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# Fundamental Issues in Manual Control Cybernetics

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**Abstract:** Manual control cybernetics aims to understand and describe how humans control vehicles and devices, such that more effective human-machine interfaces can be designed. Current cybernetics theory is primarily based on technology and analysis methods developed in the 1960s and has shown to be limited in its capability to capture the full breadth of human cognition and control. This paper summarizes some of the main fundamental limitations in cybernetics and provides a possible road-map to advance the theory and its applications. Central in this agenda will be a shift from the current linear time-invariant modeling approach, to the use of linear parameter-varying system models. Recent progress in identification methods of these latter models may allow us, for the first time, to mathematically model and identify time-varying, adaptive human control, opening up many opportunities to systematically optimize our human control interfaces and training. New foundations for cybernetics will impact all domains that involve humans in manual and semi-automatic control. *Copyright ©2016 IFAC*

*Keywords:* cybernetics, manual control, dynamic behaviour, modeling

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## 1. INTRODUCTION

The main system-theoretical, model-based approach to understand how humans control vehicles and devices is called cybernetics (Wiener, 1961). Current cybernetics theory was developed in the 1960s (McRuer and Jex, 1967) – for 1960s technology – and has shown to be limited in its capability to capture the full breadth of human cognition and control (Jagacinski and Flach, 2003). Modern interface technologies, such as haptic control manipulators and three-dimensional virtual reality visual interfaces are rapidly expanding the way humans can interact with dynamic systems. Despite haphazard attempts to update cybernetics theory, our technology leapfrogged our theory, and current tools and models fail to explain and predict how humans interact with modern interfaces.

State-of-the-art cybernetics describes humans as (quasi-)linear, time-invariant (LTI) feedback controllers. We can accurately model behavior in the highly-constrained compensatory tracking task, without preview thus allowing just *reactive* feedback control, at the point when learning has finished. In contrast to many relevant tasks we assume that the human has *no preview* on future control constraints. We also assume time-invariance, which prevents us from modeling a defining attribute of human controllers, namely their ability to *adapt* to changing situations. The unique human learning, adaptation and anticipatory feed-forward control behaviors are barely understood, which prevents us to understand human behavior and optimize present-day control interfaces in realistic tasks.

This lack of understanding is not our only problem, our tools to identify human manual control are limited to crude experimental techniques. We can only identify the overall, lumped response of a fully-trained human, based on prolonged measurement. 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.

A targeted research effort is needed to radically advance cybernetics theory, its models and tools. Relevant control tasks have preview of the future constraints and in many cases not only allow, but actually *require* human adaptation (Hess, 2009). To proceed in our understanding and application, we must therefore address a number of fundamental research questions on human control: i) How do humans use preview of future task constraints? ii) What are the mechanisms that drive adaptation? iii) To what extent are measured human adaptations caused by physiological rather than cognitive adaptations? iv) What are the temporal scales of human adaptation and learning in changing situations?

In this paper, we will briefly summarize the state-of-the-art, then elaborate on the four main problems listed above and provide a road-map to systematically address these fundamental issues. Note that the paper is by no means complete. Every section can be significantly extended, with earlier findings and many more references to literature. In addition, we limit the discussion to the single axis control task with a visual display. Other papers in this IFAC-HMS 2016 special session expand on cybernetics theory and address many of the issues not mentioned here.

