Investigating the Difference Between Single and Dual Axis Manual Control

S. Barendswaard
March 7, 2016

Single Axis Roll

Single Axis Pitch

Dual Axis

Single Axis Roll

Single Axis Pitch

Dual Axis
Investigating the Difference Between Single and Dual Axis Manual Control

MASTER OF SCIENCE THESIS

For obtaining the degree of Master of Science in Aerospace Engineering at Delft University of Technology

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Faculty of Aerospace Engineering · Delft University of Technology
The undersigned hereby certify that they have read and recommend to the Faculty of Aerospace Engineering for acceptance a thesis entitled “Investigating the Difference Between Single and Dual Axis Manual Control” by S. Barendswaard in partial fulfillment of the requirements for the degree of Master of Science.

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Acknowledgements
Introduction

General Introduction

Although autopilot systems are in use most of the time, automation is not capable to fully replace human beings just yet. There is a very crucial element that automation misses out on; flexibility and creativity. Artificial controllers can only get as good as their designers design them to be, meaning that they are good at performing specified tasks at hand. However, when we consider an open, complex and dynamical system, unexpected situations are bound to occur, which is when only the creative, flexible and multi-tasking human operator can optimally control the aircraft. Although automated systems are superior to humans in labour intensive repetitive tasks, the human’s creative element is indispensable during any unanticipated event.

By obtaining a proper grasp on the underlying mechanisms of how human operators control aircraft, it is not only possible to adjust the systems they control to improve the overall man-machine performance but also to improve pilot training programmes by understanding their control strategy. Moreover, this information can be used as input for the design of minimum flying qualities, to anticipate and avoid Pilot Induced Oscillations and set the bounds for acceptable man-machine system characteristics (Mitchell et al., 1990).

Today, not only is the pilot needed during unprecedented situations, but also during landing in bad weather conditions. The auto-land systems are not safe enough to use in bad weather, so the pilot has to take over. Such realistic landing tasks are performed using a multi-axis display, requiring the pilot distribute his attention over multiple information processing channels simultaneously.

Single-axis tracking is well understood, however its relationship to dual axis tracking is not yet well established. As most realistic tasks include dual axis tracking, this thesis will try to improve its understanding. This is done by identifying the differences or additional phenomenon that come into play in dual axis compared to the single axis control behavior.

Motivation and Objectives

Understanding human control behavior is essential in the design of vehicles that need the manual control input of human operators. For dual axis, such type of control is practically
applied in aircraft and some novel drones that use joysticks to manually control attitude. It was only until World War two that vehicles were designed without taking the capabilities of the human into account. Hence, humans where trained to fit the automation, thus only the most suitable operators were selected. This made being a pilot a very load intensive and difficult task. Due to the war, technology became more advanced which also meant that aircraft were increasingly more difficult to control. It was noticed that aircraft was not designed for normal human capabilities, hence human-machine interaction models was finally looked into. Of the pioneers who established the prominent milestone in modeling human control behavior is McRuer who developed the single-axis crossover model for compensatory systems (McRuer et al., 1965).

Human pilot behavior is adaptive, multi-modal and time-varying, capable of a variety of behavior depending on the situation (McRuer & Jex, 1967) (Mulder, 1999). Human manual control behaviour is commonly modeled using McRuer’s crossover model (Flach & Jagacinski, 2009) (Pool et al., 2008) (Vaart, 1992). This model was developed for skill based behaviour in single axis tracking tasks, which are tasks with only one variable or degree of freedom to track. However, most practical tracking tasks, such as a landing an airplane using an attitude indicator (which illustrates both roll and pitch attitudes), do not consist of only one degree of freedom to control. Although dual axis manual tracking has more significance in practical tasks, the underlying principles of how humans control two degrees of freedom, in terms of possible task interference or intermittency phenomena, have not yet been properly established. In reality, the practical task not only consists of visual but also motion cues. Advancements in manual control modeling and identification have shown that the human uses motion as a separate cue, and therefore should be considered as an additional modality in the modeling of human control behaviour. Although motion has been established in manual control modeling, its combination or effect on dual axis control behavior is not as well understood.

