she might still have prior information on the future course of the target through memory or prediction. The HC might operate a feedforward response on the target, in addition to a closed-loop feedback response, which allows the HC to improve target-tracking performance without sacrificing closed-loop stability; a key sign of effective HC adaptation. In realistic control tasks, the desired trajectory often has a simple waveform-shape, e.g., constant-velocity ramp or constant-acceleration parabola segments, making the target signal predictable and easy to memorize. Although control responses involving a feedforward were frequently hypothesized [2], [68], [71], [72] and empirical evidence was presented [75], [101], [105], [108], [121], they were never explicitly investigated with system identification and parameter estimation methods until recently.

Established identification methods, such as the Fourier Coefficient method [79], [81], cannot be used with target signals that have power at all frequencies, such as ramps. Studying feedforward thus requires novel black-box HC identification methods, e.g., based on LTI AutoRegressive with eXternal input (ARX) models [137]. Fig. 5 shows identification results obtained with the novel ARX-based method of [137] from a human-in-the-loop tracking experiment featuring target signals consisting of ramp segments [138]. Black-box identification results as shown in Fig. 5, provide a means to objectively *detect* the presence of feedforward HC control responses. Also, they reveal the nature of the adopted feedforward control dynamics, which enables the *mathematical modeling* of HC feedforward behavior [104], [123].

Fig. 5(a) shows the estimated feedforward (H_{pt}) dynamics for twelve participants who performed a ramp-tracking task, compared to the theoretically ideal feedforward law, equal to the inverse system dynamics $1/H_c$. The range for which the ARX identification results are valid, based on the lowest and highest frequency component in the applied disturbance signal f_d , is indicated with two dashed vertical lines. At low frequencies, the estimated feedforward dynamics evidently approximate $1/H_c$, except for a slight difference in gain. For $\omega > 2$ rad/s the responses deviate from the theoretical optimum, flattening as a low-pass filter, with considerable spread between subjects. For most subjects, the phase response rapidly becomes more negative, suggestive of a considerable feedforward delay. For four participants, however, the phase response is mostly flat or even becomes positive, indicating a negative time delay and thus *anticipation* of the future course of the target. From observations it can be deduced that the feedforward path H_{pt} of the HC model of Fig. 5 can be

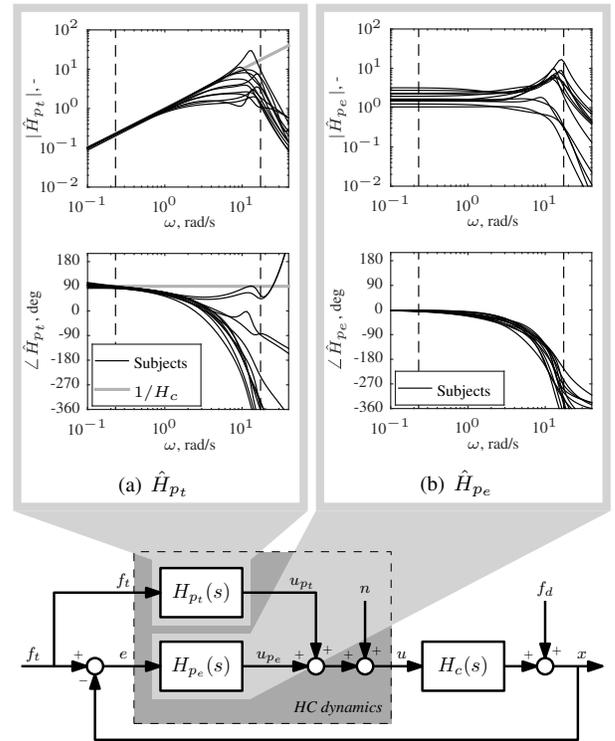


Fig. 5. HC model consisting of a feedforward path H_{pt} and a feedback path H_{pe} with estimates of the feedforward and feedback dynamics of twelve subjects tracking a predictable target signal consisting of ramp segments. Data are from [138], for $H_c(s) = 1/s$.

modeled with a gain, inverse system dynamics [101], a low-pass filter [123], and a time delay:

$$H_{pt}(s) = K_{pt} \frac{1}{H_c(s)} \frac{1}{(T_{I_t}s + 1)^2} e^{-\tau_{pt}s} \quad (3)$$

As is clear from (3), H_{pt} approximates the theoretically optimal feedforward response, $1/H_c$, for $K_{pt} \approx 1$, $T_{I_t} \approx 0$ s, and $\tau_{pt} \approx 0$ s. With clearly imperfect feedforward control (see Fig. 5(a)), Fig. 5(b) shows that the feedback component H_{pe} of the combined feedforward-feedback HC model is indeed required. It can be modeled with a structure identical to well-known models of compensatory HC behavior [69], [101], [104], [123], such as the precision model of (2).