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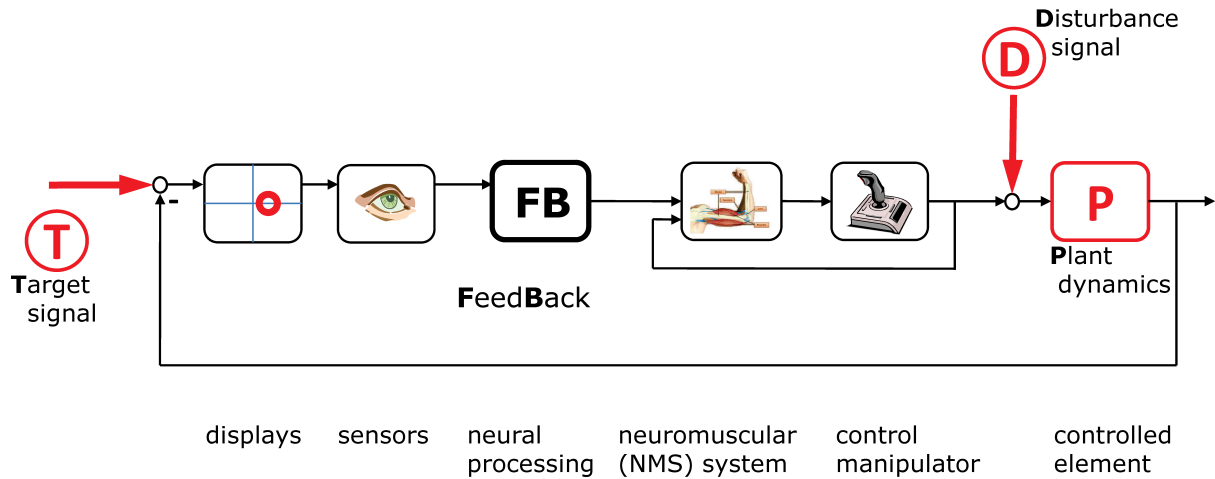


Fig. 1. CURRENT CYBERNETICS theory is dominated by the compensatory tracking task: here the red circle (display) shows the instantaneous tracking error.

## 2. STATE-OF-THE-ART: FIRST STEPS AHEAD

Quoting McRuer and Jex (1967): “*The human pilot is a multimode, adaptive, learning controller capable of exhibiting an enormous variety of behavior*”. The ability of the human controller (HC) to adapt to – and learn from interactions with – the environment is phenomenal and makes the study of HC behavior a fundamental challenge. When it comes to learning in control, two phases are generally distinguished (McRuer and Jex, 1967): i) *system organization*, where the HC detects patterns and uses coherences, the causal effects of action and perception, to create feedback and/or feedforward control loops, to obtain a *stable* control situation; ii) *system adjustment*, where the HC adjusts the established loop closures to improve control *performance*.

In this section we will discuss the state-of-the art of cybernetics theory which, as we will see, predominantly focuses on modeling the HC when *all learning is done*. We will see that, even for some of the most elementary tracking tasks, no universally accepted model exists. The next section will then discuss a possible roadmap to also include learning effects in our HC modeling theory. Before that is possible, however, the following steps to improve our modeling capabilities will need to be addressed first.

### 2.1 Compensatory tracking

In 1960, Krendel and McRuer defined the Successive Organization of Perception (SOP) hierarchy for human manual control: compensatory, pursuit and precognitive control (Krendel and McRuer, 1960). At the most basic level, compensatory control, the *crossover model* in combination with the *verbal adjustment rules* (McRuer and Jex, 1967) quite accurately describes the systematic adaptation – in steady-state – of the human controller to some of the key *task variables*: plant dynamics (P) and target signal (T) or disturbance signal (D) spectrum, see Fig. 1. The forcing functions must be quasi-random, to force the HC into a mode where she or he cannot anticipate on what comes next, and only feedback (FB) is possible.

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 many attempts to provide some rationale for the remnant component too. In fact, to reduce remnant, our common practice is to keep all task variables constant, and train all subjects extensively. Identification techniques then identify the LTI frequency response between what the well-trained HC sees or feels (the visual, motion, or tactile displays) and the control manipulator deflection.

Tracking cannot be done in a simpler way than with the compensatory display, showing only the *error* between the target signal (T) and plant output, with one moving symbol on the visual display. Although many attempts exist to extend our knowledge to higher levels in the SOP, it is safe to say that our state-of-the-art cybernetics theory predominantly deals with compensatory tracking. Only for this extremely simple task do we have a universal model, the crossover model, that allows us to predict how, in *steady state*, the well-trained HC has adapted to particular settings of the task variables.

