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New Insights, New Models, New Issues**

Mulder, Max; Pool, D. M.; Van Der El, K.; Drop, F. M.; Van Paassen, M. M.

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Manual Control with Pursuit Displays: New Insights, New Models, New Issues

Max Mulder,^{*,1} D. M. Pool,^{*} K. van der El,^{*} F. M. Drop^{**}
and M. M. van Paassen^{*}

^{*} *Control and Simulation, Faculty of Aerospace Engineering, TU Delft,
2629 HS, Delft, The Netherlands*

^{**} *Max Planck Inst. for Biological Cybernetics, Tübingen, Germany*

Abstract: Mathematical control models are widely used in tuning manual control systems and understanding human performance. The most common model, the crossover model, is severely limited, however, in describing realistic human control behaviour in relevant control tasks as it is only valid for tracking with a compensatory display. This paper first discusses the state-of-the-art in modelling human control in tracking with pursuit displays. It is shown that, although both tasks seem very similar, the separate presentation of target and system output signals allows operators to adopt a huge variety in control strategies, which makes the development of a universal model for pursuit control a challenge. Two recent models are then described which can act as precursors to such a universal model. Third, system identification choices and issues are discussed for pursuit tracking tasks. Finally, it is argued that it is inevitable that time-varying rather than time-invariant methods are needed to properly describe human behaviour in the pursuit tracking task, as skilled operators will learn to characterize the probabilistic nature of the task, which cannot be captured in a single, linear, time-invariant model.

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1. INTRODUCTION

Modelling human behaviour in manual control tasks has been an important subject of study for over 70 years, see the seminal paper by McRuer and Jex (1967) and a very recent overview by Mulder et al. (2018). In their Successive Organisation of Perception (SOP) hierarchy, Krendel and McRuer (1960) distinguish between three stages of human control behaviour: compensatory, pursuit and precognitive control. Depending on the variables that describe the task, predominantly the type of display (compensatory, pursuit, preview), the controlled element (CE) dynamics, and the shape and bandwidth of the reference signal to be followed (the target signal f_t), the human controller (HC) will learn to adapt to achieve a trade-off between achieving high tracking performance and limited control activity.

With a compensatory display, showing only the difference (error e) between the output (x) of a controlled element and target signal f_t , the human controller has just one visual input and, depending on the characteristics of the target, acts on that input in a *feedback-only* fashion. The systematic HC adaptation to task variables has been successfully captured, and can be well understood in classical control engineering terms, in the *crossover model* (McRuer and Jex, 1967). This model has been used for decades to tune all sorts of manual control devices, such as visual or haptic displays, and to understand and model human biodynamics, self-motion perception, and other phenomena (Zaal et al., 2009, 2013; Venrooij et al., 2011).

Mulder et al. (2018) argue, however, that the research community still focuses too much on modelling what can be considered as the *exception* in human control, namely feedback-only compensatory tracking. Rather, more efforts are needed to study the *rule* of human control, that is, to model the incredibly versatile, *adapting*, biological system, using more realistic and relevant pursuit and preview displays. Being able to understand and model the unique capabilities of humans to (quickly, robustly) adapt to changing circumstances may pave the way for better support systems, and human-like automation.

Although it is well-known that pursuit and preview displays yield superior performance, see e.g., (Wasicko et al., 1966; Magdaleno et al., 1969; Hess, 1981; Abdel-Malek and Marmarelis, 1988; Hynes et al., 1989; Hardy, 2002), this has not led to a generic HC model for these cases. Recent advances in system identification, however, together with abundant computational power, have inspired a new generation of cyberneticians to address the problems of modelling human control behaviour with pursuit and preview displays, see e.g., (Vos et al., 2014; Zhang et al., 2017; Drop, 2016; Van der El, 2018).

