Aerospace Science and Technology 34 (2014) 55–74

Contents lists available at ScienceDirect

Aerospace Science and Technology

www.elsevier.com/locate/aescte

Review

Review of pilot models used in aircraft flight dynamics

Mudassir Lone *, Alastair Cooke

Dynamics, Simulation and Control Group, Department of Aerospace Engineering, School of Engineering, Cranfield University, Cranfield MK43 0AL, United Kingdom

ARTICLE INFO

Article history:
Received 15 August 2013
Received in revised form 28 November 2013
Accepted 14 February 2014
Available online 26 February 2014

Keywords:
Pilot modelling
Human sensory modelling
Biomechanical modelling
Control-theoretic modelling
Aircraft handling qualities

ABSTRACT

Mathematical representations of human control behaviour have played a very important part in manned aviation, especially in the definition of aircraft handling qualities requirements. New challenges posed by advances in aerospace technologies, such as fly-by-wire flight control, large flexible airframes and flight simulation, have led to increasingly complex mathematical representations of pilot behaviour. However, all these areas tend to be investigated separately and in parallel with human factors studies. The motivation behind this review is to promote discussion between the flight dynamicists and other engineers and scientists on the methods of modelling and simulation of today's pilot. A review of pilot model components used for flight control system design that focuses specifically on physiological and manual control aspects is presented in this paper. Models of varying complexity that are considered to be the state-of-the-art within the flight control and handling qualities engineering community are discussed. These include simple sensory models, biomechanics models and complex nonlinear pilot manual control models. In each area, the challenges posed by inter-subject variations and the need to understand the aircraft as a complex man–machine system are highlighted. However, the presented discussion is limited to a thin slice of this field thought to be fundamental to modelling manual control dynamics exhibited by aircraft pilots.

Pilot modelling has evolved to into a wide engineering field with contributions from many disciplines that consider interaction with human beings, either as an operator or a customer. Aspects from this field are included either implicitly or explicitly during the design of day-to-day objects like a cup to complex machines such as the space shuttle. Modern understanding of human perception and information processing alone has advanced considerably over the last twenty years, prior to which researchers focused on mainly qualitative descriptions of possible human actions. Present day scientists are taking advantage of the available computational power and investigating the deeper functions of the brain by identifying and developing functional maps of neurons within the brain [33,71,99]. Yet, each miracle landing credited to skilled manual control or an accident attributed to human error demonstrates the complexity of the human pilot and highlights our ignorance of his/her capabilities [13]. A detailed review of pilot modelling techniques merits many years of research and hence, the discussion presented in this paper is limited to a thin slice of this field that considers particular aspects thought to be fundamental to modelling manual control dynamics exhibited by aircraft pilots. These are the sensory, biodynamic and control aspects. The reader should note that the discussions presented in this paper augment past work done by Lone and Cooke [63,65] and more recent work done in the ARISTOTEL project [52,67].

Investigation of such scenarios not only requires an understanding of aircraft manual control, but also an understanding of the pilot–vehicle-system (PVS) as a whole. Modern civil aircraft effectively have three modes of operation:

1. Aircraft control can be established through complete manual control with objectives from the pilot's mind or objectives from a flight director.
2. The mode control panel which commands the various autopilots can also be used. The pilot plays a more supervisory role here and his/her input is required only at particular stages of the mission.
3. The flight management computer can be programmed on the ground. Based on this information the flight director can establish control through the autopilots. The pilot may presume a fully supervisory role for the duration of the mission.

Fig. 1 presents the key components involved in the manual control mode that are necessary to model manual control dynamics. Here, the system is motivated by an *objective* that is processed by *higher brain functions* to derive a process through which it can be achieved. In scenarios of high urgency the objective is simplified

* Corresponding author. Tel.: +44 (0) 1234 750111.
E-mail address: m.m.lone@cranfield.ac.uk (M. Lone).

http://dx.doi.org/10.1016/j.ast.2014.02.003

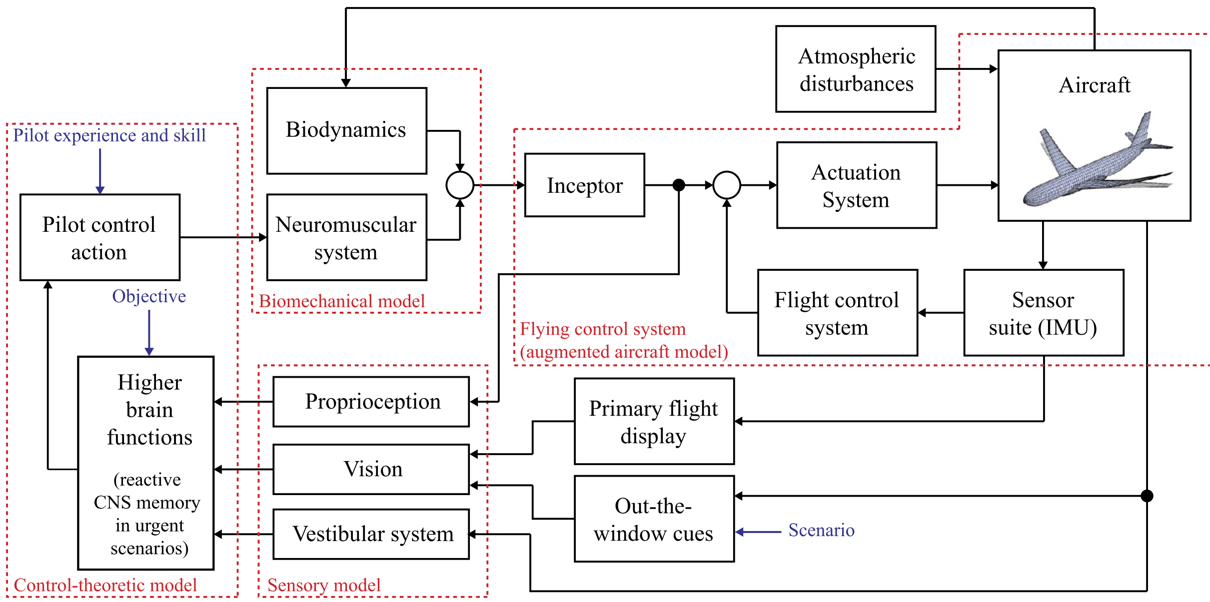


Fig. 1. Block diagram representing the pilot–vehicle-system under manual control.

and control action is either generated based on recall of emergency procedures or even reactive muscle memory. Pilot training plays a critical role at this stage. The resulting *pilot control action* then determines the cues and gains selected by the pilot to establish feedback control. These are typically a function of pilot *experience and skill*. The control action is executed via the forces generated by the muscles in the *neuromuscular system* and exerted on the *inceptor*. Signals from the inceptor are used by the *flight control system* as demands for flight dynamic parameters such as pitch rate or normal acceleration. These are met with the help of the *actuation system* that provides the appropriate movement of the control surfaces on the wings and empennage or changes in engine thrust. Thus, forces and moments are generated to change the orientation of the *aircraft* relative to the oncoming air flow. This change is perceived by the pilot primarily through his/her *visual sensory modality* that delivers information regarding the *scenario* from *out-the-window cues* to the brain. The *primary flight display* (PFD) delivers information from the *aircraft's sensor suite*. *Vestibular dynamics* play a critical role in the perception of aircraft accelerations. The pilot also perceives the commanded inceptor input via the *proprioceptive sense*. These cues effectively close the feedback control loops. However, the pilot's position within the aircraft also means his/her body is subjected to the resulting accelerations that arise either due to his/her commands or *atmospheric disturbances*. Therefore, the neuromuscular forces acting on the inceptor are affected by a disturbance generated when the aircraft accelerations pass through the pilot's *biodynamic* response. The key pilot model components can now be grouped together as the *control-theoretic*, *sensory* and *biomechanical* models.

1. Sensory dynamics

The natural sensory organs have evolved to become a very sophisticated sensory suite, which in conjunction with the central nervous system (CNS), is an elaborate example of data collection and fusion. However, this system is best suited for moderate angular rotations of short durations experienced on a daily basis on the ground. Although the dynamics of the individual sensory organs are well understood, their joint role with the CNS for perception is only being investigated now. Although it is normally taken for granted that reality is being perceived, (whilst true for most day-to-day scenarios) the frequent low intensity and long duration rotations experienced in flight can easily result in erroneous perceptions leading to disorientation. Spatial disorientation (SD) is defined as a situation when the pilot fails to correctly perceive position, motion or attitude of the aircraft within a fixed coordinate system provided by the surface of the Earth and its gravitational field. A human sensory model should at least be capable of simulating certain pilot SD.

Research in SD was initiated by Ernst Mach whose work in supersonics actually had roots in earlier studies of the human vestibular sense and audio perception. It was a decade later in 1877 that he published his work on supersonic projectile motion. Research in the context of aviation began later towards the end of World War I and true progress only came in the 1990s. SD has now been divided into three categories [108]:

- Type I: where the pilot is unaware that the perceived orientation is incorrect.
- Type II: where there is a conscious recognition of a conflict between the senses and instruments.
- Type III: where the pilot has a sense of helplessness and an inability to maintain control due to an overwhelming confusion about orientation.

It should be noted that majority of SD mishaps are of Types I and II, during which the pilot often refuses to believe the instruments and/or misinterprets out-the-window cues. For example, a near-fatal Type II SD occurred when the pilot of a United States Air Force (USAF) C-5 refused to believe the PFD just prior to entering a stall. The cause of this SD was found to be the perceived gravito-inertial force (GIF) vector (felt by the vestibular system) that falsely indicated level flight [108].

Mathematical modelling of SD requires knowledge of the mechanisms and processes involved in developing spatial orientation. At the conscious level auditory and focal visual cues are used to obtain estimates of aircraft states at any given time. Subconsciously the visual, vestibular and proprioceptive inputs are processed to provide positioning, angular and linear acceleration estimates. The CNS is then responsible for the interpretation and comparison with an internal model. These models are formulated from past experience and training that in turn generate expectations concerning aircraft dynamics [89]. Such qualitative descriptions and relationships can be found in most human factors literature. On the other

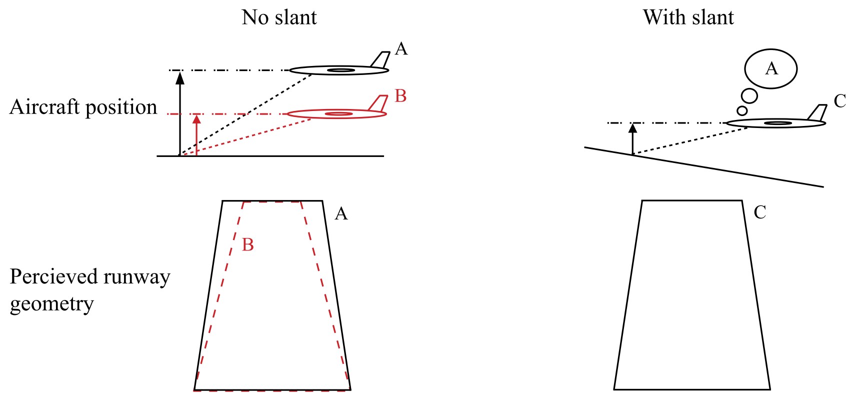


Fig. 2. Effects of slant on pilot altitude judgement.

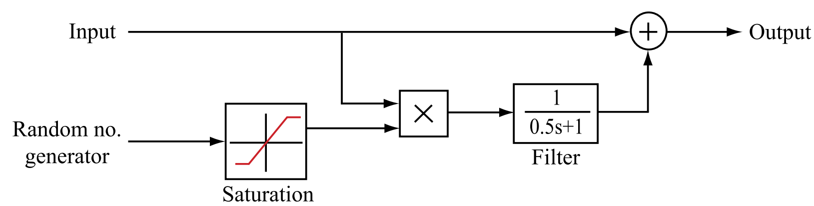


Fig. 3. Visual cue perception model proposed by Hess.

hand, quantitative relationships are harder to come by due to the difficulties involved in experimental design, measurement and also medical ethics.

1.1. Visual system

The human visual system is the primary source of information required to maintain orientation in Earth-fixed space. It operates in two modes: ambient and focal. The dominance of this sensory modality is reflected by the fact that even today most airframe manufacturers rely on fixed-base simulation for evaluation of flying and handling qualities.

The ambient mode helps mainly in spatial orientation and relies on certain types of cues within the central and peripheral fields such as motion, linear/aerial perspective, texture and brightness gradients. It then provides a sense of self-motion, distance, slant and tilt within a three dimensional framework. Majority of the cues inducing visual SD tend to be monocular; binocular cues within an aircraft cockpit only contribute to perception within the first few surrounding metres. The astonishing feature of this visual mode is its capability to subconsciously process the aforementioned cues and provide a stable perception of the surroundings over a large spatial range. It does so by contributing sustained low frequency signals to the CNS that then determines spatial orientation. This is in contrast to the remaining sensory systems that provide signals of a more transient nature and relatively high frequency to help stabilise the perceived surroundings immediately after self-motion [108].

An area where the ambient mode has significant contribution is the perception of distance and ground slant. Correct judgement requires many of the same cues and so there exists a fundamental ambiguity in their perception leading to difficulties in estimating altitude when in flight. For example, consider Fig. 2 which shows that an upsloping terrain decreases the perspective splay angle and the pilot feels as though he/she is flying at a higher altitude. In a degraded visual environment, observers have been found to rely on size and shape of familiar objects and memorised spatial layouts [108].

The focal mode is concerned with object identification and relies on cues (mainly binocular) within the central visual field. It gathers highly detailed information at high spatial frequencies and is usually well represented in consciousness [89]. Instrument flight is dependant on this visual mode.