A key example of where feedforward HC models provide increased understanding, is HCs' sensitivity and adaptation to predictable target signals [72], e.g., signals that consist of only one or two sine waves [108], [121]. For instance, in [120] HCs were asked to track three pairs of "harmonic" (H) and "non-harmonic" (NH) multisine signals, consisting of 2, 3, or 4 sinusoids with a pursuit display. Analytical analysis with a (linear) HC model as shown in Fig. 5 predicted identical tracking performance for such H and NH signals, because such a prediction is not sensitive to the predictability of the target. Real HCs, however, performed distinctly better with the harmonic signals. As shown in Fig. 6, this is explained by an anticipatory feedforward response that is developed for these more predictable signals: the feedforward gain K_{pt} is higher, and the feedforward delay τ_{pt} is considerably smaller and close to zero. Such data suggests that the predictability

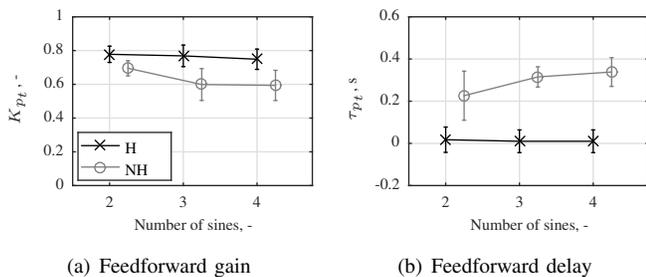


Fig. 6. Estimated feedforward HC model parameters from [120] for tracking of harmonic (H) and non-harmonic (NH) reference signals.

profoundly affects HC behavior, and demonstrates the effectiveness of feedforward HC models for quantifying the underlying HC adaptations. With only a severely limited database of studies that explicitly focus on target signal predictability, future studies should seek to understand *how* HC model parameters change as a function of target signal properties.

In conclusion, the established feedforward HC model enables unique insight into control strategies that involve feedforward, such as pursuit and precognitive control. Identifying and modeling feedforward responses does, however, in itself not reveal *how* the feedforward was established – e.g., pursuit, preview, precognitive – or whether multiple parallel feedforward mechanisms coexist; we have thus not yet arrived at the desired universal model of pursuit and preview. For developing this universal model, it will be paramount to better understand how the predictability properties of the target signal affect the ability of the HC to utilize a feedforward. In realistic scenarios, it is, however, likely that target signal predictability varies considerably in time, possibly on a timescale of a few seconds, calling for methods to identify time-varying HC adaptations.

C. Time-Varying Adaptations

Most of our knowledge on human control behavior is restricted to stationary, time-invariant control tasks, where HCs are considered as stationary, time-invariant controllers. In reality, however, it is the adaptive nature of the HC, and how she or he is able to respond to sudden changes in the environment, that is of interest, yet still largely unknown [2], [110], [139]. Relevant real-world scenarios where HCs are forced to adapt their control behavior are, for example, time-varying changes in the controlled system dynamics (e.g., failure) [98], [99], [140]–[144], instantaneously modified task constraints (e.g., decreased road width) [135], loss-of-control [145], automatic-to-manual control transitions, and control with time-varying information feedback (e.g., adaptive simulator motion feedback) [146]. Such time-varying HC adaptations are inherently highly variable, nonlinear, short-duration, and strongly task-dependent, making them immensely more complex to grasp than LTI HC behavior. Both our current *knowledge* of HCs’ capabilities for temporally adapting control, as well as the capabilities of our *methods* for measuring adaptive HC dynamics, are insufficient.