Yet, even for this basic control task, it is relatively easy to make the theory break down. For instance, when the target forcing function is chosen such that the HC can detect a repeating pattern (in the extreme case: tracking one low-frequency sinusoid), the HC will learn to use this pattern in an attempt to improve performance, stability and reduce control effort: a feedforward (FF) control loop will emerge. So *only* in the case the target (or disturbance) signal contains no ‘recognizable’ pattern – it is (quasi-)random – will the HC close only a feedback control loop, and the observed control behavior can be captured relatively well with a linear, time-invariant model. The whole experimental set-up and identification procedure is meant to suppress any further human adaptation.

### 2.2 Pursuit tracking: Step 1

In a pursuit display, two symbols are shown on the visual display that represent the target signal (T) and the plant output, leading to the pursuit tracking task of Fig. 2. It may seem like a small step, but it makes the life of cyberneticists a lot harder. Even for this still rather elementary tracking task, *no universally accepted model*

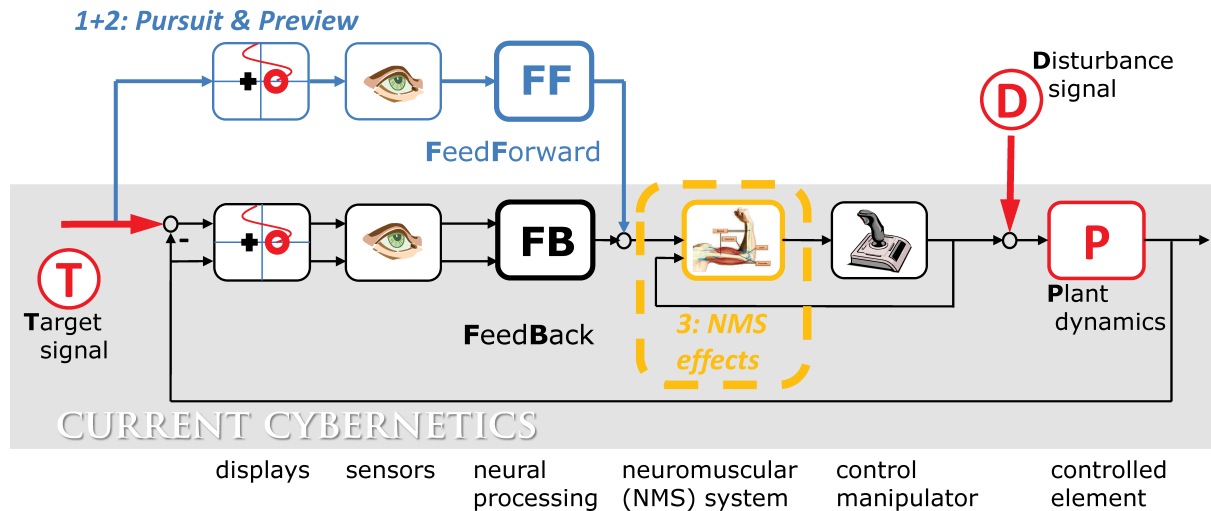


Fig. 2. FIRST STEPS AHEAD: Pursuit tracking (Step 1), showing CE output (cross) and target signal (circle); Preview tracking (Step 2), showing the future of the target (red); Isolating NMS adaptations (Step 3).

for the HC exist. One of the main reasons of this, is that the pursuit display enables the HC to apply a *feedforward* (FF) control loop, in addition to the feedback loop. From an identification perspective, the pursuit task requires *two* independent signals (T and D in Fig. 2) to disentangle the human FB and FF responses, and model both using LTI model structures. Up until quite recently, this has almost never been tried (Drop et al., 2013).

The feedforward loop allows the HC, especially in cases when the target signal is more predictable and/or when the HC becomes more proficient in the task, to *anticipate* on what is going to happen. The ability to do this depends on a huge number of variables, predominantly the shape and spectrum of the target signal (T). Again, one can easily construct a pursuit control task where parts of the target signal, at some instances in time, are more predictable than other parts, which will eventually be picked up by the ever-adapting HC, eager to improve performance or reduce control effort. This leads to periods in time when the FF loop is strong, other periods where the FB loop will be dominant: *time-varying* behavior. Our current identification techniques, taking the whole measurement time as a basis for their calculations, will simply *average out* these subtle changes in the HC.