This paper focuses on pursuit tracking and will discuss some of the recent new insights gained, the new models developed, and will also shed some light on the inevitable non-linearity that one can expect when modelling skilled HCs. We start in Section 2 with a brief summary of the pursuit tracking task, and discuss recent advances in our lab in modeling HC behaviour with pursuit displays in Section 3 and Section 4, respectively. Non-linear issues that arise with pursuit displays will be discussed in Section 5.

¹ m.mulder@tudelft.nl

2. THE PURSUIT TRACKING TASK

A typical pursuit display, illustrated in Fig. 1, presents two symbols: the to-be-followed target signal f_t (circle), and the output of the controlled element x (cross). The (in this example, horizontal) offset between both markers is the tracking error $e = f_t - x$. The HC must keep this error e as small as possible by giving control inputs u with a control manipulator. Although the display is extremely simple, the HC performing a pursuit task has shown to be much more difficult to model than in a tracking task with a compensatory display, only showing e .

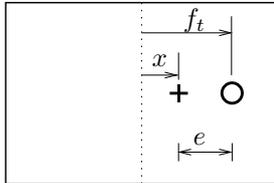


Fig. 1. Pursuit display, on a 4:3 computer screen.

The origins of these difficulties can be explained in the light of the advantages that pursuit displays offer the HC. That is, whereas a compensatory display only allows the HC to close a single error-minimizing control loop, the pursuit display allows a wealth of alternative control strategies. First of all, with a pursuit display the HC can see what she is doing with the system (x), and also what is the reference (f_t). Showing x improves the eye-hand coordination, as a left/right movement of the manipulator will typically lead to a left/right movement of the output symbol (depending on CE dynamics), which is not necessarily true for a compensatory display.

Second, because x is shown explicitly the HC can explore the characteristics of the CE dynamics, and can also see the first derivative \dot{x} (some even the second derivative \ddot{x}), which allows even notoriously difficult CE dynamics (such as the double integrator) to be more easily controlled.

Third, because f_t is shown separately, the HC may learn to characterize its properties, allowing for some form of prediction. When tracking a single sinusoid, or the sum of just a few sinusoids, the signal will become more *predictable*, allowing the HC to anticipate on its movement (Magdaleno et al., 1969; Drop et al., 2016a). But even when using a larger number of sinusoid components, yielding a quasi-random signal, some skilled operators can remember parts of the reference trajectory and benefit from this knowledge. To prevent this from happening, often multiple phase realizations of the target are used.

Fourth, as a consequence of showing the target and output separately, the HC can anticipate the movement of the target, as will be discussed in detail in this paper.

It is clear from the above, that the pursuit display allows the HC to explore a much larger variety in control strategies than the feedback-only compensatory tracking task. Capturing HC behaviour in a mathematical model is therefore challenging, and previous attempts have not lead to a generally-accepted HC model (Wasicko et al., 1966; McRuer and Jex, 1967; Hess, 1981; Abdel-Malek and Marmarelis, 1988; Vos et al., 2014).

3. MODELLING PURSUIT BEHAVIOUR

Fig. 2 shows a block diagram of the HC (dynamics H_{hc}) involved in a pursuit tracking task, with single integrator CE dynamics H_{ce} . The operator has three inputs, f_t , x and e , which are dependent as $e = f_t - x$ (Wasicko et al., 1966). The HC may choose to mechanize feedforward (FF) and/or feedback (FB) control responses driven by these signals, but because of their dependency the HC model structure is inherently over-determined. As a result, for pursuit control various model structures (e.g., using e and f_t , or x and e , etc.) have been proposed and applied. This, together with the fact that in order to separately estimate the two independent describing functions with an instrumental variable technique, *two* independent forcing function signals are required (Van Paassen and Mulder, 1998; Steen et al., 2011), will be further discussed in the next section. Here we will consider only two of the more recent HC models developed in our laboratory.