In the context of pilot modelling, the quality with which visual cues are perceived can be modelled at various levels. The simplest of these is the injection of a filtered Gaussian white noise into the control loop to account for all potential non-linear inceptor movements; these may arise from factors such as degradation of cue quality. The visual perception model proposed by Hess [41] (Fig. 3) and considered by Kleinman [56] provides simple models for visual observation. The saturation limits are set to twice the variance of the zero-mean Gaussian random number generator. The variance of this random number generator implicitly determines the visual cue quality. Hess [42] relates this variance to the relationship between usable cue environment (UCE) and visual cue rating (VCR) found in military rotorcraft design standards [1]. It is selected as follows:

$$\begin{aligned} &0 < \sigma_{vis}^2 < 0.1 \quad \text{for UCE} = 1 \\ &0.1 \leqslant \sigma_{vis}^2 < 0.2 \quad \text{for UCE} = 2 \\ &0.2 \leqslant \sigma_{vis}^2 < 0.3 \quad \text{for UCE} = 3 \end{aligned} \tag{1}$$

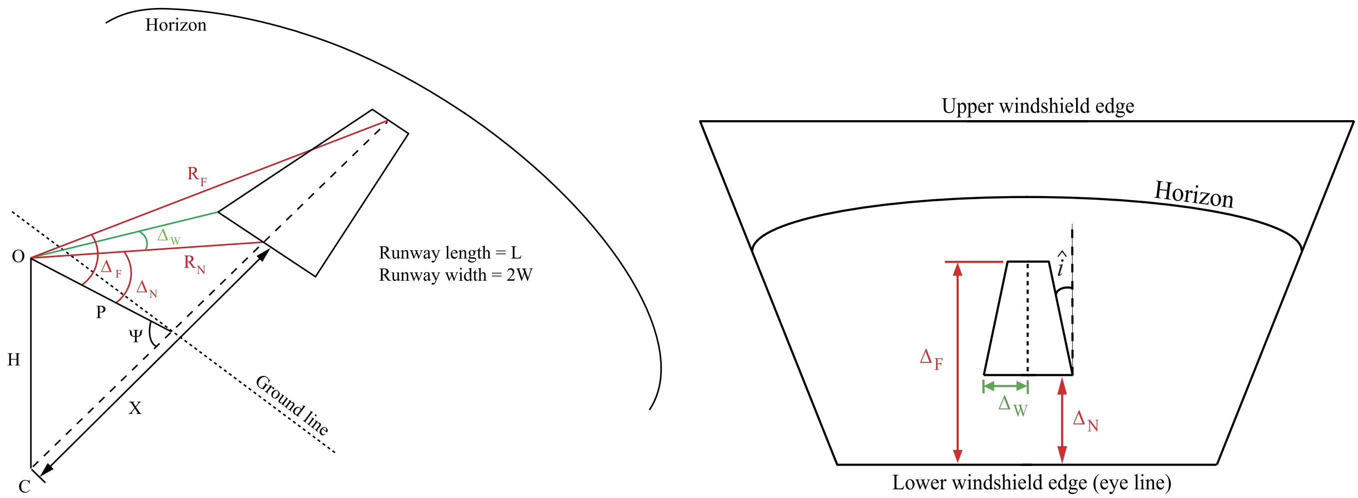
This has been extended to visual perception in multiple axes by introducing a task dependant variance as follows:

$$\sigma_{task}^2 = \begin{cases} 0.01n & \text{for } n > 1 \\ 0 & \text{for } n = 0, \end{cases} \tag{2}$$

where n is the number of axes being controlled. This term is incorporated through the following 'f' factor which is later considered in the control-theoretic component of the pilot model:

$$f = 1 + 10(\sigma_{vis}^2 + \sigma_{task}^2) \tag{3}$$

Now, typically a large civil aircraft is under manual control in the low to mid subsonic areas of the flight envelope; usually near an airport where the pilot tends to be fully involved in the control loop. It is also during this time that major out-the-window cues are utilised by the pilot. Therefore, the ability to model such cues is also necessary for investigating scenarios that take place during



(a) External perspective of runway geometry.

(b) Cockpit view geometry with runway.

Fig. 4. Geometric layout for human perception modelling with runway included (reproduced from Schmidt and Silk [96]).

the approach, flare and takeoff. One of the earliest attempts was made by Naish [82] where the apparent runway geometry was related to observer position and velocity using variables shown in Fig. 4.

This approach is useful for rapid/cheap desktop simulations. The role of flight simulation has dramatically changed since the days of Naish et al., both in terms of simulation environment quality and costs due to technical complexity. However, these relationships can be linearised or directly implemented in a non-linear simulation environment to simulate visual cues used for judging altitude, flight path angle and speed, as found by Schmidt et al. [96]. Their investigation of the cues obtained from a typical outside scene during landing showed that given a perfect internal model, the visual cues provided more information than motion cues. Furthermore, these can be included in the framework of certain control-theoretic pilot models for the analysis of handling qualities in the approach and landing flight phases.

1.2. Vestibular system

The vestibular system is mainly responsible for postural control and sensing body motion. It is physically housed within the inner ear and consists of the otoliths and the semicircular canals. Together these function in a similar manner to an inertial reference system. The otoliths provide a sense of tilt and specific force whilst the semicircular canals help perceive angular acceleration. Accurate estimation of their dynamic response is critical to modelling pilot perception; especially during instrument flying where the ambient visual mode has little influence. The understanding of vestibular dynamics has also played a crucial role in the development of motion based flight simulators. A detailed discussion of motion cues in flight simulation is given by Allerton [3].

Low amplitude perception of angular motion through the vestibular system is limited due to inherent thresholds that are a function of stimulus magnitude and duration. Angular accelerations lasting less than 10 seconds must satisfy Mulder's law, which states that the product of angular acceleration and its duration is approximately equal to 2.5°/s [89]. Therefore, the weaker the acceleration, the longer it takes for it to be perceived. Data regarding lower human sensory thresholds for prolonged angular velocities and accelerations are summarised in Table 1.

It is suggested that these thresholds will be slightly higher in flight due to the more stressful environment and the pilot's attention allocation [75]. However, studies by Heerspink et al. [34] have concluded that since a trained pilot has expectations arising from

Table 1
Typical lower vestibular system thresholds.

	Angular velocity (°/s)	Angular acceleration (°/s^2)
Roll axis	3.20	0.50
Pitch axis	2.60	0.50
Yaw axis	1.10	0.14

an internal aircraft model, the threshold would in fact be lower. Nevertheless, the threshold values remain a function of pilot workload, stress and his/her understanding of aircraft dynamics; all are difficult to quantify. Therefore, accurate modelling of dynamic variations in these thresholds is very difficult.

The system relies on the relative motion of a fluidic substance and sensory nerves for detecting head or whole body angular acceleration. Nerves within the canal walls are excited by the movement of this fluid within the semicircular canals [89]. However, reliance on such relative motion, has inherent disadvantages as illustrated in the following example.

Consider a pilot rolling the aircraft to the left. A signal reflecting the roll rate is generated by the semicircular canals after an initial time constant of 3–5 ms. During prolonged angular rotation the perceived roll rate progressively becomes less than the actual angular velocity until a point is reached when no signal is generated by the semicircular canals. Upon recovery, the apparent sensation of rotation becomes directionally opposite and continues to persist for a while after the actual rotation has stopped in what is known as a post-turn illusion. Responding to this illusion might cause the pilot to enter a 'graveyard spiral' where the pilot enters into a sub-threshold descending turn under a false perception of steady level flight [108]. The increased g-loading then gives rise to a false sensation of pitch and the situation may be further exacerbated by attempts to recover by first pitching upwards; this would only tighten the turn, increase the g-load and rate of descent.

The otoliths' primary role in spatial orientation is to sense the vertical, which under ideal conditions can be estimated within a threshold of around 2°. However, they are also sensitive to linear accelerations (with a lower threshold of 0.1g) and function in a similar way to mechanical accelerometers. They cannot differentiate between gravity and other linear accelerations and the perceived acceleration is therefore, not relative to the true vertical but relative to the GIF vector; also referred to as the apparent vertical. This also means that there is no difference in the way humans sense tilt and linear acceleration. Assuming no visual cues, the human sensory suite is incapable of differentiating between

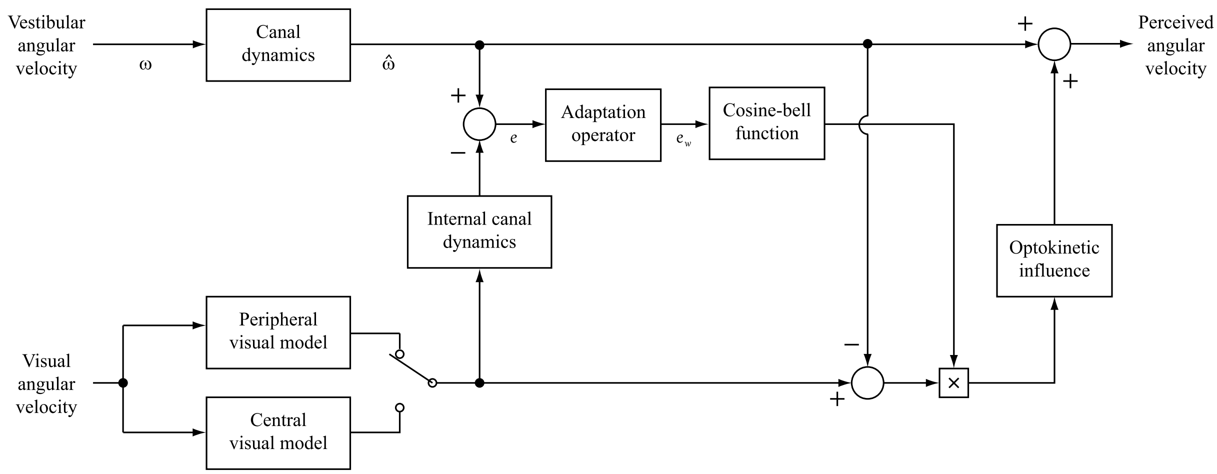


Fig. 5. Rotational perception model.

the two. This ambiguity is the source of numerous SDs, often applied in full-motion flight simulators to induce a sense of self-motion. The means by which the brain resolves this area of conflict has been a subject of much debate but no firm theory has been proposed as yet. More recent attempts at modelling the vestibular system emanate from the field of flight simulator design and development, such as Hosman's descriptive pilot model formulation discussed later in Section 3. The significance of this inability to distinguish between the GIF vector and the resultant force vector is highlighted in two of the most common SDs related to the vestibular system which are described below.

The first SD may be encountered when turning an aircraft at a positive load factor. Once steady state is achieved in a coordinated bank turn, the resultant force due to gravity and centripetal force is aligned with the aircraft vertical, giving a sensation of wings level flight. Similarly in a flat turn, the resultant force not being aligned with the aircraft vertical gives an illusion of bank in the opposite direction.

The second SD is the false sensation of pitching during acceleration and deceleration. During an acceleration, the resultant force pushes the pilot backwards into the seat, giving a pitch up sensation. During a deceleration the opposite occurs and the pilot perceives a pitch down sensation. It has been found that a 0.1g acceleration leads to the resultant force vector being rotated by approximately 6°. This type of SD was reported in 64% of night takeoff mishaps in Australian general aviation [108].

1.3. Tactile and proprioceptive systems

Tactile and proprioceptive senses are believed to be the first to develop in infants because they are required for determining the GIF vector and the development of 'anti-gravity' muscles necessary for walking. Skilled movements can be accomplished when this sense is combined with the remaining sensory systems.

Proprioception or kinesthesis, are the terms used when referring to the sensory modality that take advantage of sensors within the muscles (such as muscle spindles), which are used to determine body position, spatial limb movements and forces required for moving and maintaining joint positions against resistive loads. In aviation the role of proprioceptive and tactile sensors is to provide feedback of aircraft motion through forces or displacements felt via the inceptors. Modern inceptors are designed to engage with this sense through pressure receptors within the skin. Present all over the human body, these receptors are primarily responsible for the *seat-of-the-pants* sensation. Many early aviators wrongly believed that aircraft orientation may be deduced from this sensation. It is very important for a pilot to understand that this sense has evolved to provide relative body part motion and not a sense of orientation in space.

The modelling of this system is complicated by the number of physical stimuli to which it responds. Factors such as linear and angular velocity, muscle tension and orientation relative to the GIF vector, all simultaneously affect the sense's output to the CNS. The variables sensed by this mode are also sensed by other sensory modalities. Usually they are not in conflict but when a conflict does arise it is believed that the CNS uses the combination of sensory information to develop a proprioceptive sense. Therefore, proprioception cannot be seen as a unitary sense such as vision, but has to be considered as a sense gained by combining the outputs of various other sensory organs.

The structural pilot model proposed by Hess includes a transfer function representation of the proprioceptive sense that is active prior to the triggering of an aircraft–pilot-coupling (APC) event [40]. The model is discussed in detail in Section 3.

1.4. Inter-sensory dynamics

Current scientific understanding of human cognition in the context of multi-sensory stimuli is still in the early stages of development. Results presented by leading neuroscientists like Ramachandran [91] and Lotto [90], only cover a small number of observed sensory interactions that are not necessarily relevant here, such as certain forms of synaesthesia, and point towards a highly complex brain function.

Most pilot modelling approaches focus on either the resulting flight dynamics of the PVS or study pilot dynamics only through monitoring inceptor inputs. Multi-sensory perception is either modelled simply through a linear summation of cues [46,75] or a weighted sum with a seemingly arbitrary selection of weightings (like that proposed by Hess [38,39]). In the majority of cases, flight dynamics under the effects of SD are either left to qualitative human factors research or flight simulator based trials. The model proposed by Telban and Cardullo [103] allow SD effects to be incorporated within the greater pilot modelling framework shown in Fig. 1. The more complex model is a nonlinear combination of the visual and vestibular senses that is capable of capturing SDs such as vection. It allows the investigation of interactions between visual and vestibular cues, whilst ensuring the sensory model remains decoupled from the control-theoretic component. It also uses Hosman's approach to model the visual, otolith and semicircular canal dynamics and so remains relatively simple.

The model is parameterised to match latencies observed in medical experiments conducted in the 1970s by Berthoz et al. [15] and Goldberg et al. [23]. Fig. 5 presents the model structure for the

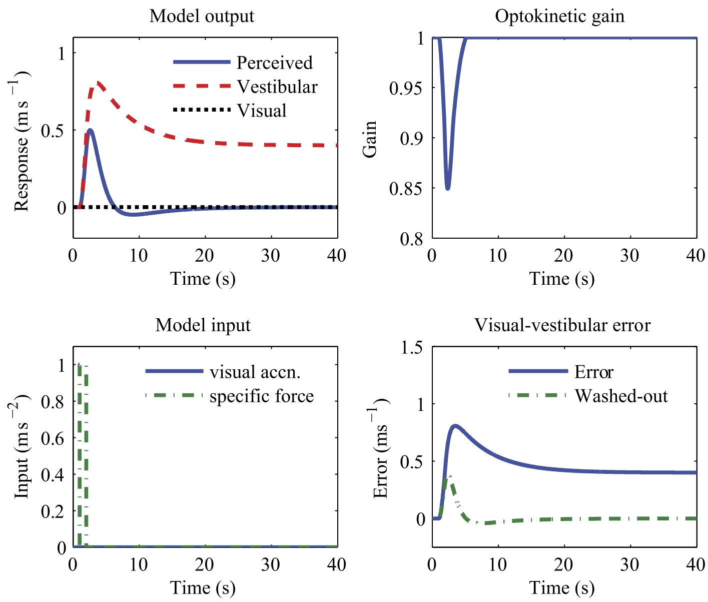


Fig. 6. Translational model response to vestibular only input of 1 ms^{-2} pulse.

perception of rotational motion. It has been modified to allow the treatment of cues in both the peripheral and central visual fields.

The rotational perception model provides a means of calculating a single perceived angular velocity given the actual angular velocity input to the visual and vestibular senses; where the latter is represented by the semicircular canal dynamics. Similarly, the translational perception model provides a means of obtaining the perceived velocity given the actual specific force (GIF per unit mass) and acceleration. Vestibular dynamics are represented here by the otolith organs that respond to specific force whilst the visual dynamics process velocity information (that can be presented here in the form of integrated acceleration).

Peripheral and central visual dynamics are modelled as time delays; 90 ms and 150 ms for peripheral and central vision respectively [46]. The user may define variables that occupy the pilot's peripheral or central vision through a switch. This allows modelling of scenarios involving multi-axis tasks, where a pilot observes roll rate in the peripheral vision simultaneously with pitch rate in the central vision.

Various psychophysical experiments [46,104] have found that visually obtained perception of self-motion induces an artificial vestibular response, and to a limited degree the vice versa is also true. The primary feature of Telban and Cardullo's model is its ability to capture such influenced estimates of self-motion and thus, simulate SD. The optokinetic influence components constitute a nonlinear gain and a first order low pass filter with a time constant of 1.59 seconds. The gain effectively captures the weightings given to vestibular and visual perceptions. It is computed by a modified cosine-bell function that relates it to the difference between the visual and vestibular output. The filter then models the gradual build-up of perceived self-motion. The overall perceived motion is the sum of the vestibular estimate and the optokinetic influence output. The secondary feature is the use of internal models of the semicircular canals and otoliths which, implicitly assumes that the CNS compares visual stimuli against its estimate of vestibular response.