In studies on the adaptive HC, a distinction is often made between “fast” adaptations in response to sudden changes in the task or environment, and “slow” variations attributable to

factors such as fatigue, loss-of-attention, and learning [110]. While the latter can still be studied to some extent without explicitly accounting for time-varying HC behavior, as shown here in Section V-C, this does not hold for fast HC adaptations. For certain fast adaptations, HC dynamics seem to remain largely quasi-linear [98], [99], [147], but with time-varying HC parameters, resulting in Linear Parameter Varying (LPV) HC dynamics. However, in extreme scenarios such as loss-of-control [145], HC dynamics are truly nonlinear, in addition to time-varying. Understanding HCs’ capacity for adaptation means grasping *which* of HCs’ control parameters are critical, and *what* HCs’ limitations in the adaptation of these parameters are. It is highly likely, but not yet proven, that some HC parameters will change faster, while less critical parameters may change more gradually.

Knowledge of the “life expectancies” of HC parameters, and how this may vary for changes in (combinations of) different critical task variables, is needed. This fact also directly applies to certain control scenarios that are typically studied with the assumption of time-invariant HC, such as pursuit or preview tracking [111], [112], where in fact small, local, time-varying adaptations in HC behavior are suspected to occur. By assuming an LTI HC, temporal variations due to, for example, the perceived difficulty of the applied test signals, are averaged out, irrespective of how strongly they are present. A thorough, explicitly time-varying, analysis of *all* HC data is actually needed to prove that the “time-invariance” hypothesis that is implicitly applied through the use of describing function estimates and quasi-linear models is, in fact, valid.

To increase our knowledge of time-varying HC adaptations, the traditional LTI framework for modeling and analyzing HC behavior needs to be abandoned, as this requires methods and model structures that inherently include additional degrees-of-freedom to account for time-varying behavior. Given how little we currently know about time-varying HC behavior, this requires both methods for time-varying *identification* – i.e., detect and quantify time-varying changes in the HC with preferably no *a priori* explicit assumptions on the nature of the temporal variations – and time-varying *parameter estimation and model fitting*, to extract high-accuracy time-varying HC models from measured data. Also, we need to investigate what excitation techniques and test signals will yield the most reliable results, with the lowest possible level of intrusiveness.

Examples of time-varying identification methods are those that rely on windowed LTI HC modeling [148], wavelets [148], [149], recursive least-squares [147], [150] or Kalman filtering [147], [151], [152]. Such methods are indispensable for studying what actually varies in HCs and which “function approximators” can best describe the adapting HC parameters. Once known which time-variations in the HC need to be modeled, promising approaches for the second step of fitting intrinsically time-varying manual control models to measured HC data are time-domain modeling [99], [146] or LPV model-based methods [135], [153], [154]. The main challenge for time-varying HC identification lies in developing methods that are sufficiently sensitive and that can reliably pick out quick and short-duration temporal variations in HC behavior from inherently noisy data. Of great value to real-world applications

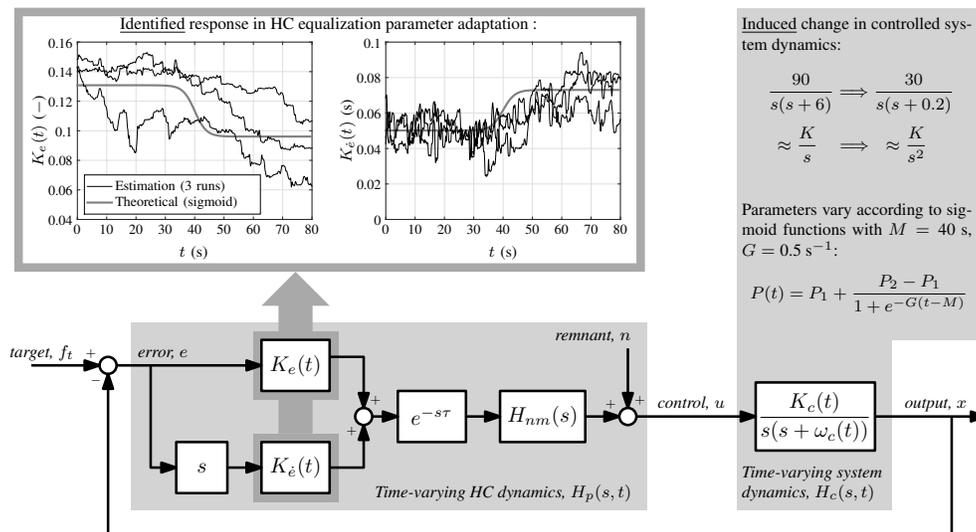


Fig. 7. Example of time-varying manual control identification for the scenario of [99] with a Kalman filter-based approach.

such as HC monitoring or adaptive support systems would be methods that are suitable for recursive, real-time implementation.