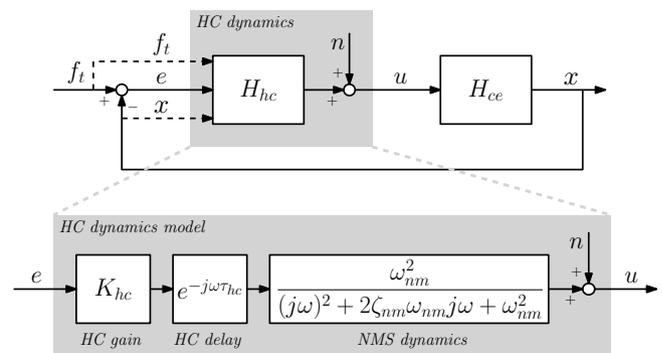


Fig. 2. Block diagram of the pursuit tracking task (top) and the HC error feedback dynamics as typically found in compensatory tracking tasks (bottom).

3.1 Open-Loop HC feedforward model

Apart from pioneering work in the 1960s-1980s, the pursuit tracking task has received only meagre attention. A notable exception is the work on HC FF dynamics performed by Drop (2016), who studied the HC response in more realistic control tasks with predictable target signals such as ramps. He showed that HCs can improve target-tracking performance without sacrificing closed-loop stability through a FF response on the target, in addition to a FB response. Up to a certain frequency, the FF response dynamics mimic the inverse of the CE dynamics (Drop et al., 2013), beyond which the FF response weakens. These FB/FF models provide better understanding of the HC's capability to adapt to predictable target signals (Drop et al., 2016a), with higher FF response gains and even close to zero effective time delays acting on predictable targets. Drop's work also showed that one has to be extremely careful interpreting the modelling results. The high human remnant can lead to false positives, that is, erroneously attributing data trends to HC FF responses, or vice versa, missing the FF dynamics when they are actually there (Drop et al., 2016b, 2018).

3.2 Target pre-processing HC model

Another recent approach to model pursuit control proposes that HCs process the visible target signal f_t into an *aim point* that provides the reference input f_t^* for a compensatory control response (Van der El, 2018; Van der El et al., 2018). This is illustrated in Fig. 3.

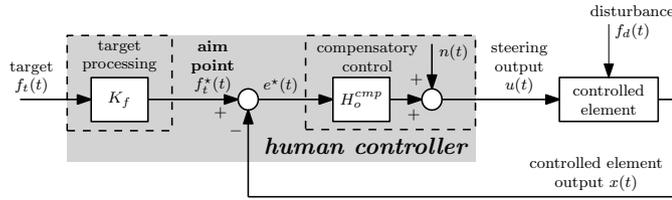


Fig. 3. Block diagram of the HC, modeled as a compensatory controller with a reference “aim point” obtained by pre-filtering the target signal f_t .

In contrast to the model by Wasicko et al. (1966), this HC model does *not* include an explicit feedforward response in parallel to an error-feedback response. Data obtained in pursuit tasks suggest that the pre-filter involves at least *scaling* of the target, indicated by gain K_f in Fig. 3. An increasingly high gain K_f reflects a stronger feedforward response. A lower gain indicates that HCs are ignoring more of the target signal variations, ultimately fully ignoring the target when $K_f = 0$.

Estimated K_f values from (Van der El et al., 2018) in tasks with gain ($K_f > 1$), single- ($K_f \approx 1$), and double-integrator ($K_f < 1$) CE dynamics reveal that HCs ignore more of the target signal with higher-order controlled element dynamics. For example, in double-integrator tasks, the gain lower than one suggests that HCs select an aim point on the *inside* of the displayed target marker, in order to avoid overshoots. A unity gain ($K_f = 1$, e.g., found in single-integrator tasks (Van der El et al., 2018)) indicates that the minimized error is the *true error* and that the HC exhibits pure compensatory control behavior.

4. IDENTIFICATION OF PURSUIT BEHAVIOR

4.1 Choice of HC model structure

Humans in pursuit tasks can mechanize control responses to the three displayed signals: 1) feedforward H_{o_t} on the target trajectory $f_t(t)$, 2) feedback H_{o_x} on the controlled element output $x(t)$, and 3) feedback H_{o_e} on the error $e(t)$. The most general control diagram of the human in a pursuit control task therefore has three response channels, see Fig. 4 (top), H_{o_t} , H_{o_e} , and H_{o_x} .