The vestibular model from Fernandez et al. [23] and the otolith model suggested by Telban et al. [104] are almost identical to those developed by Hosman [46]. The otolith organs are responsive to specific force (f) defined as follows:

$$f = \hat{g} - a_h \tag{4}$$

where $\hat{g}$ is the local gravitational force vector and a_h is the acceleration of the head with respect to a body-fixed reference frame. For simplicity, it can be assumed that the pilot's head remains aligned with the aircraft's body axes. Transfer function relating sensed specific force ($\hat{f}$) to actual specific force is as follows:

$$\frac{\hat{f}(s)}{f(s)} = \frac{0.4(13.2s + 1)}{(5.33s + 1)(0.66s + 1)} \tag{5}$$

It has been shown that the following transfer function adequately relates perceived angular rotation rates ($\hat{\omega}$) to actual rotation rates (ω) [23]:

$$\frac{\hat{\omega}(s)}{\omega(s)} = \frac{456s^2}{(5.7s + 1)(80s + 1)} \tag{6}$$

and thus provides an adequate representation of vestibular canal dynamics.

The adaptation operator determines the duration for which conflict between the visual and vestibular cues is allowed. It relates the inter-cue error to the washed-out error through the following transfer function:

$$\frac{e_W(s)}{|e(s)|} = \frac{\tau_W s}{\tau_W s + 1} \tag{7}$$

The time constant, τ_W for the adaptation operator has been found to be eight and one seconds for rotational and translational perception respectively.

Dynamic response of the two perception models is shown in Figs. 6 and 7. These simulation results demonstrate the model's capability to capture the fact that whilst vestibular senses have transient characteristics, induced motion through the visual channel still dominates human perception of motion.

Fig. 6 presents a more interesting scenario regarding the modelling of translational perception. Only the vestibular sense has been given the pulse input here, whilst the visual channel has been kept blind. The resulting perceived motion consists of an initial transient peak and a steady state velocity of zero. The transient is due to the vestibular output, but it is rapidly nullified by the optokinetic influence. The larger error leads to a greater change in optokinetic influence gain resulting in the cancellation effect.

Fig. 7 presents the response of the rotational perception model to a visual and vestibular step input of 1°/s. The response shows

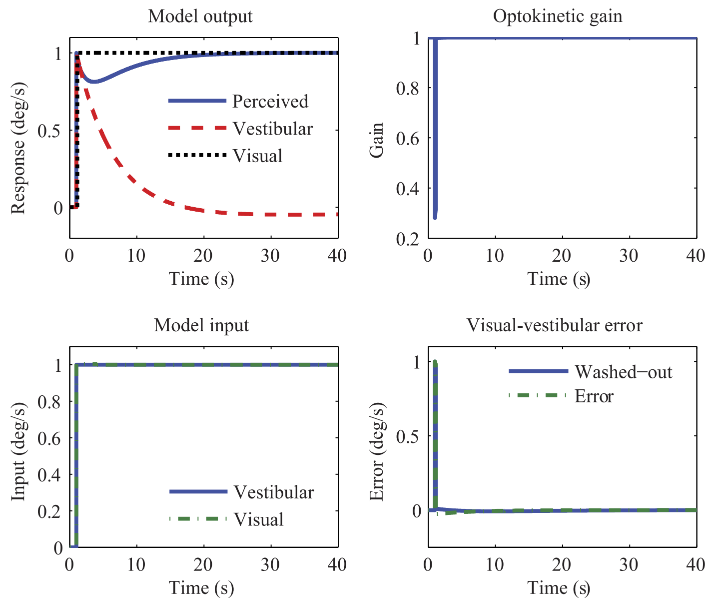


Fig. 7. Rotational model response to vestibular and visual step input.

a sharp and accurate visual response and a decaying vestibular response. Since both senses are provided with the same information, the steady state angular velocity is accurately captured.

2. Biodynamic modelling

The excitation of aeroelastic modes often produces periodic motion in the cockpit. For aircraft with more rigid airframes this tends to be characterised by high frequency vibrations that a pilot may associate immediately with structural dynamics. However, flexible aircraft are prone to interactions between low frequency aeroelastic modes, pilot's body motion and neuromuscular dynamics. One such interaction is called *biodynamic feedthrough* where vehicle accelerations are involuntarily fed back via the pilot's body through the inceptor. In some extreme cases, it may lead to aircraft instability or excessive airframe loadings [93]. The only adequate course of action is to either ease the grip on the inceptor or completely release it. The latter being the definitive solution to any unwanted APC scenario. Modelling this effect requires representations of the human body and neuromuscular system. Fig. 8 is a diagram from Serafini et al. [98] clearly showing the overlaps in frequency ranges between biodynamics and other aircraft dynamics. The diagram was presented in the context of rotorcraft but remains relevant and highlights the necessity to consider biomechanics during the FCS design process.

Within the aerospace community, it is well known that manual control behaviour is significantly affected by vertical accelerations above a root-mean-square value of 0.05g in the frequency region between 2 Hz and 16 Hz. The highest levels of degradation are expected to be around the body's resonant mode that occurs between 4 Hz and 8 Hz [12].

2.1. Modelling of biomechanics

Biodynamic models aim to represent the effects of human body dynamics on the pilot's desired control inputs within an accelerating (or vibrational) environment. Such a model can be implemented within a PVS as shown earlier in Fig. 1. These models can be categorised into three types: continuum, discrete and lumped-parameter models [53,69]. Each approach differs in the way the spine is modelled.

Continuum models treat the spine as a single flexible beam with properties tuned via comparison with experimental data. Griffin et al. [53,73] have done considerable work in this area and have shown that finite element based models can accurately capture seven of the eight modes of motion associated with the spine's response to vertical accelerations. The approach adopted by Wood et al. [114], which used beam theory to model arm dynamics also comes under this category.

Discrete models on the other hand, model the spine with a series of rigid bodies interconnected via springs and dampers. The response of such a multibody system may be found by determining the differential equations governing its motion. Both continuum and discrete modelling approaches tend to be descriptive and their complexity is dependant on the nature of the study. Discrete models attempt to reproduce the fact that the human body is a composite of a number of organs, each resonating at different frequencies. For example, the eyes and the abdomen resonate around 20 Hz and 5 Hz respectively [69,32]. Their descriptive nature can be seen in the examples shown in Fig. 9.

Lumped parameter models attempt to capture body dynamics by developing an equivalent mass–spring–damper system, as shown in Fig. 9. Although models of this type usually have only one or two degrees-of-freedom [17], they have been found to be quite useful in investigating response to vertical base excitation. However, their simplicity implies that the complete dynamics of a seated human cannot be captured. Work done by Sirouspour et al. [100] has found using this approach to model the lateral dynamics especially challenging.

A key parameter in biodynamic modelling is known as whole-body transmissibility. This is the ratio of vibration at a point of interest to base vibration as a function of frequency. The transmissibility of vertical base vibrations to fore-and-aft motion of the upper body is also of particular interest here. Examples of experimental transmissibility data from Kitazaki [53,54] and Matsumoto [72,73] are presented in Figs. 10 and 11. A model aimed at the study of biodynamic feedthrough should fit the data reasonably well and capture the low frequency peaks.

In the late 1970s, AMRL at Wright-Patterson Air Force Base conducted a series of investigations to understand the effect of vibrational environments on pilot biodynamic response and manual control performance [2,60]. Unlike the modelling and simulation based European work in this area, the American effort was

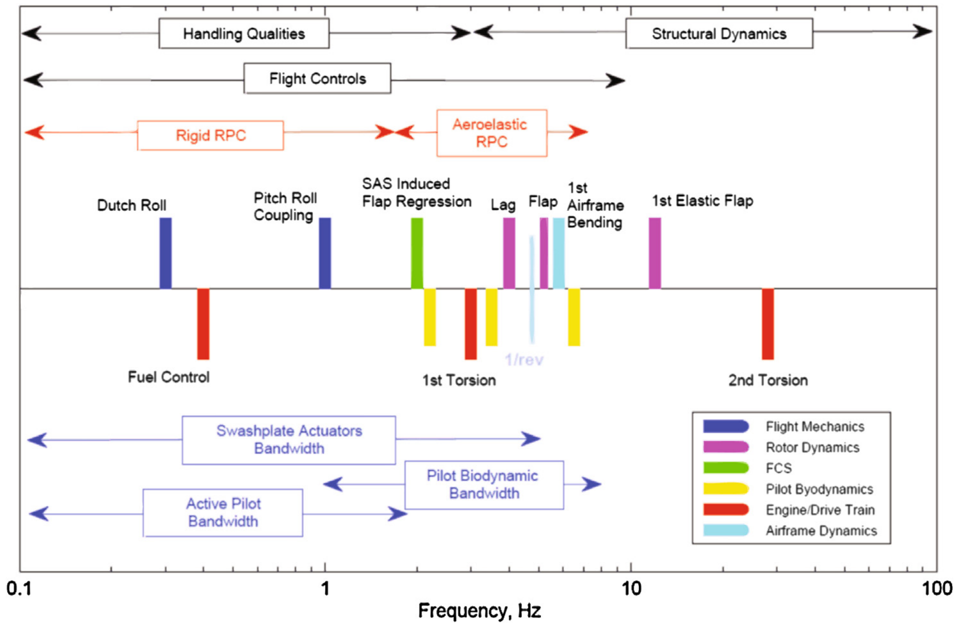


Fig. 8. Frequency ranges of pilot and aircraft dynamics (reproduced from Serafini et al. [98]).

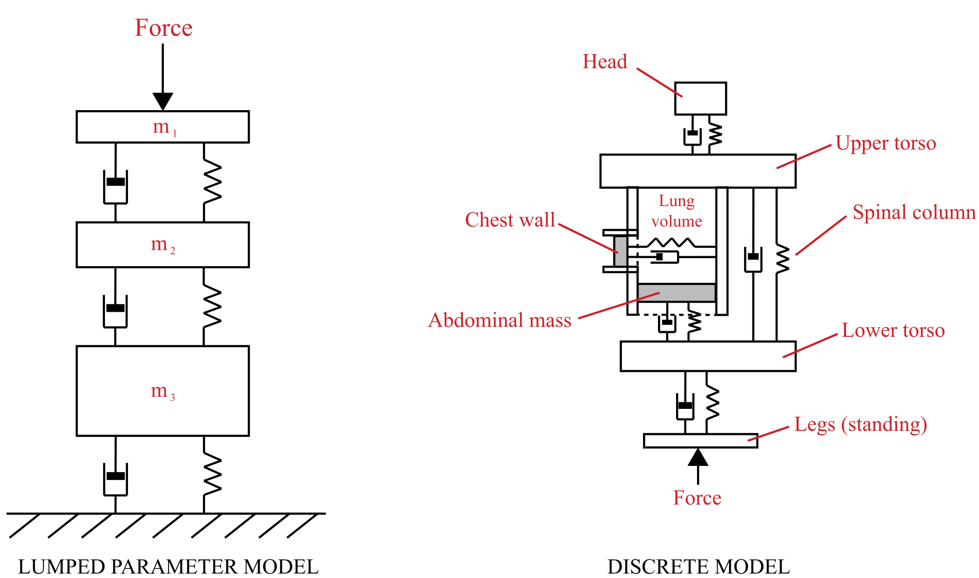


Fig. 9. Examples of lumped parameter and discrete modelling approaches.

heavily experimental and relied on human subjects placed on a large amplitude multi-degree of freedom hydraulic vibration table. Describing function data was then obtained for shoulder and elbow responses to rotational and translational vibrations in different axes. The vibration frequency range explored was 12 rad/s to 60 rad/s. It was found that vibrations causing front-back body motion, that is the motion in the longitudinal and pitching senses, produced the greatest amount of stick feedthrough. Vibrations in the vertical, roll and yaw senses had much smaller effects. The research also highlighted the roll of the inceptor dynamics in biodynamic feedthrough. Stiff sticks were found to be more affected by the vibrational environment when compared to spring sticks that provide limited proprioceptive feedback [60]. However, it should be noted that the experiments used centre sticks without any elbow rests. The AMRL effort also highlighted that the upper end of manual control frequency range cannot be ignored and aeroelastic modes at those frequencies may significantly affect aircraft handling qualities.

Höhne and Koehler have highlighted the complexities in modelling the upper body as a multibody system whilst demonstrating techniques on how to model such systems. However, just like any proposed model, a biodynamic model requires validation to prove its accuracy. Guidelines and a detailed discussion concerning the validation of biodynamic models are provided by Griffin, who argues that a quality check may be conducted by considering the following features of a model: assertions, evidence, assumptions, accuracy and appropriateness [30]. Table 2 summarises Griffin's checklists.

2.2. Biodynamics in handling qualities

Höhne [43] and Koehler [57] have investigated simplified biomechanical pilot models to study roll axis APC (also known as *roll ratcheting*) experienced during the General Dynamics F-16XL test program. As shown in Fig. 12(a) Koehler's approach has the hip, torso and arm with single degrees of freedom and uses

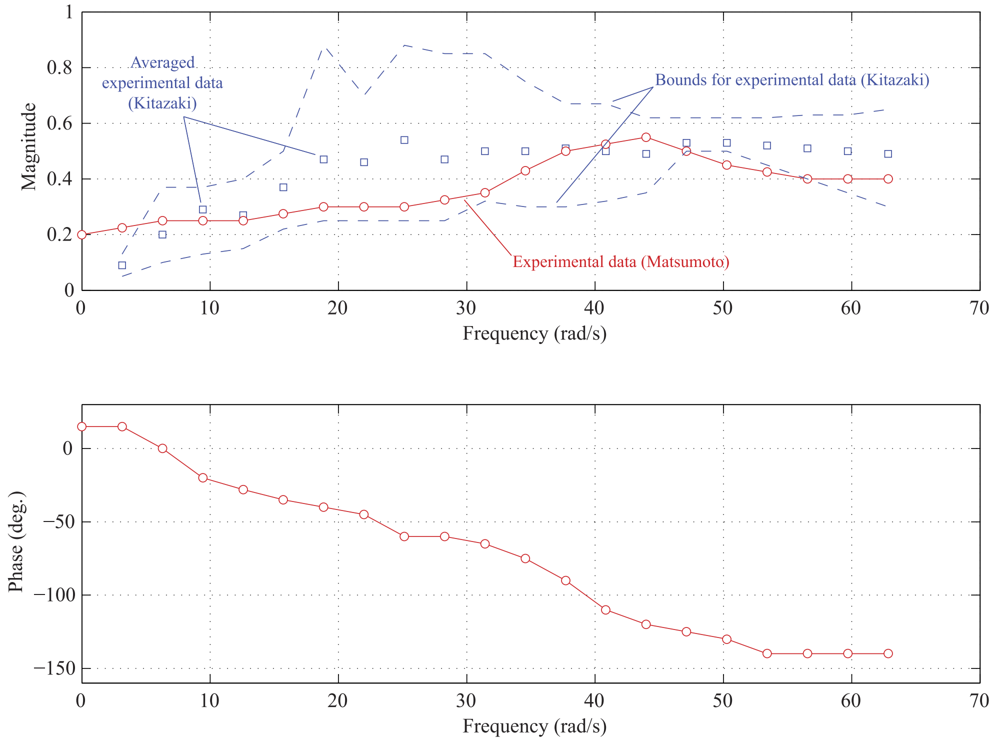


Fig. 10. Comparison with experimental data: horizontal shoulder acceleration due to vertical base acceleration (data from Kitazaki and Griffin [53] and Matsumoto and Griffin [73]).