The state of the art dual axis manual control modeling uses two independent single-axis configurations based on McRuer’s crossover model (McRuer & Jex, 1967). Therefore, this research aims to establish the differences between single and dual axis manual control behaviour as a means to distinguish the additional phenomenon that is commonly overlooked when modeling dual axis manual control behaviour. Four main phenomenon are expected to come into play with dual axis control behaviour; performance degradation, crossfeed, intermittency and asymmetry. Intermittent control behaviour (due to switching attention between axes) means that the control behaviour is time variant, however, due to the limitations of a 9 months thesis, time variant behaviour will not be explicitly identified, rather, an indication of its presence is made. This pilot-study will give way for some of the identified phenomena to be elaborated in future studies.

**Report Structure**

This report consists of three parts. Part I presents the Master thesis paper. The paper gives a summary of the background on literature, the experiment conducted, dependent variables used, results, analysis and finally a conclusion. The preliminary work is presented in Part II. The preliminary work consists of a literature survey on past work. A mathematical techniques section that explores the effectivity of certain techniques on detecting the dual-axis phenomena. The experimental design and choices of the task variables are discussed in detail. Finally,
the experimental checkout and final choice of controlled element is discussed. All in all, it
describes the work done up to the conducted human-in-the-loop experiment. In part III, the
experimental briefing and latin square design is elaborated. Finally, part IV the details of the
results from the experiment that did not fit in the paper are presented here. It consists of an
analysis of the error and control actions variances, the crossover frequencies and phase mar-
gins, the identified operator describing functions, the estimated operator model parameters,
phase plane plots, single axis motoric identified crossfeed responses and statistical tests.
Part I

Paper
The Differences Between Single and Dual-Axis Manual Control Behavior in Moving and Fixed-Base Simulations.

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Abstract—Aircraft manual control tasks require simultaneous control of multiple degrees-of-freedom. Unfortunately, most multi-axis human-operator modeling is limited to the modeling of multiple fully-independent axis. Therefore our goal is to contribute to the understanding of multi-axis manual control behaviour and develop a more realistic picture of dual axis manual control behaviour. The results of the human-in-the-loop experiment carried out in SIMONA Research Simulator has facilitated the study of four distinctive phenomena which are proven to occur in multi-axis control tasks: performance degradation, axis asymmetry, crossfeed and intermittency. Crossfeed occurs when operators’ inputs in one controlled axis feed into another controlled degree-of-freedom, thereby affecting overall control performance. Intermittency is a type of non-linear behaviour, caused by time-varying axis prioritization. Three conditions were experimentally tested in the presence and absence of motion: the full dual-axis control task, single-axis roll task and single-axis pitch task. The results of the data analysis show that the error variance and crossover frequency indicate that the performance is worse in dual axis than it is for its baseline single-axis condition. The performance in the roll axis is consistently worse than pitch, thereby proving axis asymmetry. Motion has been found to improve the error variance and stability of the system. The application of independent forcing function signals in both controlled axes, resulted in the detection of crossfeed in dual-axis tasks from spectral analysis. Furthermore, using a novel extended Fourier Coefficient method, the identified crossfeed dynamics explains up to 20% of the measured control inputs and improves modeling accuracy by up to 5%. Dual axis control behaviour is less accurately modeled with linear time-invariant models, and with more unaccounted for peaks, gives an indication of intermittency.