In our view, the first step in making the cybernetics theory more complete and useful for designing and tuning current-day interfaces, is to solve the main questions regarding how humans control with pursuit displays. Similar to the compensatory tracking task, there is a need for a *universal* model for HC pursuit control, with an extensive set – in fact a much more extensive set given the additional degrees of freedom in HC adaptation – of adjustment rules.

### 2.3 Preview tracking: Step 2

What is stated for pursuit control, is even more true in the situation when the HC has *preview* on the future task constraints, e.g., the future state of the target signal (T), see Fig. 2. When considering everyday manual control tasks, it is difficult to think of tasks that have *no preview* on what is coming next. A preview display may allow the

HC to move to the highest level in the SOP: pre-cognitive control, where the HC *recognizes* key characteristics of externally-imposed constraints on the control task (e.g., the shape of the curve in the road ahead – target signal), and based on *experience* developed a ‘mental’ model of the internal control constraints (e.g., the lateral-longitudinal dynamics of an automobile), can exert strong, perhaps even open-loop, feedforward control actions.

Accounting for how humans use preview is an absolutely crucial element that is missing in cybernetics theory. We already know that, from sampling and cueing theories, humans become almost optimal samplers with preview, and that the Internal Representation (IR) (Stassen et al., 1990) of task variables (the ‘mental’ model referred to above) rapidly improves with preview. Although many attempted to model manual control with preview, no universal model exists. The difficulty lies in the fact that, when preview information becomes available, a multitude of control strategies becomes possible. The human response to preview is a convolved, complicated and very likely *time-varying* weighing of future information, which cannot be directly measured, as an infinite number of weighing mechanisms theoretically yield the same control response.

In our view, the second step in updating cybernetics theory would be to develop a universal human preview model. Three possible sub-steps are foreseen. First, we should theoretically investigate what are the optimal weighing strategies that exist for a human preview controller (including human limitations), with different preview times, while varying the main task variables – plant dynamics and target signal spectrum (i.e., its stochastic properties) – using optimal control models, e.g., (Tomizuka, 1976). These computer simulations may reveal how information on future target could affect the feedforward “weighing”, or “signal shaping” that takes place within the human.

In the second sub-step, these “best possible” internal weighing mechanisms need to be experimentally validated. New experimental techniques are needed to obtain estimates of the continuous (rather than current one-point or two-point approximations) weighing of future target,

through visual blurring or occlusion manipulations. This blurring of future target will affect the ways in which the HCs determine the stochastic properties of the target, the knowledge of which allows them to tune and adapt their feedforward/feedback control strategy. Through systematic visual blurring we then “perturb” the internal weighing functions of future information, and from the identified adaptations (in steady state) we can map these back to how HCs select and adapt their weighing strategies.

Whereas the first two sub-steps focus on target signals that have a continuous spectrum, in the third we propose to investigate HC adaptation to target signals that have distinctive predictable characteristics, such as ramp-like signals that are very relevant for realistic control tasks. Here the possible pre-cognitive, open-loop, or even “switching mode” manual control strategies need to be investigated, as a function of the *level of predictability* of the future target signal. This connects to what will be discussed later on, human learning and adaptation, as these predictable target signals also become part of the HC internal representation.

This second step – understand how humans control systems with preview – will allow designers of manual control interfaces to better support humans in realistic, real-life control tasks. An example is the haptic shared control systems developed to support drivers in controlling their vehicles with preview of the road ahead (Mulder et al., 2011). The absence of understanding how the driver processes the preview information ahead leads to a sub-optimal design in our current support systems.