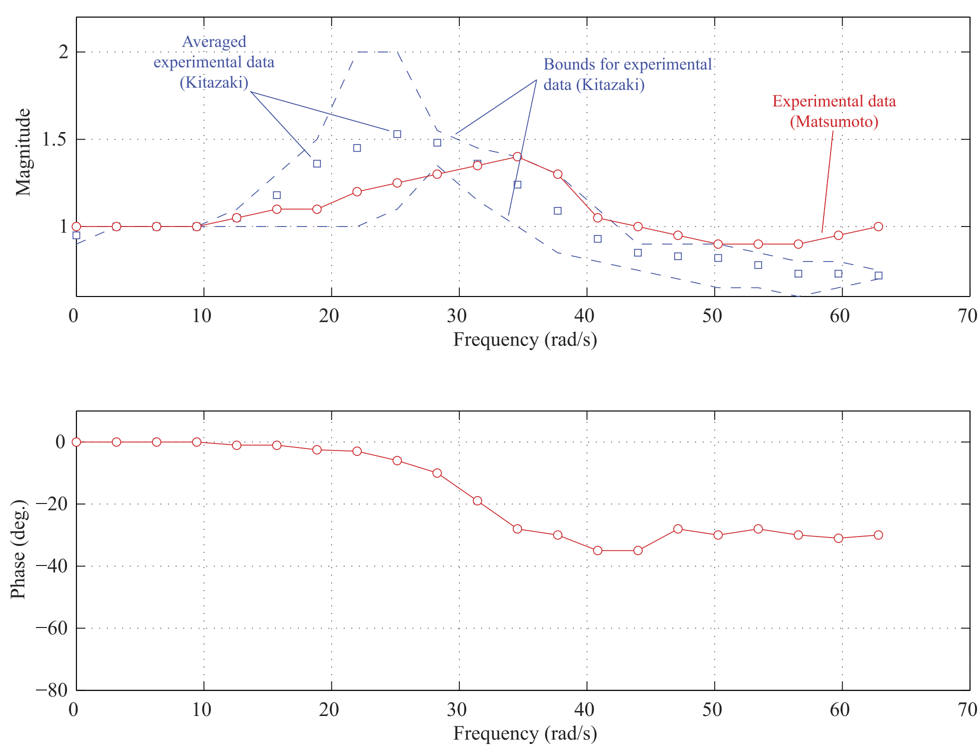
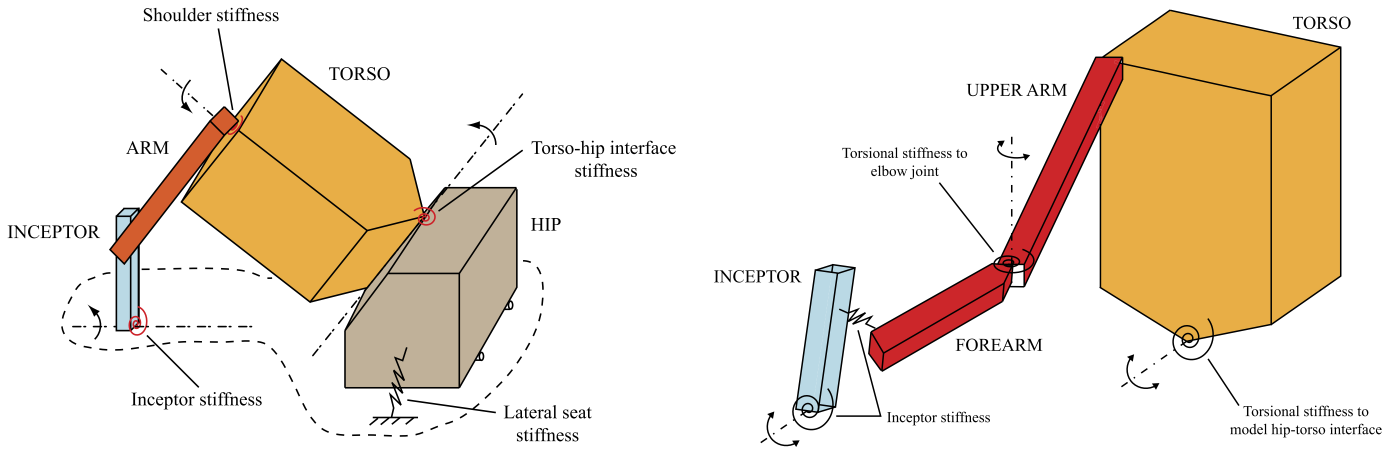


Fig. 11. Comparison with experimental data: vertical shoulder acceleration due to vertical base acceleration (data from Kitazaki and Griffin [53] and Matsumoto and Griffin [73]).

spring–damper connections to connect the multibody system together and to the aircraft. The arm–torso and hip–torso joints were rotatory joints because the studies were mainly concerned with roll axis dynamics. The model inputs were the pilot's intended control moment and accelerations at the pilot's position. Although the model was successful in reproducing the roll ratchet incident it had various shortcomings. The most significant were the unrealistic torso inclination angle together with the joint stiffness and damping coefficients.

To address the shortcomings, Höhne [44,45] re-derived the equations of motion and conducted parameter identification on the Koehler model. Fig. 12(b) shows one of the four biomechanical



(a) Koehler's model.

(b) Höhne's improved model.

Fig. 12. Discrete models used by Koehler and Höhne for investigating roll ratchet.

Table 2
Griffin's list of requirements for the validation of biodynamic models.

Assertions:	Clear and adequate definition of input–output relationship.
Evidence:	Experimental data proving the input–output relationship.
Assumptions:	Definition of any assumptions made during model development. Definition of the conditions in which the model is applicable. Specification of the range of each dependent and independent variables. Accounting for inter-subject and intra-subject variability.
Accuracy:	Quantification of model output sensitivity to changes in model parameters. Specification of likely errors in model predictions.
Appropriateness:	Description of improvements over other models representing the same phenomena.

models that were found equally capable of predicting roll ratcheting behaviour. Since analytical derivation of equations of motion for such a multibody system can be very lengthy, Höhne used a software package called SIMPACK® (SImulation of Multibody system PACKage) to obtain system response to various forcing functions. Use of SIMPACK® and a revised optimisation problem statement for parameter identification helped address the shortcomings of the Koehler model.

Roll ratchet was also investigated by European Aeronautic Defence and Space (EADS) company within the Eurofighter program where it was found to prohibit tracking in aggressive tasks [31]. Here, the pilot was also assumed to be a passive and linear contributor and a lumped parameter model was used to model the arm. This was found to be valid only for large accelerations and the study concluded that the damping contribution from the pilot's muscles was a function of acceleration. For small accelerations the muscles provide significant damping to overcome the consequent effects. It was also suggested that further research be done to obtain an understanding of this relationship. However, the conclusion from this study is only partly correct. Muscular damping and stiffness are both also functions of the task and its urgency: that is whether the pilot is relaxed or not. During urgent tracking tasks, the body stiffens and the grip around the inceptor tightens. The opposite is true for non-urgent compensatory tasks. More in-depth investigations done by Venrooij et al. [111] have resulted in similar conclusions.

Sirouspour et al. [100] have developed robust control methods to avoid instabilities due to biodynamic feedthrough. However, a simple lumped parameter arm/joystick model was used for controller synthesis and the moving base used for the experiments could not generate sustained accelerations or transient accelerations greater than $+1.5g$ and $-2g$. Furthermore, only a single subject was tested with a force sensing joystick. Gillespie et al. [102, 27] have also contributed to this field and published results for feedthrough due to lateral accelerations. In the proposed model-based cancellation schemes, parametric fitting of transfer function equivalent models to experimental data was found to be challenging due to difficulties in matching phase characteristics. Moreover, large inter-subject variations of around 15 dB and 50° phase were found at the peak resonant mode.

In the light of such variations, a number of researchers have focused on accurate detection of biodynamic feedthrough using advanced signal processing methods. For example, work done at STI Inc. implements real-time wavelet-based PVS identification to identify roll ratcheting [106,9]. Earlier work done by Serafini et al. [98] in Italy and Raney et al. [92,93] at the National Aeronautics and Space Agency (NASA) rely on the identification of equivalent transfer functions for biodynamic modelling. These models were then used to develop mitigation schemes employing a mixture of passive and notch filters. In fact, the motivation behind work done at NASA is very relevant to this research; that is the biodynamic incidents experienced during the development of the high speed transport aircraft. These were observed during motion-based flight simulation trials in which pilots were asked to land from an offset starting point. Accelerations due to rigid body and aeroelastic modes were calculated via a model developed using Waszak's [112] approach. Biodynamic resonance occurred for two subjects following a gust encounter, which in turn excited low frequency fuselage bending modes. As the accelerations increased in magnitude, pilots tightened their grip on the side-stick and throttles to simply brace themselves, further amplifying the biodynamic coupling effect. Compensations on the attitude indicators and limited structural stiffening were found to have little impact when compared to side-stick modifications. However, the observed behaviour highlights the applicability of biodynamic models to investigate involuntary coupling arising due to pilot physiology.

The main drawback within existing guidelines such as the British Standards [8,51] and current research in biomechanics is the assumption of linearity. Work done by Mansfield and Griffin [70] is beginning to shed light on the nonlinear response of the human body; albeit from a medical perspective. Future work in aerospace engineering can and should take advantage of

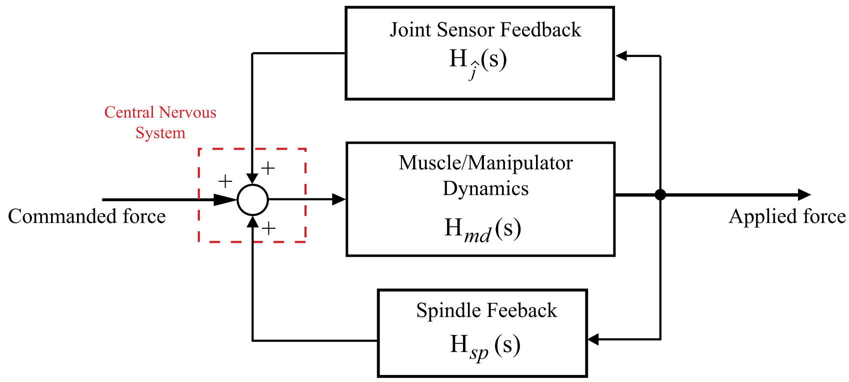


Fig. 13. Neuromuscular model proposed by McRuer and Magdaleno.

advancements made in the development of virtual humans (also called avatars) used for military training simulations [115]. Such work has started to consider the nonlinear relationships in whole body transmissibility.

2.3. Neuromuscular system

Since the 1950s, handling qualities and FCS engineers have appreciated that the basic dynamics and precision of manual control are critically limited by the properties of the neuromuscular system [77,78]. In most research, the neuromuscular dynamics are represented by second order transfer functions, quite similar to the treatment of aircraft control surface actuators.

The structure of the neuromuscular system is based upon the physiological operation of the human muscle. It consists of two types of muscles: extrafusal and intrafusal. Extrafusal muscles are responsible for the generation of force and make up most of the muscle. Intrafusal muscles on the other hand are scattered throughout the muscle in the form of spindles and provide the central nervous system with a degree of feedback information. They are able to detect what in physiological terms are known as 'phasic' stretch and 'tonic' length. The term phasic refers to the feedback of stimulus rate of change whilst the term tonic refers to feedback directly proportional to the stimulus. Muscle spindles are not the only source of information feedback. A significant role is also played by Golgi tendon organs that are analogous to muscle spindles and detect changes in tendon tension and the forces applied by a muscle [94].

The details of the human actuation system even for the simplest of motions are enormously complicated if individual components are considered. However, the actions of the overall system can be modelled by considering ensembles. The foundation for neuromuscular modelling in the context of pilot models was laid by McRuer and Magdaleno using this approach [68]. The form of the individual blocks in the system shown in Fig. 13 was developed to fit data obtained from experiments involving a number of human subjects and their use various inceptor types when executing manual control tasks. The following transfer function was found to fit data obtained from experiments designed to isolate extrafusal muscle dynamics:

$$H_{md}(s) = \frac{-K_{md}e^{-\tau_a s}}{(1+T_N s)(1+2\zeta_a/\omega_a s+s^2/\omega_a^2)} \tag{8}$$

The spindle feedback block could be modelled using the following transfer function, which is effectively a delayed equalisation ability:

$$H_{sp}(s) = \frac{K_{sp}(s+Z_{sp})e^{-\tau_{sp}s}}{s+P_{sp}} \tag{9}$$

The joint sensor feedback block is the ensemble that represents the Golgi tendon organ feedback as well as various other modes of feedback that are difficult to isolate. It has been modelled by a simple gain and delay:

$$H_{\hat{j}}(s) = K_{\hat{j}}e^{-\tau_{\hat{j}}s} \tag{10}$$

The experiments were done using both fixed force sensing and free moving deflections sensing sticks. Data fitting procedures then determined the values of the parameters in these equations. An interesting result was the differences obtained for the central processing delay: 66 ms and 82 ms for the force and deflection sensing inceptors respectively. However, McRuer and Magdaleno's study [68] only involved two subjects; making it impossible to comment on the statistical significance of the results.

Due to the simplifications, the model has lost a certain degree of realism and is incapable of replicating some important neuromuscular capabilities such as adaptability. Another loss of fidelity comes from the assumption of direct connection of muscle spindles to the central nervous system. In reality the information gathered via the spindles goes through a series of motor neurons before reaching the CNS. Whereas, the information gathered through the Golgi tendon organs arrives directly at the spinal chord through the spinal interneurons.

Considering the scope of typical flying and handling qualities studies such an approach which employs simple transfer functions has been found to be more than adequate. As a result neuromuscular models used in flight dynamic analysis have not changed significantly and researchers have mainly focused on addressing problems related biodynamic feedthrough. The fact that biodynamic feedthrough is dependent on the task type and neuromuscular admittance must be kept in mind [111].

3. Control-theoretic pilot models

McRuer proposed the underlying principle in manual control theory during the 1970s as a fundamental assumption in the formulation of the crossover model of the human operator. It stated that he/she adjusted control action such that the PVS open loop dynamics was driven towards the following transfer function: [76]

$$Y_P(s)Y_C(s) = \frac{\omega_c e^{-\tau_e s}}{s} \tag{11}$$

where Y_P, Y_C, ω_c and τ_e represent the pilot transfer function, vehicle transfer function, crossover frequency and effective time delay respectively. Eq. (11) is known the *crossover law* and effectively states that the PVS behaves as an integrator around the crossover region. The crossover frequency differentiates between the regions where the open loop input to output amplitude ratio exceeds unity and the regions where it is below unity. It is also dependant on

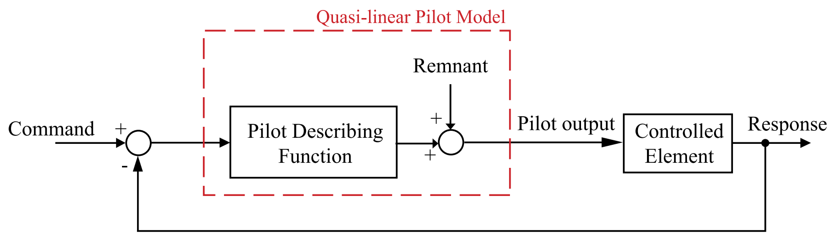


Fig. 14. Quasi-linear pilot model.

the characteristics of the controlled plant. The effective time delay is the time taken by the human body to perceive and initiate action.