NOMENCLATURE

\( A(k) \) Amplitude of \( k^{th} \) sinusoid, deg
\( \omega(k) \) Frequency of \( k^{th} \) sinusoid, rad/s
\( n(k) \) Frequency integer factor for \( k^{th} \) sinusoid
\( e_r \) Roll tracking error signal, deg
\( e_p \) Pitch tracking error signal, deg
\( u_r \) Human operator roll control output, deg
\( u_p \) Human operator pitch control output, deg
\( f_{dr} \) Roll disturbance forcing function, deg
\( f_{dp} \) Pitch disturbance forcing function, deg
\( f_{tr} \) Roll target forcing function, deg
\( f_{tp} \) Pitch target forcing function, deg
\( n_r \) Roll remnant signal, deg
\( n_p \) Pitch remnant signal, deg
\( H_e \) Controlled pitch dynamics
\( H_{p_r} \) Human roll operator visual response
\( H_{p_p} \) Human Pitch operator visual response
\( H_{p_r} \) Human roll operator crossfeed response
\( H_{p_p} \) Human Pitch operator crossfeed response
\( H_{ps} \) Human roll operator motion response
\( H_{ps} \) Human pitch operator motion response
\( K_m \) Human operator motion gain
\( K_s \) Stick gain
\( K_v \) Human operator visual gain
\( K_c \) Human operator crossfeed gain
\( s \) Laplace operator
\( T_l \) Visual lead time-constant, s
\( T_{cl} \) Crossfeed lead time-constant, s
\( \tau_v \) Visual time-delay, s
\( \tau_m \) Motion time-delay, s
\( \tau_c \) Crossfeed time-delay, s
\( \omega_{nm} \) Neuro-muscular frequency, rad/s
\( \omega_{nm_c} \) Crossfeed neuro-muscular frequency, rad/s
\( \zeta_{nm} \) Neuro-muscular damping, rad/s
\( \zeta_{nm_c} \) Crossfeed neuro-muscular damping, rad/s
\( t \) Time, s
VAF Variance accounted for, %
ANOVA Analysis Of Variance
\( S_{xx} \) Power spectrum of \( x \)

I. INTRODUCTION

Despite the fact that most operationally relevant manual control tasks – especially those in the aerospace domain – typically require human operators to perform simultaneous control of multiple degrees-of-freedom, our understanding of the intricacies of such multi-axis control is still severely limited. In fact, the current state-of-the-art for the analysis and modeling of multi-axis manual control takes account only for multiple independent single-axis tasks [1]–[3]. While somewhat successful, such approaches cannot account for the inherently multi-input-multi-output nature of the human operator in a multi-axis case. Furthermore, due to task and operator limitations, additional dual-axis phenomena may occur. We argue that for meaningful understanding and prediction of human operator performance in multi-axis tasks, the presence...
of such phenomena needs to be verified, if not explicitly accounted for in our analysis methods and operator models.

Early investigations into human control in dual-axis tasks have shown that marked differences with single-axis manual control do indeed exist [4]–[7]. For instance, degraded task performance has been reported in dual-axis tracking, in addition to increased operator remnant and non-linear control behaviour levels. Furthermore, a focus on one axis or a consistent prioritization has been found [8] resulting in axis asymmetry. While some studies have postulated that this may be explained by a systematic reduction in operator aggressiveness (reduced crossover frequency) compared to the single-axis case [3], [9], others have proposed that the characterization of multi-axis control should include task interference phenomena, such as those resulting from divided attention (e.g., switching between axes), prioritization between axes – axis asymmetry [10] and time varying axis prioritization – intermittency [4]. A number of earlier investigations [4], [5], [7], have proposed to analyze and model crossfeed between axes, which occurs when operators are unable to fully decouple their separate tasks. However, no study to date has successfully used objective operators are unable to fully decouple their separate tasks.

This investigation uses novel means to analyze the occurrence and nature of crossfeed and intermittency in manual control. A human-in-the-loop experiment is performed in the SIMONA Research Simulator at TU Delft, to collect measurements of human operators in a dual-axis roll and pitch tracking task with physical motion feedback. Application of two independent multisine forcing functions in each controlled axis facilitates the detection of crossfeed through analysis of measured signals with spectral methods [11]. Furthermore, the multi-channel human operator identification method developed by [12] is extended to identify the dynamics of the additional crossfeed responses and the changes in other responses. To analyze the intermittency, a time domain analysis of peaks deviating from the modelled response and the variance accounted for are looked into.

This paper has the following structure. Background information can be found in Section II. The dual-axis control task, experimental design and the system identification approach is elaborated in Sections III and IV. The details of the results are presented in Section V and the paper ends with a discussion and conclusions.

II. BACKGROUND

In contrast to single-axis manual control behavior, there are four main additional phenomena that come into play with dual-axis control in literature: performance degradation, crossfeed, asymmetry and intermittency. These four main phenomena form the focus of this paper.