#### 2.4 Neuro-muscular adaptations: Step 3

Whereas the first two steps that we introduce above aim at modeling HC behavior at higher levels of the SOP, the third step is an interlude. Since our identification techniques work on human ‘inputs’ and ‘outputs’, our models lump together all effects of HC adaptation to the task variables. In order to get a better view on the primarily ‘higher’ level cognitive adaptations as described in the SOP, we would like to separate these from the effects coming from ‘lower’-level physical adaptations, primarily those that occur in the HC neuro-muscular system (NMS).

NMS adaptations, such as increased stiffness from co-contraction or reflexive activity, often occur subconsciously. These – faster – adaptations can be beneficial to task performance but also blur the effects that changing task variables have on the – slower – higher-level learning, adapting HC. Simply ignoring the NMS dynamics, as is done in the majority of studies, leads to an incomplete picture. We need a better understanding of neuro-muscular adaptations and develop methods for *dissecting* these from the measured, lumped adaptation effects.

In realistic control tasks, subjects perform those tasks using various neuro-muscular settings. In previous research this variability in NMS setting between and within subjects is reduced through artificial control tasks which allow the identification of “extreme settings” of the NMS admittance (i.e., maximum stiffness, maximum compliance), yielding insight with respect to the boundaries between which the NMS can vary (Mugge et al., 2010). In realistic

control tasks, neither the admittance level is known, nor whether it is time-varying, or not.

Current linear NMS models are comprehensive and can explain complex interactions such as in biodynamic feedthrough. We therefore propose to first improve the measurement techniques, to obtain more accurate and less intrusive estimates of the possibly time-varying neuro-muscular settings, and then use this knowledge to dissect it from the lumped control response. Again three sub-tasks are foreseen: i) to investigate the adaptation in time of the NMS and study which of the parameters change the most, ii) to obtain a mapping of non-intrusive *grip force* measurements to NMS admittance settings, and iii) to dissect the NMS adaptations from the lumped adaptive human control model.

The additional, independent measurement of grip force may allow us to isolate, and therefore dissect, the NMS adaptations from the lumped response, in the third sub-step. Through applying subspace identification techniques, a better view can be gained on the “higher-cognitive” elements of human adaptation to the main task variables.

### 3. THE LEARNING, ADAPTIVE CONTROLLER

Whereas in the previous section we continued with studying the well-trained HC behavior, in this section we will move towards time-varying control. First, the framework for studying the learning, adaptive human controller will be introduced, followed by a discussion of what is needed in our modeling and identification approach – our tools and models – to make this possible. The final two sections discuss how we propose to study the learning human controller, and the adapting human controller, respectively.

#### 3.1 Framework for adaptive human control

Fig. 3 illustrates the proposed framework for adaptive human control. It will build further on Steps 1 to 3 discussed above. Central in our approach is the concept of the human Internal Representation (IR) of the task variables (P, T, D). The IR is developed during learning, when the HC is exposed to the task constraints inherent in mainly, but not exclusively, the plant dynamics P and the statistical properties of the target and disturbance signals, T and D. Basically, a good IR allows the feedforward path to ‘invert’ the plant dynamics, and bring it quickly from one state to another, while the feedback path compensates for disturbances and deficiencies in the model inversion. The more experience with the events that occur, the better the IR, the more versatile the feedforward loop, and the smaller the contribution of the feedback path will be, very beneficial for closed loop stability and performance.

The IR evolves during learning and is used by the brain to continuously adjust the FB/FF controller and NMS dynamics to achieve a desired performance-effort balance. When task variables change, humans detect these changes because their expectation (driven by the IR) does not match their observation: the innovation  $\hat{z}$  triggers cognitive adaptations in the IR and the FB/FF controllers and also physiological changes in the NMS. Where up until now we experimentally suppress (implicitly hold fixed) this continuous adjustment of the brain, we propose to