Once the pilot model is placed within a closed loop system, the pilot perceived vehicle output effectively determines whether the model acts in a compensatory or pursuit mode. In compensatory mode the pilot has been found to follow error perception, whilst in a pursuit mode perception of a selected output state is dominant. The comparative study of both modes in the field of display design has found pilot performance to be superior in pursuit mode where a target is being tracked [75].

The main challenge in pilot modelling is determining the pilot model parameter values that are all effectively task dependant. To date certain manoeuvres thought to give the greatest insight into handling qualities (e.g. pitch tracking) have been investigated with pilot models. Such investigations may be split into three stages: (1) the development of a pilot model structure, (2) the simulation of human subjects in simulators, and (3) pilot model parameter estimation using the simulation data and parameter identification techniques. Only after these steps, demonstrated by Grant et al. [29] and Lone et al. [66,62], can handling qualities analysis be conducted. Investigation of different tasks requires some repetition of these stages making the whole process very time consuming and expensive.

Prior to discussing the details of control-theoretic models it is important to note that each model assumes, that given a particular task, the pilot adopts the control strategy defined by the structure of the pilot model. Although all models output inceptor deflections or forces and care must be taken when integrating the pilot model with the aircraft model, the definition of the reference input to simulate the correct task is far more critical. The reference must be designed based on the task and the mental process involved in the definition of an objective, i.e. the pilot's cognitive process. A review of cognitive modelling is beyond the scope of this paper and the reader is referred to methods such as the optical-tau applied extensively in rotorcraft handling qualities by Padfield et al. [86–88] and process modelling work by Ball et al. [11] and Kong and Mettler [58].

3.1. Quasi-linear models

Tustin first suggested the use of servomechanism theory for the analysis of manual control in 1944 [109]. He suggested the following transfer function representation for the human operator:

$$Y_P(s) = K_p e^{-\tau s}(1 + Bs) \tag{12}$$

where the operator parameters K_p, τ and B represent pilot gain, effective time delay and equalisation respectively. The term equalisation refers to the human controller's ability to adjust in order to provide good closed loop behaviour. This is characterised by the ability to provide [74]:

1. Some desired relationship between the command signal and plant output.
2. Adequate closed loop stability margins.
3. Good disturbance rejection and suppress other unwanted inputs.
4. Robustness against variations and uncertainties in plant characteristics.

McRuer later developed the crossover model that led to the development of various other quasi-linear models adhering to the general structure shown in Fig. 14. The pilot describing function is intended to represent linear behaviour whilst the remnant signal, usually a filtered Gaussian white noise, accounts for any nonlinear behaviour. The key assumption is that near the crossover frequency the pilot's linear behaviour dominates and so classical control techniques remain valid. The caveat therefore, is that the model is only accurate near the crossover frequency.

The appeal of such models is their simplicity and the ease with which they can be applied within a classical control framework. They have been found to be most useful for the analysis of closed loop compensatory behaviour. The following equation represents the quasi-linear model proposed by McRuer [75]:

$$Y_P(s) = K_p \frac{\tau_L s + 1}{\tau_I s + 1} \frac{e^{-\tau s}}{\tau_n s + 1} + \text{Remnant function} \tag{13}$$

Pilot equalisation characteristics are represented by τ_L and τ_I. Pilot's physical reaction time and neuromuscular delay are represented by τ and τ_n respectively. The pilot's gain is dependant on the task, environment and the pilot's adaptive ability.

The equalisation parameters are chosen such that the open loop system behaves as an integrator around the crossover frequency (i.e. a -20 dB slope around ω_c), enforcing the crossover law. The gain is then tuned such that the closed loop characteristics approximate those of a good feedback control system, which itself is defined by engineering judgement.

At this point it is only natural to discuss the pilot model explicit in the Neal–Smith handling qualities criteria [83]. Expressed as the following transfer function:

$$Y_P(s) = K_p \frac{\tau_L s + 1}{\tau_I s + 1} e^{-\tau s} \tag{14}$$

it only lacks the remnant and neuromuscular components. It takes a simple form, but the criteria quantify the aforementioned qualitative description of equalisation through ensuring the parameters are selected such that the following performance requirements on open-loop PVS are satisfied:

- Minimum bandwidth of 3.5 rad/s at a phase difference of 90°.
- Maximum low frequency droop of -3 dB.
- Minimum closed loop resonant peak.

A detailed discussion of the model used in the original frequency domain Neal–Smith criterion [84] and revised time domain Neal–Smith criterion [10,24] is not included here. This is because the de facto contributions of Neal and Smith have been the compilation of a handling qualities database and the successful linking

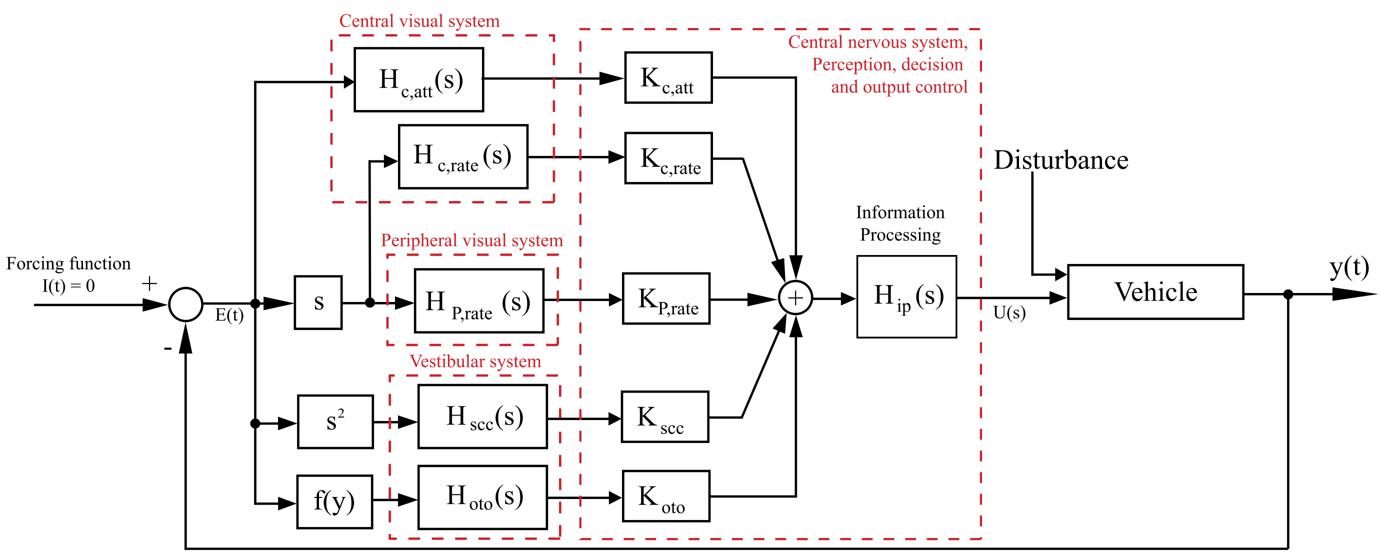


Fig. 15. Descriptive model of the human pilot as proposed by Hosman.

of pilot compensation to handling qualities levels; not pilot model development.

The determination of the remnant function is a complicated procedure as it attempts to represent the nonlinear component of pilot behaviour. Its primary source is the pilot's ability to learn and adapt, which is the cause of nonlinear and non-steady behaviour. The secondary contribution comes from such things as the experimental setup and experimentally injected noise that affect pilot response to other inputs. However, careful selection of the pilot model and task can help minimise remnant effects [75].

Although the form of such a model is based upon experimental results, the main disadvantage is that they are incapable of parameter variation with respect to changes in task. The model has no ability to initiate an APC event and so for their analysis sinusoidal forcing functions of varying frequencies are used to drive the system towards instability. The phase difference between the inputs and outputs is then used to predict any APC behaviour. These models also tend to be restricted to single-input–single-output analysis. Multiple-input–multiple-output modelling can be accomplished but it is not practised due to the increased complexity in specifying loop closures. Due to such disadvantages, although first proposed for predictive purposes, quasi-linear models nowadays are primarily used for matching and validating experimental data. Over the years, this concept has been adapted by researchers, such as Cardullo [16] and Heffley [35], for a number of tasks where the pilot model is only piecewise linear. Quasilinear models have also been extended to include certain nonlinear elements and used for studies investigating the effects of nonlinear flight control elements [66,116] and handling qualities of large aircrafts [64,61].

3.2. Hosman's descriptive model

In Europe, the development of FBW aircraft motivated a renewed research effort in man–machine-interaction [25,107]. Within the United Kingdom researchers like Gibson [26] and Padfield [85] studied pilot modelling as a means towards understanding flying and handling qualities; as opposed to specifically model manual control action. Although researchers around the world acknowledged the complexities, the research and engineering communities primary focus was the linear approach discussed previously. This was not only due to the ease associated with their application and interpretation, but also because these models were capable of capturing most of the observed behaviour. Therefore, it is no surprise that the state-of-the-art in pilot model identification, which is effectively represented by work done at TU Delft [110,14,120,119] and motivated by the desire to improve the quality of flight simulator cueing, is based on linear (or piecewise linear) models.

The descriptive model is one such model that was a result of Hosman's research during the 1990s aimed at understanding the influence of visual and vestibular stimulation on pilot's perception and control behaviour [46]. The outcomes have mainly been used to improve motion-based simulator realism via the optimisation of motion control algorithms. Various stimulus-response experiments were used to distinguish the contributions of individual senses towards pilot perception from the actual pilot response. The results were then applied to closed-loop control tasks assuming the human being to be a finite capacity single-channel information processor with multiple sensory inputs. This level of sensory distinction allowed for a descriptive model shown in Fig. 15 to be developed.

Hosman relied on earlier work done to model visual and vestibular systems and obtained transfer functions relating the error signal $E(t)$ to the outputs of sensory systems. Therefore, the overall model was based on physiological sub-models that related aircraft states to pilot perceived states. The visual perception of displacement was modelled by the following time delay:

$$H_{att}(s) = e^{-\tau s} \tag{15}$$

Delay associated with attitude perception is given by τ, which was found to be around 50 ms. Visual perception of velocity was modelled similarly:

$$H_{rate}(s) = e^{-(\tau+\tau_1)s} \tag{16}$$

Here, the total time delay is the sum of that associated with the detection of stimulus by the eyes (τ) and that associated with information processing during perception (τ_1). This is effectively the same time delay referred to by McRuer in the crossover model. However, an important part of Hosman's research was the distinction between contributions from central and peripheral visual perception. Hosman postulated that the peripheral sensory system is only able to sense rates and uses the same perception model of Eq. (16), but with a different value of τ_1 [46]. Experiments designed to relate peripheral perception and roll rate found τ_1 for peripheral visual field to be shorter ($\simeq$60 ms) than that for the central visual field ($\simeq$110 ms).

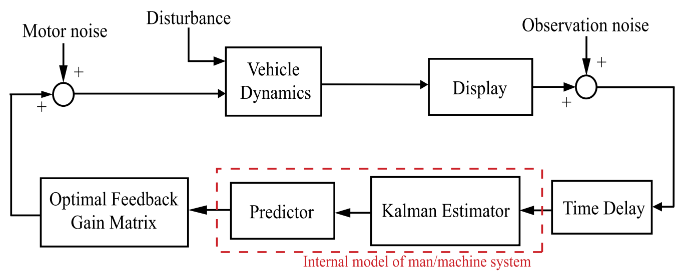


Fig. 16. The optimal control pilot model performing a compensatory task.

Hosman's work also confirmed that the otolith can be modelled as an accelerometer with over-damped mass–spring–damper characteristics. This may be described by a second order differential equation, represented by the following transfer function:

$$H_{oto}(s) = \frac{1+\tau_n s}{(1+\tau_a s)(1+\tau_b)s} \tag{17}$$

In Fig. 15, the function $f(y)$ preceding $H_{oto}(s)$ converts displacement input to a specific force output. For example, for bank angle, ϕ:

$$f(\phi) = \ddot{\phi} l - g\sin(\phi) \tag{18}$$

where l is the distance of the pilot's head from the rotational axis and g is gravitational acceleration.

Similar to the otolith, the semi-circular canals may be modelled as an over-damped torsion pendulum, represented by the following second order transfer function:

$$H_{scc}(s) = \frac{1+\tau_L s}{(1+\tau_c s)(1+\tau_d)s} \tag{19}$$

Since Hosman's model is based on human physiology the transfer function parameters in Eqs. (15), (16), (17) and (19) are independent of the simulation scenario. Only the gains in the CNS model are scenario dependent. Hosman used the following gain delay model for information processing:

$$H_{ip}(s) = K_{ip} e^{-\tau_{ip} s} \tag{20}$$

The tactile and proprioceptive senses were assumed to be implicitly modelled within the vestibular system.

The model has been modified and applied in numerous studies ranging from the design of optimal forcing functions for pilot model parameter identification [118], the study of crossover regression in pilot control behaviour [14,117], to the investigation of the pilot's use of visual stimuli [81]. These studies have not only shown the theoretical approach required for formulating pilot models but also developed the experimental design and method required to identify pilot model parameters. To date, the model has seen considerable application focussed towards improving flight simulation and investigating fundamental aspects of manual control behaviour. However, as demonstrated by Zaal et al. [120], its application towards the understanding aircraft handling qualities challenges posed by novel aircraft configurations can provide valuable guidance in the early aircraft design stage and flight control law design processes. Moreover, direct comparisons with other pilot models may help address the limitations and drawbacks associated with models that are not supported by such an extensive experimental database.

3.3. Optimal control models

Pilot modelling in the context of modern control was accomplished in the 1970s by Wierenga [113] and Kleinman et al. [56] who developed the optimal control (pilot) model (OCM). This model assumes that a well trained and motivated human operator behaves in an optimal manner whilst remaining subject to inherent psycho-physical limitations. These limitations are modelled as a time delay, motor noise and observation noise. Fig. 16 presents the conceptual block diagram of the OCM.

The Kalman filter models the ability of deducing system states from perceived information and the predictor represents the pilot's compensation for his/her inherent time delay. This filter, linear predictor and the optimal gain require a model of the aircraft being controlled and so effectively represent the pilot's understanding or his/her internal model of the aircraft dynamics. This should contain a description of aircraft behaviour expected by the pilot. Therefore, it would capture the control augmented aircraft dynamics linearised for a certain trim point and represent the pilot's psychological limitations [47]. The order of this model is a function of pilot training and experience and may include limited models of the actuation systems. This model is presented usually as a state-space system in practice, but the internal structure of this model can never be validated against the model contained within a pilot's mind. Validation may only be achieved with a black box approach where the model outputs are compared to that of real human control outputs. This problem is inherent to any attempt at modelling human control behaviour. The OCM approach therefore, allows an explicit definition of the pilot's internal model.

Assuming a linear state-space representation of the internal model, the pilot's task is defined through the appropriate choice of a cost function. The optimal pilot gains are found by solving the linear-quadratic-Gaussian (LQG) problem for the following quadratic cost function:

$$\mathcal{J}(\mathbf{u}) = E\left\{\lim_{\eta\to\infty}\frac{1}{\eta}\int_0^{\eta}\left(\mathbf{y}^T\mathbf{Q}\mathbf{y} + \mathbf{u}^T\mathbf{R}\mathbf{u} + \dot{\mathbf{u}}^T\mathbf{S}\dot{\mathbf{u}}\right)dt\right\} \tag{21}$$

where $\mathbf{Q}$ and $\mathbf{R}$ are the weightings on the outputs of the internal model and the pilot's control action respectively. The matrix $\mathbf{S}$ is a weighting on the pilot's control rate and represents a limitation on the pilot's bandwidth due to the neuromuscular system as well as the natural tendency against abrupt control actions. It cannot be over-stressed that the validity of the OCM is dependant on the accurate specification of the cost function and its weightings because these quantify the pilot's control objectives. Their selection represents the drawback of the OCM as it requires engineering judgement, experience and an iterative process. Otherwise, the algorithm certainly provides a stabilising and a robust controller representation; both qualities being characteristic of human beings in manual control.