Our key challenge is to understand *how* the HC uses each signal for control, which requires measurements of the dynamics in H_{o_t} , H_{o_e} , and H_{o_x} . However, directly measuring the dynamics of all three control responses is impossible, because the general three-channel response structure is over-determined, due to the linear relation between the three inputs, $e(t) = f_t(t) - x(t)$. Consequently, only two out of the three possible control responses can, and have been, directly measured (Van der El, 2018).

It comes as no surprise, therefore, that the dominant theories for pursuit control, introduced in the previous two sections, are *two-channel* models. The three two-channel control organizations that are available for analyzing human control behavior are also shown in Fig. 4 (bottom):

XT: A *feedforward* and *output* feedback response; the error feedback block is omitted.

ET: A *feedforward* and *error* feedback organization; the output feedback response is omitted.

EX: An *error* and *output* feedback organization; the feedforward response is omitted.

Assuming a linear HC, all three two-channel models are equally capable of capturing the human’s full three-channel control dynamics. This can be proven mathematically, by writing the Fourier transform of the HC’s output $U(j\omega)$ in the general three-channel control diagram:

$$U = H_{o_t} F_t + H_{o_e} E - H_{o_x} X + N \quad (1)$$

Here and in the following, the dependency of the signals and dynamics on $j\omega$ is dropped for brevity, and capitals indicate the Fourier transform of the respective signals. Substituting $E = F_t - X$ into Eq. (1) yields:

$$\begin{aligned} U &= H_{o_t} F_t + H_{o_e} (F_t - X) - H_{o_x} X + N \\ &= (H_{o_t} + H_{o_e}) F_t - (H_{o_x} + H_{o_e}) X + N \end{aligned} \quad (2)$$

Comparing Eq. (2) with the expression for the HC’s output in the two-channel *XT* control organization, given by $U = H_{o_t}^{XT} F_t - H_{o_x}^{XT} X + N$ (see Fig. 4), shows that:

$$H_{o_t}^{XT} = H_{o_t} + H_{o_e} \quad (3)$$

$$H_{o_x}^{XT} = H_{o_x} + H_{o_e} \quad (4)$$

The implication of Eq. (3) is that the feedforward dynamics $H_{o_t}^{XT}$, as estimated in an *XT* structure, are *not* the HC’s true feedforward dynamics H_{o_t} , but the *lumped combination* of H_{o_t} and H_{o_e} .

Similarly, the estimated controlled element output response in Eq. (4) is the lumped combination of H_{o_x} and H_{o_e} . Using similar derivations, the responses in the *ET* and *EX* two-channel organizations can also be expressed as a function of the true human responses in the general three-channel structure; these are given in Fig. 4. Regardless of the selected two-channel model structure, the two estimated response dynamics are “contaminated” by the dynamics of the omitted third response, *if* the human mechanizes this third response in sufficient strength.

4.2 Instrumental-Variable system identification

Several of the first attempts to use multiple forcing functions to estimate the HC model in pursuit tracking tasks were performed by (Drop et al., 2013), (Vos et al., 2014) and (Laurense et al., 2015). Using an instrumental-variable technique, *two* independent forcing functions are inserted in the closed loop, the target f_t and the disturbance f_d , see Fig. 4. A key question that needed to be addressed in successfully separating the two HC responses, was that the addition of the second forcing function f_d , which is done merely for identification purposes, does *not change the HC dynamics*. That is, the target-following disturbance-rejection task that comes with the insertion of both f_t and f_d should remain a predominantly target-tracking task, similar to the case where only the target signal is available.