Fig. 7 shows preliminary results from a current effort to further develop time-varying HC modeling approaches based on the Kalman Filter [147], [151], [152]. For three runs of experimental HC data from a compensatory tracking task with an induced change in the controlled system dynamics $H_c(s, t)$ (centered at $t = 40$ s) matching that of [99], Fig. 7 shows representative estimated HC equalization parameters: the HC control gains on the tracking error (K_e) and error rate ($K_{\dot{e}}$). Matching the expected “theoretical” time-variation (sigmoid) to counter the induced change in the controlled dynamics, Fig. 7 shows a distinct drop in K_e after the change in $H_c(s, t)$, and a notable increase in the error-rate gain $K_{\dot{e}}$. However, Fig. 7 also clearly shows aspects of time-varying HC behavior that are currently poorly understood: 1) a considerable variation over different runs of data, 2) significant time-variations other than those in direct response to the change in $H_c(s, t)$, and 3) HC adaptations that clearly lag behind the theoretically optimal responses.

V. EXAMPLE APPLICATIONS

In this section we will give three examples of novel applications of knowledge and models of human manual control behavior. Presented are applications in haptic shared control, simulator fidelity evaluations, and training.

A. Haptic Shared Control/Neuromuscular Adaptations

Understanding the contributions of the time-variant neuromuscular system to overall HC behavior is essential when relevant forces are present on the control device, from external perturbations (e.g., from wind gusts, potholes, turbulence), biodynamic feedthrough (e.g., from undesired body movements) [130] or support forces from haptic shared control [44]. Current developments in NMS cybernetics focus on three applications: 1) understanding fundamental motor control, by

enabling identification of both the NMS non-linearities and time-variance, 2) enabling unobtrusive estimation of NMS admittance during a flying or driving control task and 3) understanding co-adaptive systems in human-machine cooperation.

The first goal was already worked towards in early work aimed at obtaining time-varying and non-linear identification of NMS dynamics. Recent approaches used small-window FRFs [42], wavelets [156], recursive least-squares algorithms [150], and LPV methods [135], [157]. The second goal requires perturbation techniques to estimate endpoint admittance, which do not significantly influence manual control behavior. This can be approached either by using small rapid transient perturbations [158], or by using continuous perturbations to estimate full-bandwidth admittance. The latter technique has been used to estimate the arm NMS admittance during aircraft control [159]. A particularly useful technique to design continuous force perturbations is the Reduced-Power Method [129], which allows full-bandwidth admittance estimates while evoking unperturbed low-bandwidth control behavior. It has been applied when comparing the NMS admittance with and without haptic shared control, of the lower limb during car-following [45] and of the arms while steering a car [46]. Such analyses show that drivers can increase their neuromuscular admittance to physically give way to the guidance forces, thereby executing part of the control actions suggested by the automation. An additional application for the quantified NMS admittance is that it allows for a formal design of the strength of the guidance forces of haptic shared control [44], [64], as opposed to trial-and-error tuning. The third goal is being pursued to understand physical co-adaptation of two mutually adaptive controllers. Examples include human-human physical interaction [56], the interaction between driver and intelligent vehicle [44], and physical human-robot interaction [56]. Time-varying NMS identification techniques will prove essential in all these efforts.