The remnant component within the quasi-linear model is represented here by observation and motor noise. These are filtered Gaussian white noise which, in the case of observation noise may be tuned to represent levels of instrument observation accuracy and the distribution of attention levels towards different flight instruments. It has also been shown that this approach is capable of

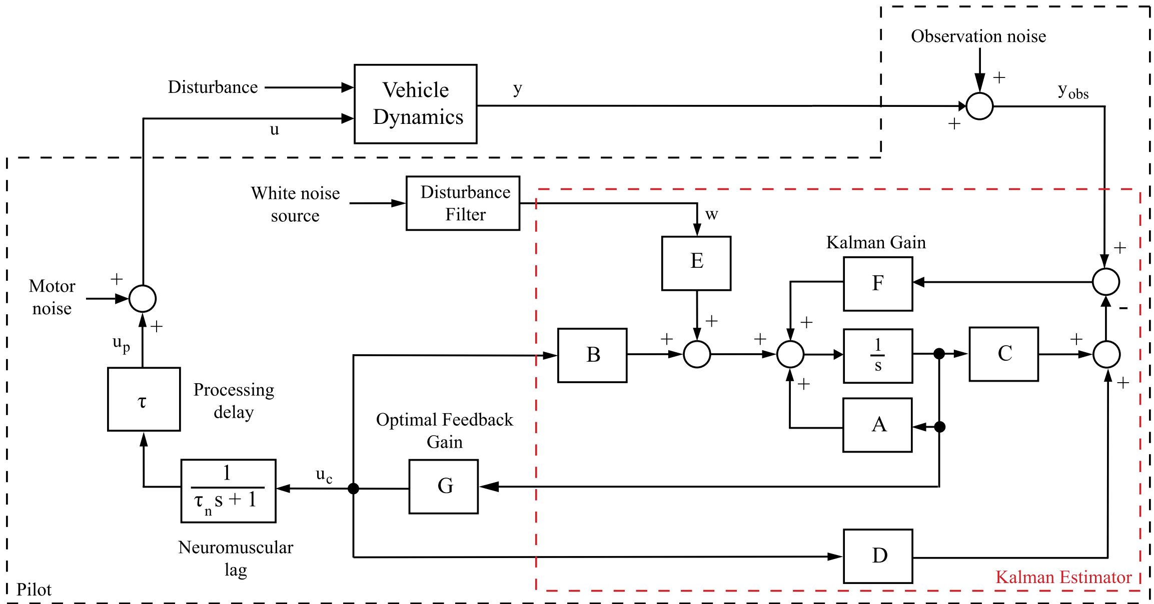


Fig. 17. Conceptual block diagram for the modified optimal control pilot model.

tracking more complex systems involving visual scanning between instruments and attention-sharing by assuming that observation signal to noise ratio varies directly with pilot attention towards a particular instrument [59]. The model is then completed by introducing components representing the remaining human physical limitations. These are the central processing time delay and neuromuscular dynamics. The latter requires explicit inclusion if the control rate component is ignored in the cost function of Eq. (21).

The accuracy in matching experimental data using the OCM has not been significantly superior in relation to the classical control models, indicating a degree of over-parameterisation [105]. This has lead to a number of comparative studies with classical models and also various attempts to simplify the OCM algorithm. The Modified OCM (MOCM) [19] and the fixed order OCM [4] are some results from such efforts. Both produce transfer function representations that retain the most important features for frequency domain analysis and comparison. Such studies have acted as bridges between the classical frequency domain and modern time domain approaches to the same problem. However, the complications in the simplification process far outweigh the advantages and the degree of simplification makes such models unsuitable for modern simulation purposes. Work done by Schmidt in the area of pilot-in-the-loop analysis with aeroelastic aircraft models has found the full order OCM most appropriate for capturing the full effects of aeroelasticity [95]. Over the years, OCM implementation has changed very little. The problem of over-parameterisation has been slowly addressed along with improvements to match experimental data [20].

The OCM has mainly been applied in the analysis of time delay affects on aircraft handling qualities, such as the identification of APC prone configurations [95]. Another area of research has been the investigation of display dynamics on the overall manual control loop and in doing so obtaining relationship between display types [59] and pilot ratings [21]. The third area where the OCM has been used is in the investigation of attention sharing, task interference and pilot workload. Kleinman and Baron have focused on techniques to incorporate pilot sampling behaviour based on information-theoretic ideas with the OCM [55]. This approach assumed that the pilot periodically sampled, either via the natural senses or cockpit instruments, a particular aircraft state and attempted to reconstruct it in the time-domain. Another area that has received considerable focus is the attempt to relate Cooper–Harper pilot opinion rating to the OCM cost function in single and multi-axis tasks [36,22]. Thompson and McRuer showed that the OCM cost function could be used to predict pilot opinion ratings reasonably well. The relationship was based upon the realisation that the control rate component of the cost function represents the physical and mental workload of the pilot [105].

On the other hand, $\mathcal{H}_\infty$ based pilot models such as that proposed by Goto et al. [28] have not been so popular. Goto et al. concentrate on the pilot compensation required when controlling vehicles that are statically or dynamically unstable. Comparison with experimental pilot describing functions show good agreement at high frequencies but there remains significant overestimation of pilot gains at frequencies below 20 rad/s [28].

The OCM concept has seen more recent application in the form of the MOCM algorithm. This model differs primarily in the placement of the processing time delay, as shown in Fig. 17, and its implementation as a Padé approximation. It has been applied firstly, in an attempt to model pilot control action in wake vortex encounters [97] and secondly, in the development of pilot-model-in-the-loop simulation frameworks [64] for assessment of airframe flight loads [62]. In both applications the output of the MOCM remains debatable due to the inherent limitations of the validation process. Flight simulator based validation leads to uncertainty with regards to the level of urgency displayed by the pilot. Moreover, simulation of any scenario that requires considering the aircraft in flight conditions near the boundaries of the simulators validated flight dynamic model can present the pilot with incorrect dynamics and in turn result in unrepresentative pilot behaviour. Ideally, appropriate validation can be done using data from reported incidents of actual wake vortex or gust/turbulence encounters. However, unavoidable limitations exist even with the availability of such data. The main limitation is simply the fact that these incidents are very rare and tend to be unique. Therefore, there is no repeatability and pilot behaviour in a single incident is not representative of the pilot population.

3.4. Nonlinear models

Around the same period in which McRuer was investigating the relationship between pilot dynamics and handling qualities, many

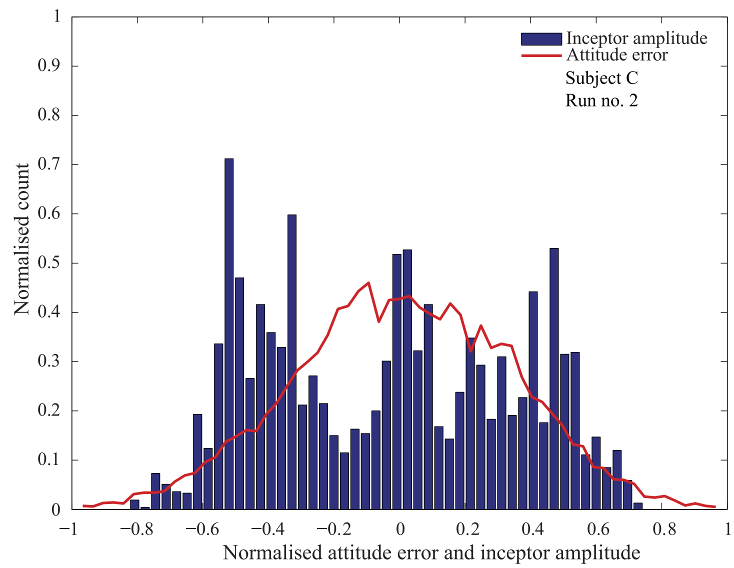


Fig. 18. Example bimodal inceptor and error amplitude distributions (reproduced from Lone [62]).

researchers focusing specifically on manual control learnt that when presented with a difficult task, human operators demonstrated highly nonlinear control behaviour. A feature of this was the bimodal amplitude distribution of inceptor deflections observed in response to tasks characterised by Gaussian forcing functions, as shown in Fig. 18. Examples of such early research are Costello [18], who suggested the 'surge' model in 1968, and Hess [37], who published a model-based explanation of this pulsive behaviour a decade later.

Hess' investigation was motivated by observations that (a) often human operators adopt control strategies resulting in discrete or pulsive inceptor motion, and (b) this behaviour was not an inherent feature of classical linear models. The study assumed that an operator, when faced with a situation where high order vehicle dynamics are combined with a demanding task, reverts to a low order controller. That is, he/she avoids the computational effort necessary for complex inputs and adopts a simple nonlinear strategy relying on very few parameters. Hess further extrapolated from this assumption that pulsive control is a result of an attempt "to reduce the computational burden associated with time integration of sensory inputs" [37]. Consequently candidate models must either be based on simple nonlinear control theory (such as minimum-time optimal control also known as bang-bang control) or require only the addition of basic nonlinear elements to the classical linear model structures.

Hess then applied the above assumption to an early version of his model that was linear but maintained its emphasis on proprioceptive feedback of inceptor deflection [37]. The outcome was the addition of the following logic just before the operator's compensation is executed by the neuromuscular system:

$$\begin{aligned} \frac{du'}{dt} &= 0 \quad \text{for } \left|\frac{du}{dt}\right| < \acute{\upsilon} \\ u' &= \bar{\upsilon} u \quad \text{for } \left|\frac{du}{dt}\right| \geqslant \acute{\upsilon} \end{aligned} \tag{22}$$

where u and u' are the input and output variables respectively. $\acute{\upsilon}$ and $\bar{\upsilon}$ are the only parameters required to successfully reproduce pulsive behaviour. Reliance on just these two parameters clearly avoids model over-parameterisation; in turn simplifying the tuning process when attempting to match experimental data. Yet it should be noted that these parameters require tuning and are not obtained analytically. The qualitative agreement with experimental data demonstrated by Hess [37] satisfactorily linked the assumptions associated with the model to the explanations given for pulsive behaviour in the frequency domain context established by McRuer. This nonlinear element can be seen as the origin of the various switches currently found in Hess' structural model shown in Fig. 19. This model attempts to describe pilot behaviour whilst keeping with the crossover law philosophy and at the same time borrowing some ideas from the OCM.

In the mid-1970s Smith suggested that from the standpoint of perceived aircraft handling qualities, the pilot's control of vehicle rate (for example pitch rate) in a closed loop system was of fundamental importance [101]. Smith based this theory on the belief that physiologically, a measure of pilot opinion rating is the rate at which nerve impulses arrive at a point within the CNS where they are processed. Hess later interpreted Smith's theory within the structural model by including proprioceptive feedback and showed that this feedback signal was proportional to the plant's rate output due to the pilot's control input [40]. The dependency on pilot control input also allowed a relationship with the Cooper–Harper handling quality ratings to be developed.

With regards to APC, the model assumes that after a triggering event, the pilot regresses to a tracking behaviour where error rate is controlled with no proprioceptive feedback. Therefore, switches S1 and S2 of the model shown in Fig. 19 are assumed to operate in unison. To simulate normal flight and flight during an APC, the model represents both the error and error rate tracking ability of the pilot. Again it should be noted that this model is incapable of generating a triggering event on its own. Switch S3 allows either displacement sensing or force sensing inceptors to be modelled, whilst switch S4 allows either rate or acceleration cues to be used for control.

Since only the neuromuscular and proprioceptive models need parameterisation the model remains quite simple. Hess used a second order representation of the neuromuscular block in his studies and the following representation of the proprioceptive sensory model (Y_{pf}) [121]:

$$Y_{pf}(s) = \begin{cases} K_{pf}(s+a) \\ K_{pf} \\ K_{pf}/(s+a) \end{cases} \quad \text{selected such that } Y_{pf}(s) \propto sY_C(s). \tag{23}$$

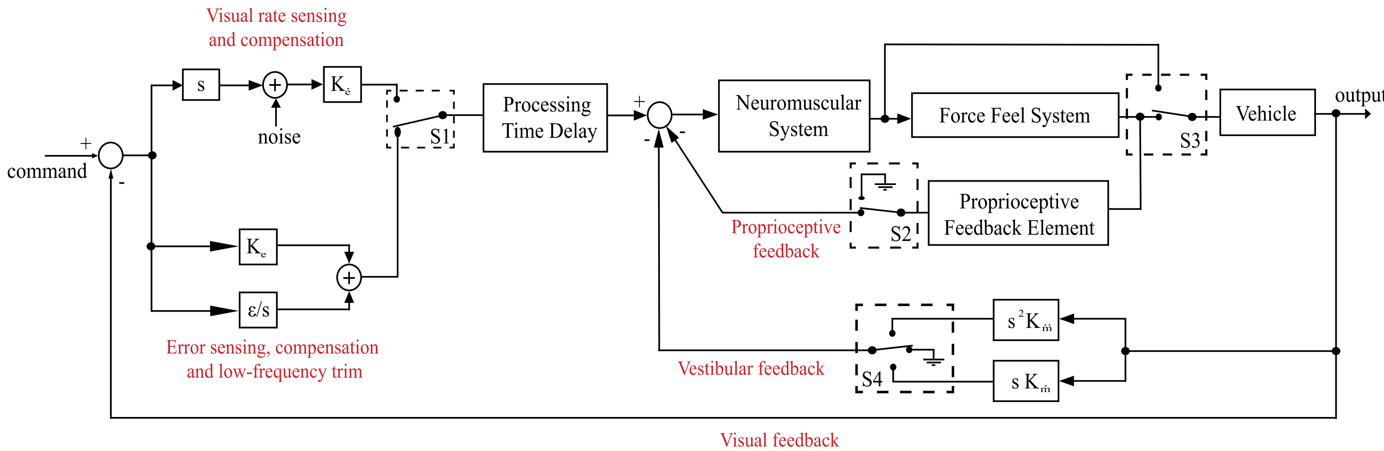


Fig. 19. Compensatory structural model of the human pilot as proposed by Hess.