Multiple investigations have clearly found a degradation in performance with dual axis in comparison to single axis tasks [7] [13] [4]. In fact, the relation between crossover frequency and the number of axis was postulated to be proportional to the reciprocal of the square-root of the number of axis [14]. That is, with dual axes, the crossover frequency is \(1/\sqrt{2}\) of that of the single axis case. A similar relation deduced by [3] states that the crossover frequency is proportional to the reciprocal of the number of axis used. These relations are based on modeling the human brain as a multi-channel processor, the more channels being used, the less amount of continuous attention given to each of the tasks.

Asymmetry of manual control behaviour in each axis is shown by the performance measures being distinctly different in each axis [4], this can be a consequence of the differences in visual representation, or emphasis on a particular axis during pilot training, or the different neuromuscular properties in each axis [2]. Furthermore, it can also result from the human operator prioritizing one axis over the other [10], which is found when the crossover frequency is consistently higher in one axis than in the other.

Crossfeed is described as a type of task interference, or the human operators' inability to completely decouple the two tasks. Crossfeed can be motoric and can be perceptual, evidence for linear time-invariant perceptual crossfeed was found [7] in a task that used a separate manipulator for each axis. However, [4] did not find any consistent evidence for crossfeed, rather crossfeed was only found for a short period of time, making the phenomenon time-varying in contrast to it being linear time-invariant. Previous investigations have either used subjective time-domain iterative model matching techniques [5] [4] or open loop frequency-domain methods [7]. Neither of the techniques used in [5], [4] or [7] could accurately capture the dynamics of crossfeed in the frequency domain. Therefore, using the accurate objective frequency-domain identification method developed in [12], an accurate description of crossfeed dynamics can be provided.

The phenomenon of time varying prioritization or intermittency is found with integrated displays and separated displays alike [13]. When one axis has a larger error than the other, the larger error axis is prioritized over the other [10] [4]. This type of intermittent behaviour can be mitigated by the use of motion [9], thereby producing more consistent, linear time invariant pilot behaviour. Intermittency is traditionally lumped up with pilot remnant [15], and has been found to proportionally increase with each additional axis used [6].

III. CONTROL TASK

The control architecture is elaborated in this section with Fig. 1, illustrating the most model-intensive control task, dual axis with motion, with all other tasks being derivatives. Namely, without motion \(H_{ps}\) and \(H_{ps}\) are omitted and for single axis \(H_{ps}\) and \(H_{pc}\) are omitted. The distinctiveness of this control structure is that it combines the multiple independent single axis with motion from [2] and the crossfeed component from [7]. In the experiment, participants performed both dual-axis and single-axis tasks in the presence and absence of motion. For the dual axis with motion case, the pilot simultaneously controls the aircraft’s roll and pitch attitude \(\theta\) and \(\phi\) as depicted in Fig. 1. For the single-axis cases, the
participant would either control roll or pitch. For the sake of accurate identification, the participant executes a simultaneous target-following and disturbance-rejection task, being excited with two independent forcing functions per axis: $f_t$ and $f_d$ respectively.

The roll and pitch axis tracking errors; $e_{φ}$ and $e_θ$, were presented on a compensatory visual display, similar to an attitude indicator, elaborated in Section IV-A2. It was the participants’ task to continuously minimize these tracking errors. Physical roll and pitch motion feedback was taken as vestibular input provided by SIMONA’s motion system without any scaling or filtering. Due to the motion limitations of SIMONA, the specific forces resulting from simulator rotations, could not be compensated for and therefore, were experienced by the subjects.

The human is modeled through six different operator responses. $H_{pφ}$ and $H_{pθ}$ respond to the error signals, $H_{pφ}$ and $H_{pθ}$ respond to the vestibular input whereas the crossfeed responses $H_{cφ}$ and $H_{cθ}$ react to the off-axes error signals. The addition of the output of these responses; $u_c$, $u_e$ and $u_o$, along with the addition of operator noise $n(t)$, result in the complete operator output; $u_r(t)$ for roll and $u_p(t)$ for pitch. The output is attenuated by the control stick gain $K_s$, having a value of 0.08, and with the addition of the disturbance, the signals are transformed by the controlled element $H_c$.