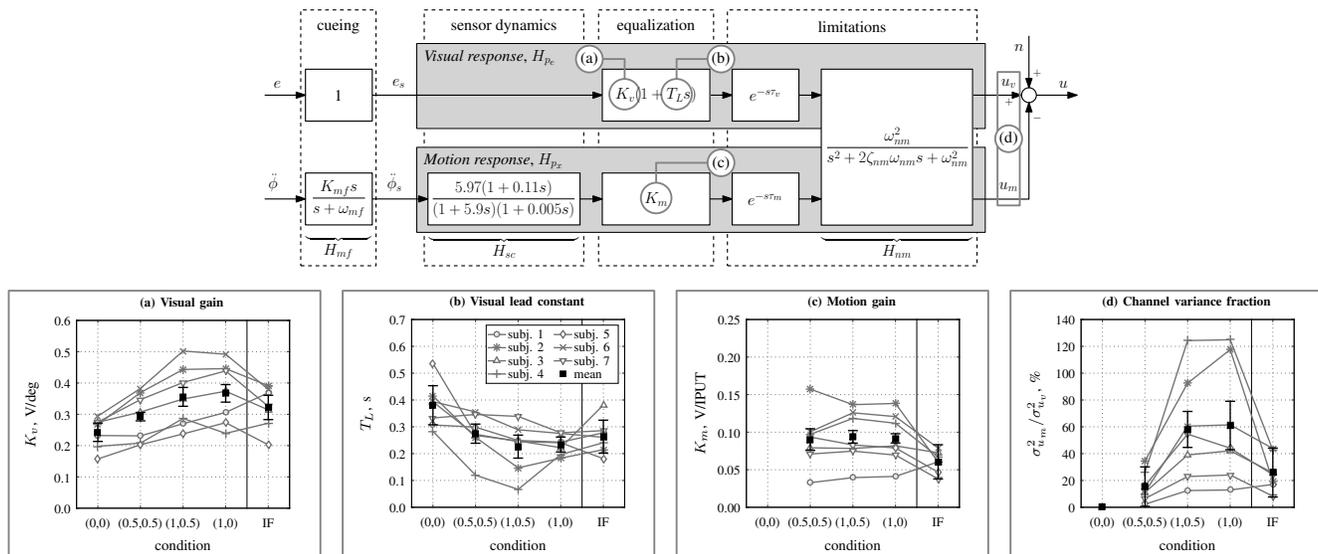


Fig. 8. Multi-modal HC model, estimated HC model parameters, and visual and motion control contributions from the combined in-flight and simulator experiment of [155]. Simulator conditions with varying motion filter (H_{mf}) settings are indicated with (K_{mf}, ω_{mf}) . IF indicates in-flight data.

B. Flight Simulator Motion Cueing Fidelity

A key application of manual control cybernetics is evaluating the fidelity – realism – of virtual environments and vehicle simulators. An example is the evaluation of flight simulator motion cueing fidelity; something that simulator manufacturers, engineers, and legislators still struggle with, even after decades of experience in ground-based simulation [160]. One of the biggest challenges in simulator motion cueing has been finding the limits: when does the feedback supplied in a simulator no longer induce “realistic”, representative, and effective control behavior?

The known HC adaptation to critical task variables [2] enables unique objective analysis of the effects of degraded motion feedback quality. For example, an analytic control-theoretic criterion based on pilot-vehicle system dynamics that is sensitive to variations in motion cueing fidelity [22], [23], [161] has been derived and successfully applied to a range of different aircraft (both fixed-wing and moving-wing) and flight maneuvers. In addition, multi-channel HC modeling and identification techniques [79], [81], [83] can be used to explicitly measure pilots responses to visual and (simulator) motion cues during tracking tasks, to discover under which motion washout filter settings pilots change their control behavior [26], [29], [155]. This approach also enables objective quantification of the behavioral discrepancies that occur in flight simulators compared to real flight [18], [162] and helps relate these discrepancies to the choices in motion cueing [29], [155].

Fig. 8 shows multi-modal HC modeling results from [155], where seven pilots performed an aircraft roll attitude tracking task both in real flight and in a moving-base flight simulator for a number of different settings of a first-order high-pass motion filter, H_{mf} . In Fig. 8, the different simulator motion conditions are indicated with “ (K_{mf}, ω_{mf}) ”, while “IF” is the in-flight data. $K_{mf} < 1$ or $\omega_{mf} > 0$ rad/s results in attenuated simulator roll cues. The multi-modal HC model

shown in Fig. 8 includes separate visual (H_{pe}) and motion (H_{px}) responses. Separating these contributions allows for calculating metrics that provide unbiased insight into 1) how pilots weigh visual and motion feedback for their control (K_v and K_m), 2) how much visual (lead) equalization they are required to perform (T_L), and 3) the overall contribution of motion feedback to their control ($\sigma_{u_m}^2/\sigma_{u_v}^2$).