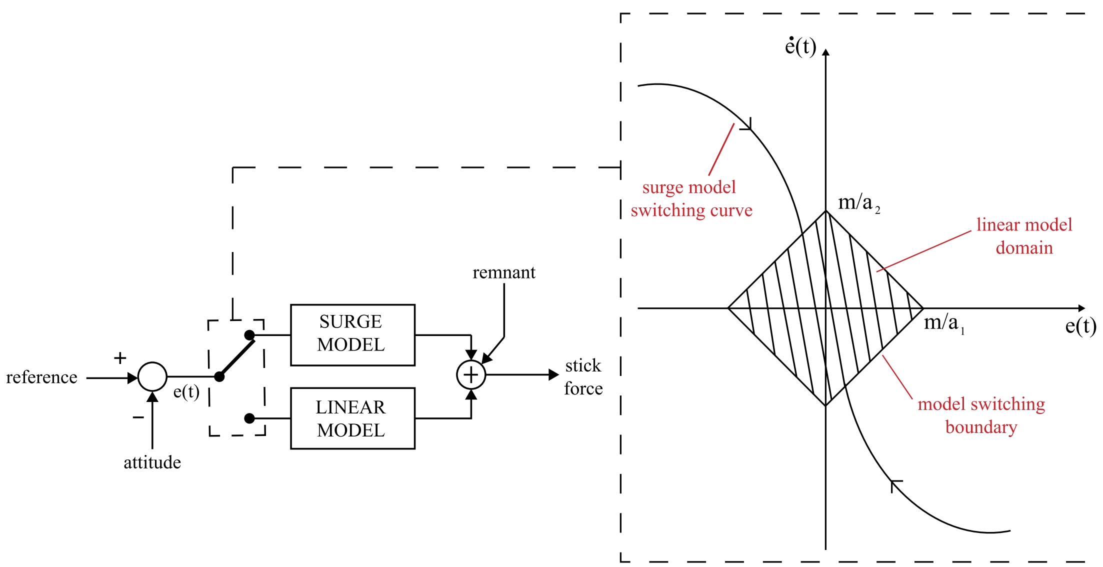


Fig. 20. Costello's dual mode pilot model with switching logic in the phase plane.

The equalisation in Eq. (23) represents the pilot's adaptability to changes in aircraft dynamics around the crossover frequency [121, 122]. It may be interpreted as the pilot's internal representation of vehicle dynamics which in the optimal control pilot model is represented by the Kalman estimator.

The main differences from other models discussed in this paper are the hypothesis that proprioceptive cues and the internal model allow the pilot to create compensatory characteristics that are appropriate for the controlled vehicle dynamics. This is quite the opposite to models that assume pilot operation based on visually sensed feedback. Hess further postulates that during an APC, the power in the proprioceptive feedback signal is the determining factor in the perception of aircraft handling qualities, but only when the crossover law is satisfied.

Overall, the approach adopted by Hess uses engineering judgement to propose a model structure that requires parameter tuning to match observed behaviour. Consequently, it lacks the mathematical basis for parameter selection and the ease with which pilot models based on modern control deal with multi-axis tasks. However, this approach (in experienced hands) has introduced the simplicity necessary for rapid analysis of the PVS.

Costello's 'surge' model was one of the early attempts at modelling the multi-modal behaviour exhibited when following discontinuous tasks. The model structure along with the switching boundary is presented in Fig. 20. The nonlinear component's reliance on three parameters (a_1, a_2 and m) lends its some similarity to Hess' model. It is a more natural adaptation of the classical approach as it retains the quasi-linear model as one of the two modes of operation. The switching boundary is defined such that the model outputs the following:

$$u = \begin{cases} M_c & \text{if } 0 \leqslant a_1|e(t)| + a_2|\dot{e}(t)| \leqslant m, \\ M_n & \text{if } a_1|e(t)| + a_2|\dot{e}(t)| > m, \end{cases} \tag{24}$$

where M_c and M_n are the outputs of the linear and nonlinear surge models respectively. The nonlinear response is effectively the same as that of a minimum-time optimal controller. Unfortunately, the concept loses its simplicity when it comes to calculating the switching time; that is the time when the output switches from a maximum to minimum inceptor deflection or vice versa. The benefit of dealing with this complexity is the removal of unrealistic transient oscillations where stick forces are generated using linear pilot models.

Although Costello's study involved twelve subjects, the experiments were conducted in laboratory conditions, which meant that certain behaviour exhibited during flight was not observed. Work done much later by Andrisani et al. [7] analysed flight test data and confirmed a number of Costello's observations but added that pilots were found to prefer particular stick amplitudes when inputting pulsive commands. Furthermore, rapid stick movements were observed before the vehicle even had a chance to respond. Andrisani's model did not aim to reproduce the observed stick movements and the model's nonlinear behaviour was only due to the quantisation of the pilot's command. It is not clear how the fixed quantisation step size was selected but variation in other pilot model parameters during pilot-model-in-the-loop simulation were found to provide insight into reasons behind the qualitative feedback from the pilots.

Andrisani's efforts, along with Hess, Innocenti et al. [48–50] and Anderson et al. [6,5], are the only significant examples utilising nonlinear elements or control theory to model manual control dynamics.

The recent paradigm shift in nonlinear operator modelling research can be attributed to the advent of soft computing techniques, like genetic algorithms and neural networks. These take advantage of the computing power available today. Hosman's and Hess' work were brought together by Cardullo who implemented Hosman's vestibular model and a haptic sensory model within Hess' structural model and proposed a time based parameter varying model. Neural networks were used to drive the structural model parameters towards agreement with the crossover model [16]. It was also proposed that the technique may be implemented in real time for purposes such as flight safety and pilot workload assessment.

3.5. Assumptions in handling qualities criteria and requirements

Modern handling quality criteria, especially those concerned with the frequency domain [1,80,79], tend to make implicit assumptions with regard to the characteristics of the 'limiting' pilot. Consequently they merit brief mention here. Criteria of this type set limits on the dynamic response of the 'open-loop' aircraft to ensure that acceptable handling characteristics exist when a human pilot is actively controlling the machine during some prescribed 'closed loop' task. A study of these limits may be used to infer the characteristics of a suitable pilot model.

ADS-33E suggests that the (phase-limited) bandwidth of a rotorcraft is the frequency when the open loop phase lag is 135°. This implies that pilots have a maximum inherent lag of 45°. Equally as (gain limited) bandwidth is set by the frequency at which the gain is 6 dB above that seen when phase lag is 180° there is an assumption that pilots are capable of 'doubling' their input as they approach the limits of controllability. Since phase rate requirements have also been proposed, there is evidence that pilots find systems will gradual phase roll-off easier to control. For example from ADS-33E it may be seen that when attempting to control a rotorcraft, in roll during operations at low speed, satisfactory handling qualities will exist provided the bank angle bandwidth is greater than 2.5 rad/s and the phase roll-off, at a phase lag of 180°, is less than about $-43°$/Hz. Interestingly this is identical to the limit proposed by Gibson in the pitch behaviour required to avoid PIO in fixed wing aircraft.

4. Conclusions

Mathematical representations of human control behaviour have played a critical part in manned aviation, especially in the definition of aircraft handling qualities requirements. New challenges posed by advances in aerospace technologies, such as fly-by-wire flight control, large flexible airframes and flight simulation, have led to increasingly complex mathematical representations of pilot behaviour. Along with the operational costs of flight tests and full-motion simulators, this has led to a revived interest in theoretical pilot modelling. A review of aspects thought to be necessary when modelling manual control dynamics in aircraft flight dynamic studies was presented in this paper. Literature covering sensory, biodynamic and control-theoretic modelling have been summarised and used to discuss the state-of-the-art used by the flight control and handling qualities engineers today. To date, such a review that brings together these areas and provides a holistic view of pilot modelling has not been presented. For brevity it has not covered aspects associated with decision making, such as human error modelling and information processing. Furthermore, pilot models based on soft computing methods and processes associated with manual control experiments and parameter identification have not been reviewed because of literature already available in the public domain [29,119].

In this paper, the review of human sensory modelling has included subjects such as spatial disorientation, out-the-window cue modelling and vestibular sensory modelling. Various approaches to biodynamic modelling have been reviewed and guidelines for validating such models have also been summarised. Classical crossover and modern optimal control based control-theoretic modelling have also been discussed with emphasis on models derived from the quasi-linear, structural, descriptive and optimal control pilot models.

Pilot models used by flight dynamicists lag considerably behind those developed for application in other scientific domains, especially those used in perception research [90] and neurology [91]. These models have been effective because of (a) the careful application to scenarios within which the associated assumptions remain valid, and (b) the relative simplicity of these models and corresponding methods of analysis. Recent high profile flight incidents involving adverse aircraft–pilot-coupling have led to a renewed focus on man–machine interaction and the effects of automation on pilot manual control. In the mean time, modelling challenges posed by pilot control behaviour during gust encounters and flight control system failures have highlighted the need for a paradigm shift that addresses key limitations of today's models. Techniques possibly drawn from robust control theory and methods used for uncertainty propagation, are needed to provide statistical insight into the effects of inter-pilot variations. More critically, methods to analyse flight incident data together with improvements in flight simulator fidelity are required to address the problem of validating pilot modelling approaches.

References

[1] ADS-33E-PRF, Aeronautical Design Standard performance specification: Handling qualities requirements for military rotorcraft, 2000.

[2] R. Allen, H. Jex, R. Magdaleno, Manual control performance and dynamic response during sinusoidal vibration, Tech. Rep. AMRL-TR-73-78, Aerospace Medical Research Laboratory, October 1973.

[3] D. Allerton, Principles of Flight Simulation, John Wiley & Sons Inc., 2009.

[4] M. Anderson, D. Doman, Fixed order optimal pilot models, in: AIAA Guidance, Navigation and Control Conference, July 1996, No. AIAA-96-3871.

[5] M. Anderson, J. Phillips, A variable strategy pilot model, in: AIAA Atmospheric Flight Mechanics Conference, AIAA, Denver, CO, August 2000, No. AIAA-2000-3983, pp. 195–204.

[6] M. Anderson, C. Clark, G. Dungan, Flight test maneuver design using a skill- and rule-based pilot model, in: IEEE International Conference on Systems, Man and Cybernetics, 1995. Intelligent Systems for the 21st Century, 1995.

[7] D. Andrisani, G. Ching-Fu, A nonlinear pilot model for hover, Journal of Guidance, Control, and Dynamics 8 (3) (May–June 1985) 332.

[8] Anonymous, Mechanical vibration and shock – Evaluation of human exposure to whole-body vibration, British Standard, International Organization for Standardization.

[9] E. Bachelder, D. Klyde, Wavelet-based analysis of roll ratchet using a flight test database, in: Atmospheric Flight Mechanics Conference, Austin, TX, 11–14 August 2003.

[10] R. Bailey, T. Bidlack, Unified pilot-induced oscillation theory, Volume IV: Time-domain Neal–Smith criterion, Tech. Rep., Wright Laboratory, Wright-Patterson Air Force Base, 1995.

[11] J.T. Ball, K.A. Gluck, M.A. Krusmark, S.M. Rodgers, Comparing three variants of a computational process model of basic aircraft maneuvering, in: Proceedings