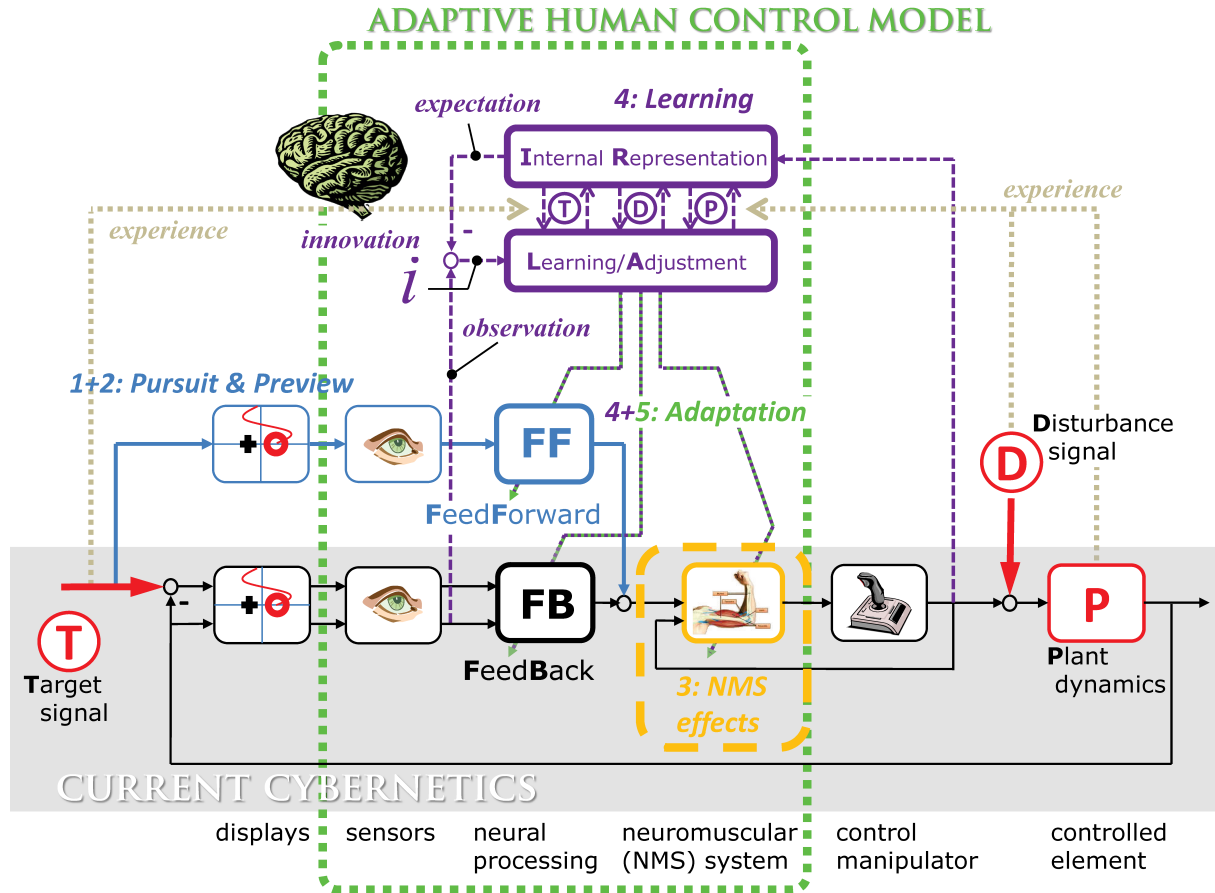


Fig. 3. The learning, adaptive human controller.

experimentally stimulate it (explicitly make variable) to investigate how human controllers learn and adapt. But this means that we cannot longer use the LTI modeling approach, we must change our modeling paradigm to include time-varying model descriptions.

### 3.2 System identification of the adaptive human controller

To develop our framework for adaptive human control, new identification methods to capture the time-varying nature of human controllers need to be employed, perhaps even in real-time. We need to investigate what excitation techniques and test signals will yield the most reliable results, with the lowest possible level of intrusiveness

Suppose we would start with the case of constant task variables, and first develop recursive, 5-to-20 seconds sliding-window (Extended) Kalman Filter (EKF) techniques that estimate the linear time-invariant (LTI) manual control model parameters. With existing tracking data, we can already investigate the extent to which these parameters vary in time, both within-subjects as well as between-subjects. It can be expected that the different parameters have different “life expectancies”, that is, some parameters change faster than others, knowledge that we can use to make our methods more clever, e.g., to keep a longer “memory” of certain variables relative to others. This first step would allow us to study the “averaging effect” of current techniques which use data from the full measurement run, our baseline LTI estimate.