The HC modeling results in Fig. 8 show that, in general, pilot behavior is found to be strongly affected by degraded simulator motion fidelity. With simulator roll motion cues that are increasingly attenuated compared to the “perfect” (1,0) case, pilots rely less on the presented motion information, leading to a distinctly decreased contribution of the motion feedback channel H_{px} , see $\sigma_{u_m}^2/\sigma_{u_v}^2$ in Fig. 8(d). Consistent for all pilots, this suboptimal control strategy is characterized by reduced control gains (K_v) and increased visual lead equalization (T_L). Pilots are also not found to compensate for lower magnitude motion feedback ($K_{mf} < 1$) by a matching increase of their motion response gain, K_m . Finally, from the in-flight (IF) data from [155], pilots were found to control with a lower gain during in-flight tracking than for the 1-to-1 simulator motion configuration, a result that might be attributable to other factors than the quality of the supplied motion feedback (e.g., environmental variables, see Fig. 2).

Overall, HC modeling results as shown in Fig. 8 are unique in their ability to reveal the adaptation of pilot low-level control behavior to reduced simulator cueing and have great potential for the optimization of simulator motion cueing in aircraft, but also automotive, simulation.

C. Control Skill Training

Another relevant application for manual control cybernetics is evaluating the development of control skills during training programs and verifying the overall effectiveness and transferability of learned skills. Explicit quantification of HC dynamics, as facilitated by cybernetic HC modeling techniques, allows for opening-up the black box of human control

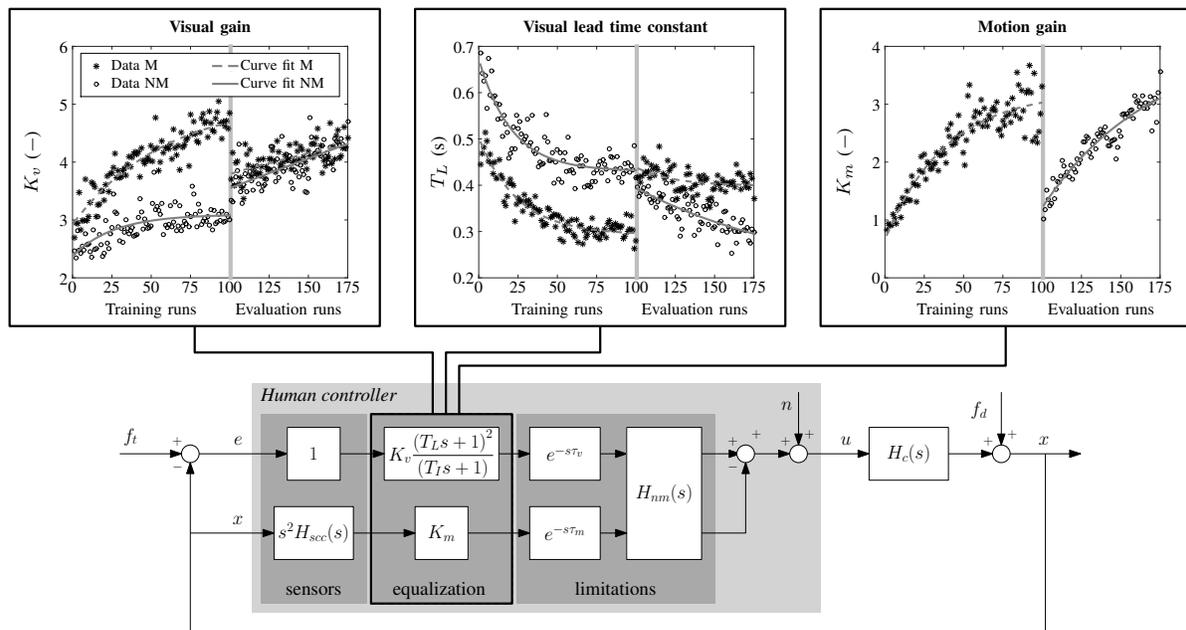


Fig. 9. Estimated HC equalization parameters for visual and motion feedback responses from a training experiment with task-naive participants of [163]. Data from two training groups is presented: Group NM performed the first 100 runs in a non-moving (NM) simulator and was then transferred to a motion setting (M), while Group M followed the opposite schedule.

adaptation, and observe the progression of HC feedback, feedforward, and NMS dynamics through learning. This is especially relevant for evaluating simulator-based training, as for skill-based control HCs develop low-level automated responses to continuous feedback signals from the environment [164]–[166]. This strong environmental dependency means that a risk exists of teaching skills that do not fully transfer to the real environment [164], [166].