of the 12th Conference on Behavior Representation in Modeling and Simulation, Institute for Simulation & Training, Orlando, FL, 2003, pp. 87–89.
[12] R. Banks, J. Brinkley, R. Allnutt, R. Harding, Fundamentals of Aerospace Medicine, Lippincott Williams and Wilkins, 2008.
[13] C. Bartlett, Air Crashes and Miracle Landings Sixty Narratives (How, When… and Most Importantly Why), OpenHatch Books, 2010.
[14] G. Beerens, H. Damveld, M. Mulder, M. van Paassen, An investigation into crossover regression and pilot parameter adjustment, in: AIAA Modeling and Simulation Technologies Conference and Exhibit, Honolulu, HI, 18–21 August 2008.
[15] A. Berthoz, B. Pavard, L. Young, Perception of linear horizontal self-motion induced by peripheral vision (linear-vection), Experimental Brain Research 23 (1975) 471–489.
[16] F. Cardullo, K. Zaychik, G. George, A conspectus on operator modeling: Past, present and future, in: AIAA Modeling and Simulation Conference and Exhibit, AIAA, Keystone, CO, August 2006, No. AIAA-2006-6625.
[17] T. Coe, J. Xing, R. Shenoi, D. Taunton, A simplified 3-D human body–seat interaction model and its applications to vibration isolation design of high-speed marine craft, Ocean Engineering 36 (9–10) (2009) 732–746.
[18] R. Costello, The surge model of the well-trained human operator in simple manual control, IEEE Transactions on Man–Machine Systems 9 (1968) 2–9.
[19] J. Davidson, D. Schmidt, Modified Optimal Control Pilot Model for Computer-Aided Design and Analysis, Technical Memorandum 4384, NASA, Langley Research Center, October 1992.
[20] D. Doman, Projection methods for order reduction of optimal human operator models, Ph.D. thesis, Virginia Polytechnic Institute and State University, 1998.
[21] D. Doman, Optimal control pilot modeling for resolving Cooper–Harper rating discrepancies, in: AIAA Atmospheric Flight Mechanics Conference and Exhibit, Portland, OR, August 9–11, 1999, No. AIAA-1999-4091, pp. 176–186.
[22] C. Edkins, The prediction of pilot opinion ratings using optimal and suboptimal pilot models, Ph.D. thesis, Air Force Institute of Technology, Wright-Patterson Air Force Base, OH, 1994, DTIC Report no. AD-278 679.
[23] C. Fernandez, J. Goldberg, Physiology of peripheral neurons innervating semicircular canals of the squirrel monkey II: Response to sinusoidal stimulation and dynamics of peripheral vestibular system, Journal of Neurophysiology 34 (1971) 661–675.
[24] L. Foringer, D. Leggett, An analysis of the time-domain Neal–Smith criterion, in: AIAA Atmospheric Flight Mechanics Conference and Exhibit, Boston, MA, August 10–12, 1998.
[25] O. Gerlach, Developments in mathematical models of human pilot behaviour, Aeronautical Journal (July 1977) 293–305.
[26] J. Gibson, The Definition, Understanding and Design of Aircraft Handling Qualities, Delft University Press, 1997.
[27] R. Gillespie, R.B. Gillespie, Model-based cancellation of biodynamic feedthrough using force-reflecting joystick, Journal of Dynamic Systems, Measurement, and Control 128 (2006) 94–103.
[28] N. Goto, K. Chatani, S. Fujita, H-infinity-model of the human pilot controlling unstable aircraft, in: IEEE International Conference on Systems, Man and Cybernetics, 1995, pp. 50–57.
[29] P. Grant, J. Schroeder, Modeling pilot control behavior for flight simulator design and assessment, in: AIAA Modeling and Simulation Technologies Conference, Toronto, ON, Canada, August 2–5, 2010.
[30] M. Griffin, The validation of biodynamic models, Clinical Biomechanics 16 (2001) 81–92.
[31] M. Hanel, Discussion of some typical handling qualities issues encountered by industry during aircraft development: roll ratchet & flight path display dynamics, Presentation to EADS Military Air Systems, November 2008.
[32] C. Harris, A. Piersol (Eds.), Harris' Shock and Vibration Handbook, 5th ed., McGraw–Hill, 2002.
[33] B. He, S. Gao, H. Yuan, J. Wolpaw, Brain–computer interface, in: Neural Engineering, Springer, 2013, pp. 87–151.
[34] H. Heerspink, W. Berkouwer, O. Stroosma, M. van Paassen, M. Mulder, J. Mulder, Evaluation of vestibular thresholds for motion detection in the SIMONA research simulator, in: AIAA Modelling and Simulation Technologies Conference and Exhibit, San Francisco, CA, 15–18 August 2005, No. AIAA 2005-6502.
[35] R. Heffley, Use of a task–pilot–vehicle (TPV) model as a tool for flight simulator math model development, in: AIAA Guidance, Navigation, and Control Conference, Toronto, ON, Canada, 2–5 August 2010.
[36] R. Hess, Prediction of pilot opinion ratings using an optimal pilot model, Human Factors 19 (October 1977) 459–475.
[37] R. Hess, A rationale for human operator pulsive control behavior, Journal of Guidance and Control 2 (1979) 221–227.
[38] R. Hess, Structural model of the adaptive human pilot, Journal of Guidance, Control, and Dynamics 3 (5) (September–October 1980) 416–423.
[39] R. Hess, Model for human use of motion cues in vehicular control, Journal of Guidance, Control, and Dynamics 13 (3) (May–June 1990) 476.
[40] R. Hess, A unified theory for aircraft handling qualities and adverse aircraft–pilot coupling, Tech. Rep. AIAA 97-0454, AIAA, Reno, NV, January 1997.
[41] R. Hess, Obtaining multi-loop pursuit-control pilot models from computer simulation, in: 45th AIAA Aerospace Sciences Meeting and Exhibit, AIAA, Reno, NV, 2007, No. AIAA-2007-247.
[42] R. Hess, Multi-axis pilot modeling: Models and methods for wake vortex encounter simulations, Presentation at Technical University of Berlin, 2010.
[43] G. Höhne, A biomechanical pilot model for prediction of roll ratcheting, in: AIAA Atmospheric Flight Mechanics Conference, 1999.
[44] G. Höhne, Computer aided development of biomechanical pilot models, Aerospace Science and Technology 4 (2000) 57–69.
[45] G. Höhne, Evaluation of the LATHOS database using a biomechanical pilot model, Tech. Rep., American Institute of Aeronautics and Astronautics, 2000.
[46] R. Hosman, Pilot's perception & control of aircraft motions, Delft University Press, 1996, No. 90-407-1384-7.
[47] M. Innocenti, The Optimal Control Pilot Model and Application, Advances in Flying Qualities (AGARD-LS-157), AGARD Lecture Series, vol. 157, North Atlantic Treaty Organisation, 1988.
[48] M. Innocenti, A. Balluchi, A. Balestrino, New results on human operator modelling during nonlinear behavior in the control loop, in: Proceedings of the American Control Conference, Albuquerque, NM, June 1997.
[49] M. Innocenti, A. Petretti, M. Vellutini, Human operator modelling during discontinuous performance, in: AIAA Atmospheric Flight Mechanics Conference and Exhibit, 1998, No. AIAA-98-4146, pp. 31–38.
[50] M. Innocenti, A. Balluchi, A. Balestrino, Modeling of nonlinear human operator in the control loop: Preliminary results, Journal of Guidance, Control, and Dynamics 4 (2000) 736–739.
[51] International Organization for Standardization, Railway applications – Ride comfort for passengers – Measurement and evaluation.
[52] M. Jump, L. Linghai, M. Jones, D. Yilmaz, State-of-the-art pilot model for RPC prediction report, ARISTOTEL – Aircraft and Rotorcraft Pilot Couplings – Tools and Techniques for Alleviation and Detection, European Community's Seventh Framework Programme (FP7/2007–2013), Tech. Rep. ACPO-GA-2010-266073, 2011.
[53] S. Kitazaki, M. Griffin, A modal analysis of whole-body vertical vibration, using a finite element model of the human body, Journal of Sound and Vibration 200 (1997) 83–103.
[54] S. Kitazaki, M. Griffin, Resonance behaviour of the seated human body and effects of posture, Journal of Biomechanics 31 (1998) 143–149.
[55] D. Kleinman, S. Baron, The human as an optimal controller and information processor, NASA Contractor Report CR-1151, NASA, September 1968.
[56] D. Kleinman, S. Baron, W. Levison, An optimal control model of human response, Part I: Theory and validation, Automatica 6 (1970) 357–369.
[57] R. Koehler, A unified approach for roll ratcheting analysis, Journal of Guidance, Control, and Dynamics 22 (1999) 718–720.
[58] Z. Kong, B. Mettler, Modeling human guidance behavior based on patterns in agent–environment interactions, IEEE Transactions on Human–Machine Systems 43 (2013) 371–384.
[59] W. Levison, Alternative treatments of attention-sharing within the optimal control model, in: IEEE International Conference on Systems, Man and Cybernetics, vol. 2, IEEE, Cambridge, MA, November 1989, pp. 744–749.
[60] W. Levison, C. Harrah, Biomechanical and performance response of man in six different directional axis vibration environments, Tech. Rep. AMRL-TR-77-71, Aerospace Medical Research Laboratory, 1977.
[61] Q. Liu, Pilot-induced-oscillation detection and mitigation, Master's thesis, Department of Aerospace Engineering, Cranfield University, 2013.
[62] M. Lone, Pilot modelling for airframe loads analysis, Ph.D. thesis, University of Cranfield, May 2013.
[63] M. Lone, A. Cooke, Review of pilot modelling techniques, in: 48th AIAA Aerospace Sciences Meeting Including the New Horizons Forum and Aerospace Exposition, Orlando, FL, 2010, No. AIAA-2010-297.
[64] M. Lone, A. Cooke, Pilot-model-in-the-loop simulation environment to study large aircraft dynamics, Proceedings of the Institution of Mechanical Engineers, Part G: Journal of Aerospace Engineering 227 (3) (March 2012) 555–568.
[65] M. Lone, C. Lai, A. Cooke, J. Whidborne, Application of pilot models to study trajectory based manoeuvres, in: AIAA Modelling Simulation Technologies Conference, 2012.
[66] M. Lone, N. Ruseno, A. Cooke, Towards understanding effects of nonlinear flight control system elements on inexperienced pilots, Aeronautical Journal 116 (1185) (2012).
[67] L. Lu, M. Jump, M. Jones, B. Dangvu, Report detailing novel pilot models developed for RPC prediction, ARISTOTEL – Aircraft and Rotorcraft Pilot Couplings – Tools and Techniques for Alleviation and Detection, European Community's Seventh Framework Programme (FP7/2007–2013), Tech. Rep. ACPO-GA-2010-266073, 2012.
[68] R. Magdaleno, D. McRuer, Experimental validation and analytical elaboration for models of the pilot's neuromuscular subsystem in tracking tasks, Tech. Rep. NASA CR 1757, National Aeronautics and Space Administrations, 1971.
[69] N. Mansfield, Human Response to Vibration, CRC Press, 2005.
[70] N. Mansfield, M. Griffin, Non-linearities in apparent mass and transmissibility during exposure to whole-body vertical vibration, Journal of Biomechanics 33 (2000) 933–941.
[71] H. Markram, The human brain project, Scientific American 306 (2012) 50–56.

[72] Y. Matsumoto, M. Griffin, Movement of the upper-body of seated subjects exposed to vertical whole-body vibration at the principal resonance frequency, Journal of Sound and Vibration 215 (1998) 743–762.
[73] Y. Matsumoto, M. Griffin, Modelling the dynamic mechanisms associated with the principal resonance of the seated human body, Clinical Biomechanics 16 (2001) 31–44.
[74] D. McRuer, H. Jex, A review of quasi-linear pilot models, IEEE Transactions on Human Factors in Electronics HFE-8 (3) (September 1967) 231–249.
[75] D. McRuer, E. Krendel, Mathematical models of human pilot behaviour, AGARDograph AGARD-AG-188, Advisory Group for Aerospace Research & Development, January 1974.
[76] D. McRuer, D. Graham, E. Krendel, Human pilot dynamics in compensatory systems: Theory, models, and experiments with controlled element and forcing function variations, Tech. Rep. AFFDL-TR-65-15, Air Force Flight Dynamics Laboratory, 1965.
[77] D. McRuer, R. Magdaleno, G. Moor, A neuromuscular actuation system model, Tech. Rep., NASA, 1967.
[78] D. McRuer, I. Ashkenas, D. Graham, Aircraft Dynamics and Automatic Control, Princeton University Press, 1973.
[79] Military Standard: Flying Qualities of Piloted Aircraft – MIL-F-8785C, November 1980.
[80] Military Standard: Flying Qualities of Piloted Aircraft, Tech. Rep. MIL-STD-1797A, Department of Defence, United States of America, 1990.
[81] M. Mulder, W.J. Kaljouw, M.M. van Paassen, Parameterized multi-loop model of pilot's use of central and peripheral visual motion cues, in: AIAA Modeling and Simulation Technologies Conference and Exhibit, San Francisco, CA, 15–18 August 2005.
[82] J. Naish, Control information in visual flight, in: Seventh Annual Conference on Manual Control, 1971, pp. 167–176.
[83] T. Neal, R. Smith, An in-flight investigation to develop system design criteria for fighter airplanes, Tech. Rep. AFFDL-TR-70-74, Flight Dynamics Laboratory, Wright-Patterson Air Force Base, 1970.
[84] T. Neal, R. Smith, A flying qualities criterion for the design of fighter flight control system, Journal of Aircraft 8 (10) (October 1971) 803–809.
[85] G. Padfield, The making of helicopter flying qualities: A requirements perspective, Aeronautical Journal 102 (1998) 409–437.
[86] G. Padfield, The tau of flight control, Aeronautical Journal 115 (2011) 521–556.
[87] G. Padfield, D. Lee, R. Bradley, How do helicopter pilots know when to stop, turn or pull up?, in: American Helicopter Society 57th Annual Forum, Washington, DC, May 9–11, 2011.
[88] G. Padfield, L. Lu, M. Jump, Optical tau in boundary avoidance tracking – a new perspective on pilot induced oscillations, AIAA Journal of Guidance, Control and Dynamics 35 (2012) 80–92.
[89] F. Previc, W. Ercoline, Spatial Disorientation in Aviation, American Institute of Aeronautics and Astronautics Inc., 2004.
[90] D. Purves, R. Lotto, Why We See What We Do: a Wholly Empirical Theory of Vision, Macmillan Press, 2003.
[91] V. Ramachandran, S. Blakeslee, Phantoms in the Brain: Human Nature and the Architecture of the Mind, Fourth Estate, 1998.
[92] D.L. Raney, E.B. Jackson, C.S. Buttrill, W.M. Adams, The impact of structural vibration on flying qualities of a supersonic transport, in: AIAA Atmospheric Flight Mechanics Conference, Montreal, Canada, 6–9 August 2001.
[93] D.L. Raney, E.B. Jackson, C.S. Buttrill, Simulation study of impact of aeroelastic characteristics on flying qualities of a high speed civil transport, Tech. Rep., NASA, 2002.
[94] C. Schauf, D. Moffett, S. Moffett, Human Physiology, Times Mirror/Mosby Publishing, 1990.
[95] D. Schmidt, Pilot modeling and closed-loop analysis of flexible aircraft in the pitch tracking task, Journal of Guidance, Control, and Dynamics 8 (1) (January–February 1985) 56.
[96] D. Schmidt, A. Silk, Modeling human perception and estimation of kinematic responses during aircraft landing, in: AIAA Guidance, Navigation and Control Conference, Minneapolis, MN, August 15–17, 1988, No. AIAA-1988-4186, pp. 1117–1126.
[97] A. Schönfeld, Modified optimal control model and wake vortex encounter, Presentation at the WakeNet3 – Europe Specific Workshop: Models and Methods for WVE Simulations, June 2010.
[98] J. Serafini, M. Gennaretti, P. Masarati, G. Quaranta, O. Dieterich, Aeroelastic and biodynamic modelling for stability analysis of rotorcraft–pilot coupling phenomena, in: 34th European Rotorcraft Forum 2008, 2008.
[99] S. Seung, Connectome: How the Brain's Wiring Makes Us Who We Are, Houghton Mifflin Harcourt Trade, 2012.
[100] M. Sirouspour, S. Salcudean, Suppressing operator-induced oscillations in manual control systems with movable bases, IEEE Transactions on Control Systems Technology 11 (2003) 448–459.
[101] R. Smith, A unifying theory for pilot opinion rating, in: Proceedings of the 12th Annual Conference on Manual Control, NASA, May 1976, No. NASA TM X-73, pp. 542–558.
[102] S. Sovenyi, R. Gillespie, Cancellation of biodynamic feedthrough in vehicle control tasks, IEEE Transactions on Control Systems Technology 15 (2007) 1018–1029.
[103] R. Telban, F. Cardullo, An integrated model of human motion perception with visual–vestibular interaction, in: AIAA Modeling and Simulation Technologies Conference and Exhibit, 2001.
[104] R. Telban, F. Cardullo, L. Guo, Investigation of mathematical models of otolith organs for human centered motion cueing algorithms, in: AIAA Modeling and Simulation Technologies Conference and Exhibit, 2000.
[105] P. Thompson, D. McRuer, Comparison of the human optimal control and crossover models, in: AIAA Guidance, Navigation and Control Conference, AIAA, Minneapolis, MN, August 1988, No. AIAA-88-4183-CP.
[106] P. Thompson, H. Klyde, M. Brenner, Wavelet-based time-varying human operator models, in: AIAA Atmospheric Flight Mechanics, Conference and Exhibit, Montreal, Canada, 6–9 August 2001, No. AIAA-2001-4009.
[107] D. Towill, Man–machine interaction in aerospace control systems, Radio and Electronic Engineer 50 (1980) 447–458.
[108] P. Tsang, M. Vidulich, Principles and Practice in Aviation Psychology, Lawrence Erlbaum Associates Inc. Publishers, 2003.
[109] A. Tustin, An Investigation of the Operator's Response in Manual Control of a Power Driven Gun, C.S. Memorandum 169, Metropolitan-Vickers Electrical Co., August 1944.
[110] P. van den Berg, P. Zaal, M. Mulder, M. van Paassen, Conducting multi-modal pilot model identification – Results of a simulator experiment, in: AIAA Modeling and Simulation Technologies Conference and Exhibit, Hilton Head, SC, August 2007, pp. 20–23.
[111] J. Venrooij, M. Mulder, M.M. van Paassen, M. Mulder, D.A. Abbink, Relating biodynamic feedthrough to neuromuscular admittance, in: Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics, San Antonio, TX, USA, October 2009.
[112] M. Waszak, D. Schmidt, Flight dynamics of aeroelastic vehicles, Journal of Aircraft 25 (1988) 563–571.
[113] R. Wierenga, An evaluation of a pilot model based on Kalman filtering and optimal control, IEEE Transactions on Man–Machine Systems 10 (4) (December 1969) 108–117.
[114] L. Wood, C. Suggs, C. Abrams, Hand-arm vibration, Part III: A distributed parameter dynamic model of the human hand-arm system, Journal of Sound and Vibration 57 (1978) 157–169.
[115] J. Yang, R. Marler, H. Kim, J. Arora, K. Abdel-Malek, Multi-objective optimization for upper body posture prediction, in: 10th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, New York, 30 August–1 September 2004.
[116] S. Yingchun, Effect of flight control system mode switching on pilot dynamics, Master's thesis, School of Engineering, Cranfield University, 2011.
[117] P.M. Zaal, B.T. Sweet, Estimation of time-varying pilot model parameters, in: AIAA Modeling and Simulation Technologies Conference, Portland, OR, 8–11 August 2011.
[118] P. Zaal, D. Pool, M. Mulder, M. van Paassen, New types of target inputs for multi-modal pilot model identification, in: AIAA Modeling and Simulation Technologies Conference and Exhibit, Honolulu, HI, 18–21 August 2008.
[119] P. Zaal, D. Pool, Q. Chu, M. Van Paaseen, M. Mulder, J. Mulder, Modeling human multimodal perception and control using genetic maximum likelihood estimation, Journal of Guidance, Control, and Dynamics 32 (2009) 1089–1099.
[120] P. Zaal, D. Pool, J. de Bruin, M. Mulder, M. van Paassen, Use of pitch and heave motion cues in a pitch control task, Journal of Guidance, Control, and Dynamics 32 (2009) 366–377.
[121] Y. Zeyada, R. Hess, Modeling human pilot cue utilization with applications to simulator fidelity assessment, Journal of Aircraft 37 (2000) 588–597.
[122] Y. Zeyada, R. Hess, Modeling the human pilot in single-axis linear and nonlinear tracking tasks, in: Pilot-Induced Oscillation Research: Status at the End of the Century, 2001.