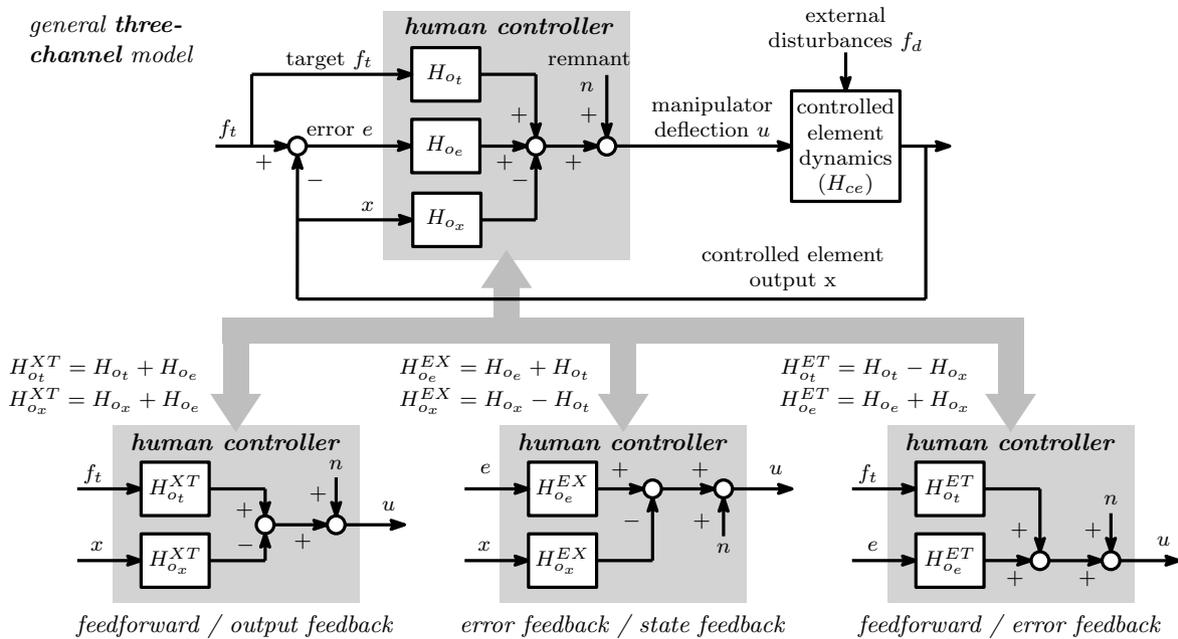


Fig. 4. Block diagram of the HC's three possible control responses in pursuit tasks (top), and the three equivalent two-channel models that can be used to estimate the human's control dynamics (bottom).

In (Drop et al., 2013) the relative magnitude of the ramp target f_t and unpredictable disturbance f_d signals was characterized by the *Steepness-Disturbance Ratio* (SDR). Their experimental data showed that, for the range of SDRs investigated, HCs adopted a FF loop for all conditions, approximating the inverse of the HC dynamics, whereas the FB (compensatory) response on error e closely resembles the response found during compensatory tracking tasks with unpredictable targets.

Computer simulations also showed, however, that when f_d became too strong (low SDR) the HC FF response becomes less strong. Hence, one should carefully trade-off the desire to identify the two separate responses from causing HC adaptation to happen because of inserting the second forcing function signal. But apart from these identification issues, HC behaviour in pursuit tracking tasks also may no longer fit the traditional quasi-linear modeling framework, as will be discussed next.

5. NONLINEARITIES IN PURSUIT CONTROL

5.1 Situation-dependent control strategy

In this section we will discuss some inevitable nonlinearities when modelling a HC performing a pursuit tracking task. It is important to realize that, when doing experiments in a pursuit configuration, one typically *scales* the target forcing function f_t such that *the target symbol does not leave the display*. It is inevitable that the HC will learn this characteristic, use it for her own benefits (reduce workload), making the HC act as an intrinsically nonlinear controller. That is, although we stated above (and always assume on our modelling attempts) that the operator inputs e , x and f_t are dependent, and only two matter, this is true for a linear *model* but will not be true for a *human controller*. That is, while e can be exactly the same, the relative positions of x and f_t actually *do matter*: in pursuit, a trained operator will be nonlinear.