In aircraft pilot training, the necessity for training simulators that use a motion system to provide a physical motion sensation as experienced during flight, continues to be a topic of much debate [167]. The main reason for the continuing controversy is the fact that collecting convincing and generalizable evidence regarding training effectiveness requires reliable and quantitative data regarding trainees’ developing skills. Most explicit transfer-of-training studies have relied on ambiguous measures of task performance [167] or “lumped” HC dynamics estimates [168], providing limited insight and unconvincing conclusions. Only recently has explicit *multi-modal* HC modeling been applied to verify the effectiveness of simulator-based training of manual control skills in fixed-base or limited-motion simulators [29], [163].

Fig. 9 shows the multi-modal HC model and data from the experiment of [163], where 24 task-naive participants, divided over two groups, were trained for a compensatory tracking task with motion feedback, to investigate the need for motion in *ab initio* skill training. The graphs in Fig. 9 present the estimated values of key HC equalization parameters that quantify HCs’ use of motion feedback [15], [25], [29], [169]: the visual response gain K_v , the visual lead time constant T_L , and the motion response gain K_m . First, these data show that initial control skill acquisition is a *very slow* process, with participants’ control parameter optimization – i.e., increasing control

gains (K_v and K_m) and decreasing visual lead equalization (T_L) – continuing until after 75 runs of the tracking task. Furthermore, Fig. 9 shows that for Group NM (no-motion training) the HC equalization parameters indicate only minor adaptation directly after transfer (run 101) and considerable *renewed adaptation* during the 75 evaluation runs. Especially the learning curves for K_m , which are essentially identical for both groups, provide clear evidence that training without motion is not effective for training control skills to be applied in an environment with motion feedback.

In conclusion, contrary to many earlier studies that relied on performance metrics for training evaluation [167], a cybernetic view on training in motion simulators, as shown in Fig. 9, provides direct and objective evidence regarding the effectiveness of such training. Applying the same methodology to the training of other critical and realistic manual control tasks (e.g., preview, feedforward) will greatly increase our understanding of HC adaptation during training, and enable fundamental training enhancements.

VI. CONCLUSIONS: TOWARDS A NEW CYBERNETICS

With this paper we attempted to give an overview of the current state-of-the-art in manual control cybernetics research. We identified several fundamental shortcomings and proposed a new framework for bringing theory and methodology to the level required for addressing current real-world issues. In our view, this requires a special focus on the *adaptive* characteristics of human control behavior in *realistic* control scenarios. A crucial step forward would be to abandon the linear time-invariant modeling framework altogether and move to modeling structures and methods that inherently include degrees of freedom to account for time-varying behavior. A

promising candidate could be the currently rapidly developing linear parameter-varying (LPV) systems framework, to model and identify intrinsically time-varying manual control models.

Developing an extended “toolkit” that will allow us to identify, model and quantify adaptive human control, will lead to (at least) three key innovations. First, the exploitation of human controllers’ capability to adapt, and adaptation “invariants”, is key to optimizing the multi-modal control interfaces that our ever-advancing modern technologies permit. True knowledge of the adaptive human controller will transform the current trial-and-error tuning of such interfaces for the “average” human to a systematic approach to create personalized support. Second, a model-based approach to quantify progress in skill acquisition will be instrumental to improve (simulator- or computer-based) training procedures and technologies, as it allows for a mathematical, and objectified, optimization of training effectiveness. Third, understanding and mathematically modeling human adaptive control will enable designers of (semi-)automated systems to create high-conformance human-like automation that is trusted and accepted in situations where control is either shared (e.g., haptic shared control) or handed-over to a vehicle, robot, or computer. And beyond the realm of supporting human-machine systems, the insights gained in the unique human adaptation capabilities could also serve as design inspiration for future generations of fully autonomous, adaptive robots, ultimately equating the control and communication in animal and machine [1].