The main thrust forward, however, would be to abandon the concept of LTI systems altogether, and move to model structures that inherently include degrees of freedom to account for time-varying behavior. For this purpose, we propose to apply novel state-of-the-art closed-loop identification methods for linear parameter-varying (LPV) systems (Van Wingerden and Verhaegen, 2009; Tóth et al., 2012) to identify intrinsically time-varying manual control models. A possible approach would be to systematically change the main task variables (P and T), use extensive computer simulations to explore how the HC may adapt, assuming optimality, and validate these findings through experiments. We can then study what “function approximators” can best describe the adapting model parameters, investigate their temporal scales, both within and between parameters, and also extend these methods to make them suitable for recursive, real-time applications. Using the baseline LTI estimate, we can then study the extent to which the universal “time-invariance” hypothesis of cybernetics, is valid, comparing the LTI and LPV modeling results.

### 3.3 Step 4: Modeling the learning human controller

Current cybernetics only studies the dynamic LTI response of well-trained subjects, at the extreme end of the learning curve. In Step 4 we propose to break with this tradition and, using the time-varying identification techniques discussed in the previous section, elucidate human con-

trol learning progress during the full learning curve, from novice to expert controllers.

To this end, we propose to identify the adapting human feedback-feedforward response in a variety of well-defined (preview) control situations, and study the strength and versatility of especially the feedforward path to “probe” the quality of the evolving IR. In this way, we may be able to quantify the extent to which novice controllers, while gaining experience, develop an accurate IR of the task constraints, becoming experts. Of special interest would be the *temporal scale* of learning controllers for key task variable combinations.

Step 4 would lead to quantitative metrics of, and tools to elucidate, progress in control skills acquisition, for the full learning curve, from novice to expert controller.

### 3.4 Step 5: Modeling situation-based adaptive manual control

Step 5 entails the development of a completely new theoretical framework for cybernetics, within which human adaptive control can be interpreted and predicted. From the above it is clear that, when task variables – which represent “situations” from a control-theoretical perspective – change during tasks, the HCs will detect these changes because their expectation (driven by the IR) 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”  $\dot{i}$ , or “surprise”, which may trigger adjustments in the IR, the feedforward/feedback controller and possibly the neuro-muscular system. Experienced controllers learn to select which of the multiple experienced inverse dynamics models are appropriate for the (changing) task at hand.

We therefore propose to train subjects to the expert level for a variety of task variables (P, T, D) in situations where these remain constant. This allows them to develop a set of IRs for different P, T and D, and develop proficient control skills to deal with combinations of those; together, these represent the variability of real-life situations from a control-theoretical perspective. We can then, *during* the following experimental runs, *change* the task variables in a systematic fashion, and through LPV identification investigate *if*, to *what extent*, and *how fast*, the HC adapts to these changes. It would be interesting to see what function approximators best match the temporal dimensions of HC adaptations, investigate within-subjects and between-subject variability, and also investigate the possible hysteresis-effects that occur when humans adapt, back and forth different control adaptations.

## 4. TOWARDS A NEW CYBERNETICS

In this paper we discussed some fundamental issues in manual control cybernetics, and propose a new framework. Moving from the LTI-models based approach to LPV models will fundamentally change our models, our tools, our theory. The capability to mathematically model and identify time-varying adaptive human control will allow for (at least) four key innovations.

First, the exploitation of the human capability to adapt is key to optimize the multi-modal control interfaces that

our ever-advancing modern technologies permit. The new framework will transform the current trial-and-error tuning of these 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 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. Fourth, the insights gained in the human capability for adaptation can serve as design inspiration for future generations of autonomous and adaptive robots.

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