Consider Figure 5, which shows two possible situations, 1 and 2, where in Situation 1 the target symbol (the circle) is close to the right screen border, and in Situation 2 it is close to the display center (the vertical dotted line). Accidentally, the CE position (the cross) is in both cases located to the left of the target, resulting in the same error e' . While the error is exactly the same, the control situation is *fundamentally different*. In Situation 1 it is likely that the target symbol will *move to the left*, and the operator will learn to *use this information* to optimize her control actions, where the optimum is typically to reduce error (increase performance) *and* control activity (reduce workload). In Situation 2, however, the target symbol is located near the center of the screen, and the likelihood that it will move to the left will be more or less the same as the likelihood that it will move to the right. In other words, the *level of predictability* of f_t depends on the value of f_t itself, and it is likely that a trained HC will *adapt* her behavior *depending on where the target symbol is located on the screen*.

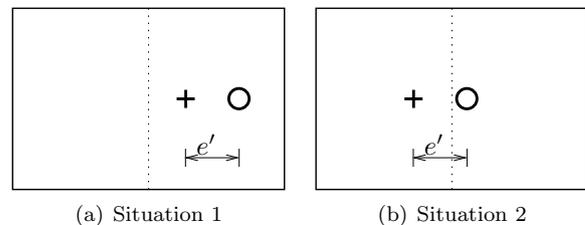


Fig. 5. Two situations with the same error e' , but which may lead to different HC responses.

5.2 Target signal characteristics

Fig. 6 shows the forcing function used in (Vos et al., 2014), as a function of time but rotated vertically to better show the left/right movement of the target symbol on the screen

(top); the distribution of the amplitudes is also shown (bottom); the measurement time is 90 seconds, sample frequency 100 Hz. Clearly, we have an approximately Normal distribution of the target symbol amplitudes, which is desired (Damveld et al., 2010), where the target symbol is mostly moving around the display center, and only rarely moves to the extremes (left, right) of the display. One can be absolutely certain that HCs, during training, will learn about this distribution *and use this for their benefit* in their control strategy, for instance by always keeping the CE symbol *at the inner side* (relative to the display center) of the target symbol, simply because the probability that it will move left increases when the target is located more to the right, and vice versa.

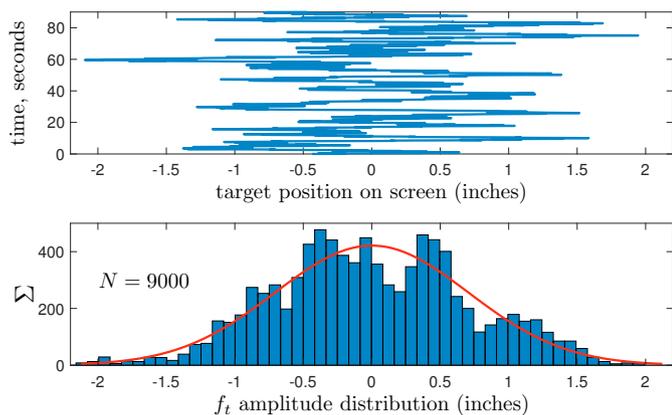


Fig. 6. Position of the reference symbol as a function of time (f_t , top); distribution (bottom, with the Normal distribution estimate in red).

5.3 Regions of probability, switching control strategies

Fig. 7 shows a probabilistic view on the target position, and the probability that the target *will move* into a particular direction. For instance, when the target symbol is located far to the left, the chance that it will move to the right will be much higher than the chance that it will move even further to the left. This is what the thick red line shows for a Normal-like amplitude distribution (\mathcal{N}) of f_t . The thick dashed red line shows this probability for a hypothetical uniform amplitude distribution (\mathcal{U}) of f_t . Similarly, the blue lines show the probability that the target symbol will move to the left, where $\Pr\{\text{moves left}\} + \Pr\{\text{moves right}\} = 1$ for any distribution. When the target symbol is located at the far right, then with a uniform or normal distribution of f_t the chance that it will move to the left (blue) is close to 1, and the chance that it will move further to the right (red), is zero.