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Max Mulder (M'14) received the M.Sc. degree and Ph.D. degree (*cum laude*) in aerospace engineering from TU Delft, The Netherlands, in 1992 and 1999, respectively, for his work on the cybernetics of tunnel-in-the-sky displays. He is currently Full Professor and Head of the section Control and Simulation, Aerospace Engineering, TU Delft. His research interests include cybernetics and its use in modeling human perception and performance, and cognitive systems engineering and its application in the design of "ecological" interfaces.

Prof. Mulder is an Associate Editor of the IEEE TRANSACTIONS ON HUMAN-MACHINE SYSTEMS.



Daan M. Pool (M'09) received the M.Sc. and Ph.D. degrees (*cum laude*) from TU Delft, The Netherlands, in 2007 and 2012, respectively. He is currently an Assistant Professor with the section Control and Simulation, Aerospace Engineering, TU Delft. His research interests include cybernetics, manual vehicle control, simulator-based training, and mathematical modeling, identification, and optimization techniques.



Kasper van der El received the M.Sc. degree in aerospace engineering (*cum laude*) from TU Delft, The Netherlands, in 2013, for his research on manual control behavior in preview tracking tasks. He is currently pursuing the Ph.D. degree with the section Control and Simulation, Aerospace Engineering, TU Delft. His Ph.D. research focuses on measuring and modeling human manual control behavior in general control tasks with preview. His current research interests include cybernetics, mathematical modeling, and system identification and parameter estimation.



David A. Abbink (M'12, SM'14) received the M.Sc. and Ph.D. degrees in mechanical engineering from TU Delft, Delft, The Netherlands, in 2002 and 2006, respectively. He is currently an Associate Professor with the Delft Haptics Laboratory, TU Delft. His current research interests include neuromuscular behavior, driver support systems, and haptics.

Dr. Abbink is an Associate Editor of the IEEE TRANSACTIONS ON HUMAN-MACHINE SYSTEMS.



Erwin R. Boer received the M.Sc. degree in electrical engineering from Twente University of Technology, Enschede, The Netherlands, in 1990, and the Ph.D. degree in electrical engineering from the University of Illinois, Chicago, in 1995.

From 1995 to 2001, he was a Research Scientist with Nissan Cambridge Basic Research, Cambridge (MA), where he conducted basic research on driver behavior. In 2001, he founded his own research consulting company – Entropy Control, Inc. – in San Diego (CA). His research interests include manual

control, driver modeling, human operator performance assessment, driver support system design, and haptic shared control.



Peter M.T. Zaal received his M.Sc. and Ph.D. degrees in aerospace engineering from TU Delft, The Netherlands, in 2005 and 2011, respectively. His Ph.D. research focused on pilot control behavior discrepancies between real and simulated flight. Peter is currently a senior research engineer with the San Jose State University Research Foundation, performing collaborative research at the Human Systems Integration Division of NASA's Ames Research Center. His research focuses on the modeling of human

visual and motion perception, and cue integration in manual control tasks, as well as the development of objective motion cueing criteria for flight simulators. His research interests include human factors, manual control, visual and motion perception, and flight simulation.



Marinus (René) M. van Paassen (M'08, SM'15) received the M.Sc. and Ph.D. degrees from TU Delft, The Netherlands, in 1988 and 1994, respectively, for his studies on the role of the neuromuscular system of the pilot's arm in manual control.

He is currently an Associate Professor at the section Control and Simulation, Aerospace Engineering, TU Delft, working on human-machine interaction and aircraft simulation. His work on human-machine interaction ranges from studies of perceptual processes and manual control to complex

cognitive systems. In the latter field, he applies cognitive systems engineering analysis (abstraction hierarchy and multilevel flow modeling) and ecological interface design to the work domain of vehicle control.

Dr. van Paassen is an Associate Editor of the IEEE TRANSACTIONS ON HUMAN-MACHINE SYSTEMS.



Frank M. Drop was born in 1986. He received his M.Sc. (*cum laude*) and Ph.D. degrees in aerospace engineering from TU Delft, The Netherlands, in 2011 and 2016, respectively. His M.Sc. and Ph.D. research focused on human feedforward manual control, in a collaborative project between TU Delft and the Department of Human Perception, Cognition and Action led by Prof. Heinrich H. Bülthoff at the Max Planck Institute for Biological Cybernetics, Tübingen, Germany. His research interests include cybernetics and modeling of human control.