The specific areas in the control architecture that relate to the phenomena of interest are indicated in the figure as A,B,C and D. When looking for performance degradation in dual axis, an adaption of both the performance parameters of the visual and motion blocks in comparison to the baseline single axis case, are focused on as indicated by A. When looking for axis asymmetry, the parameters and performance of the visual and motion blocks of pitch and roll are compared as given in B. Crossfeed is found with the existence of a crossfeed transfer block as given in C. Whereas intermittency is found through analyzing the time-domain pilot output signals as given in D.

The following subsections elaborate on elements of the control architecture; the controlled dynamics, forcing functions and pilot model.

A. Controlled Aircraft Dynamics

The aircraft roll and pitch controlled element dynamics are both defined by $H_c$ as given in Fig. 1. It is found in literature that using cross couplings or different controlled element dynamics changes the human operator’s control strategy considerably [5] [13]. Therefore, although in real nonlinear aircraft dynamics the roll and pitch axes have different and cross-coupled dynamics, in this investigation, they are kept uncoupled and identical to avoid obscuring the plain differences between single and dual-axis manual control. The dynamics in both axes are defined by the second order transfer function:

$$H_c(s) = \frac{67.9}{s(s+3)}$$  \hspace{1cm} (1)

The system defined by Eq.(1) is at a transition between single integrator dynamics $K/s$ and double integrator $K/s^2$ at the frequency 3 rad/s. Therefore, this controlled element requires human operators to generate mid to high frequency lead, which causes them to use physical motion feedback, when available [1], [11], [16]. A break frequency of 3 rad/s was chosen such that the difficulty level of the most demanding tested scenario, i.e., the dual-axis no motion task, remains at an acceptable level. Decreasing the break frequency makes the task more challenging, possibly making a greater distinction

![Fig. 1. Schematic representation of a dual-axis tracking task with motion feedback and crossfeed.](image-url)
between single and dual axis manual control, but also inducing human operator fatigue.

B. Forcing Functions

The target and disturbance forcing functions in both axes were quasi-random multisine signals, as defined by \( f_{t_r} \), \( f_{t_v} \), \( f_d \), and \( f_{dp} \), in Fig. 1 and by Eq.(2).

\[
f_{d,t}(t) = \sum_{k=1}^{N_{d,t}} A_{d,t}[k] \sin(\omega_{d,t}[k]t + \phi_{d,t}[k])
\] (2)

Each \( k \)th sinusoid in each forcing function is defined by its excitation frequency \( \omega_{d,t}[k] \), amplitude \( A_{d,t}[k] \), and phase \( \phi_{d,t}[k] \). All signals are a sum of 10 sinusoids, spanning frequencies between 0.1 and 20 rad/s, approximately equally spaced on a logarithmic scale. The forcing functions have a sampling frequency of 100Hz and have a measurement time of 81.92s. The amplitude distribution of the sine components in all forcing functions follows the low-pass filter amplitude distribution defined in:

\[
A_{d,k}(k) = \frac{1 + T_{A1} \omega_{d,t}(k)}{1 + T_{A2} \omega_{d,t}(k)}^2
\] (3)

Where, \( T_{A1} = 0.1s \) and \( T_{A2} = 0.8s \). This second-order filter is identical to the one used in [2]. The amplitudes were scaled such that the variance of the target forcing functions is 2.25 deg^2 and that the disturbances have a variance 25% of the target. This ratio of target to disturbance was successfully applied in previous pilot identification investigations [2] [17]. It should be noted that the signal amplitudes have been prefiltered by the inverse of the controlled element dynamics. This is because the disturbances are inserted into the loop before the controlled element dynamics, see Fig. 1.

Four sets of phases \( \phi_{d,t} \) were chosen from a large number of randomly generated phases. The phases were chosen such that the signals have a Gaussian distribution and an average crest factor as outlined by the forcing function requirements in [18]. The resulting forcing functions are defined in Tables I and II.

C. Pilot Model

The most elaborate model structure is the dual-axis with motion scenario as illustrated in Fig. 1. Here there are six different operator response functions to consider; two visual response functions, \( H_{p_v} \) and \( H_{p_v} \), the motion responses (in the presence of motion), \( H_{p_m} \) and \( H_{p_m} \) and the crossfeed responses (for dual axis), \( H_{p_{cm}} \) and \( H_{p_{cm}} \).