When assuming that the distribution of f_t is symmetrical relative to the display center, typical for tracking tasks, we can distinguish three areas where the operator can predict where the target will be moving with high (area III in Figure 7), medium (area II) and low (area I) probability. Of course, these three areas are arbitrary and just serve as an example. The point we are trying to make is that, dependent of where the target symbol is positioned on the display, the operator has a better or worse chance of predicting in what direction it will be moving. That is,

the predictability of the movement of the target symbol *increases* when it moves away from the center (I \rightarrow II \rightarrow III), and will be more or less 50/50 when the target is located near the center (I). Hence, this means that for instance in the model from Van der El et al. (2018), discussed in Section 3.2, the K_f parameter may *vary* from time to time, from close to 1 when the target is near the center (as then it is unclear where the target will be moving next, hence the HC tries to minimize the error whatever it takes), and will be much smaller than 1 when the target is positioned near the edges, as here it is likely that *the target will be moving towards the CE symbol anyhow*, and it is better to keep the system output on the ‘inner side’ of the target; hence, we get $K_f(f_t)$ or $K_f(t)$.

5.4 Consequences, new issues

It is clear from the above that skilled HCs, when confronted with a pursuit tracking task for a symmetrically (relative to the display center) distribution of the target signal, will learn to use the inevitable consequence of scaling the target signal amplitude to the size of the display. These variations in HC behavior, however, have not been found so far, simply because of our identification approaches which typically aim to fit *one, linear time-invariant* HC model to the entire set of data. Hence, the time-varying behaviour is typically averaged-out, as only one K_f is estimated per run. Only explicitly time-variant analysis techniques will be able to capture this behaviour, an interesting and important avenue of future research (Mulder et al., 2018). Whether the HC will be continuously adapting, e.g., the gain K_f , or whether she will switch between three modes of operation as suggested by the three regions illustrated in Fig. 7, remains to be investigated.

6. CONCLUSION

We discussed the state-of-the-art in modelling human control behaviour with pursuit displays, and showed that significant advances have been made in validating novel linear time-invariant models with experimental data. The versatile model by Van der El et al. (2018) can describe the observed behaviour very well, and because it is based on fundamental physical and control-theoretical insights, seems a good candidate to be used as the generic crossover-model-like alternative that is direly needed to model HC behaviour in more realistic and relevant control tasks. We also conclude, however, that a skilled human controller is likely to be learning the probabilistic characteristics of the target signal, inevitably leading to time-varying behaviour which is currently not captured in any of our models.

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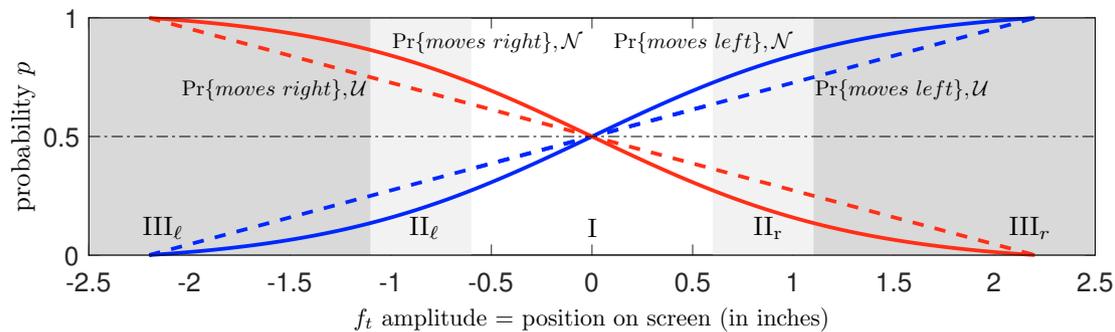


Fig. 7. Probabilistic view of HC behavior in pursuit tracking.

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