It is known that pilots adapt their dynamics such that the pilot-aircraft dynamics resemble a single-integrator in the crossover region [19]. The visual response in Eq.(4) is equivalent to the precision model as appropriate for the controlled element dynamics given in Section III-A.

\[
H_{p_v}(s) = K_v(1 + T_s) e^{-s\tau_v} \frac{\omega_{nm}^2}{\omega_{nm}^2 + 2\zeta_{nm}\omega_{nm}s + s^2}
\] (4)

The equation for the response to motion in Eq.(5) incorporates the vestibular response to the participants motion perception. Both the motion and visual responses are in line with previous research carried out on dual axis tracking with motion feedback [2].

\[
H_{p_m} = sK_m e^{-s\tau_m} \frac{\omega_{nm}^2}{\omega_{nm}^2 + 2\zeta_{nm}\omega_{nm}s + s^2}
\] (5)

The equalization dynamics are defined by the parameters \( K_v, T_s \) and \( K_m \), while the neuro-muscular dynamics are defined by a neuro-muscular frequency \( \omega_{nm} \) and neuro-muscular damping \( \zeta_{nm} \). Delays are defined by a visual \( \tau_v \) and vestibular \( \tau_m \) delay. Hence, there are seven parameters per axis. The structure of the crossfeed responses \( H_{p_{cm}} \) are to be found after the frequency domain identification and is elaborated in Section V.

IV. METHODOLOGY AND DATA PROCESSING

The data for this investigation are provided by performing an experiment in the SRS with the control tasks elaborated in Section III. This section describes the experimental methods, data processing techniques, dependent measures and hypotheses.

A. Experiment

1) Independent Variables: Two independent variables were varied in the experiment: axis configuration and motion. Axis configuration has three levels; single axis pitch, single axis roll and dual axis. Motion has two levels; motion and no motion. Both crossfeed and intermittency only need the dual axis configuration. However, to analyze performance degradation, both the dual-axis configuration and single-axis configurations
are needed for comparison. In total six scenarios are tested as described in Table III.

2) Apparatus and Cueing: The experiment was performed in the SIMONA Research Simulator (SRS) depicted in Fig. 2. The participants used a Moog FCS Ecol-8000 electrical manipulator stick for giving pitch and roll inputs. The settings of the control loaded manipulator stick were set to a linear force-displacement characteristic with a stiffness of 1.5N/deg. Moreover the side stick was left unlocked for the single-axis cases, to detect possible motoric crossfeed. Control inputs were limited to ±15 deg, whereas the input scaling (Ks, see Fig. 1) was set to 0.08 for both axes. The hexapod motion system was used to supply the participants with vestibular roll and pitch motion cues. The motion cues were designed such that the center of rotation is aligned with the pilots vertical body axis and 0.7 m below the pilots design eye point. The time delay of the SRS motion system is 30ms [20]. Moreover, such that the participants do not hear the motion base actuators, they are asked to wear noise-cancelling headphones during the experiment.

Fig. 2. The SIMONA Research Simulator.

The only visual cue available for the participants was a display illustrated in Fig. 3. For the single-axis cases, the inactive axis was locked at 0 deg. Other visual cues such as the outside visuals were switched off. The compensatory display only presents the pitch and roll errors, eφ and eθ, respectively. It was presented on the SRS primary flight display with an image generation delay of 25 ms [21].

3) Participants and Experimental Procedures: Twelve participants performed the experiment. Half of the invited participants were trained pilots whereas the other half were skilled non-pilots, with extensive experience from earlier experiments. Participants performed a minimum of 4-5 training runs to allow their performance to stabilize, each lasting 90 seconds, of which the final 81.92 seconds were used for data analysis. Thereafter, 5 more runs were collected as the measurement data. Participants were instructed to minimize the roll and pitch tracking errors. After each run, the participants were notified of their performance (RMS of the tracking errors), to motivate them to perform consistently.

B. Data Processing

1) Identification Approach: Fig. 1 shows a schematic representation of a dual-axis tracking task with motion feedback, where possible crossfeed between the controlled roll (φ) and pitch (θ) axes is explicitly accounted for. In this representation, the operator controls the system based on feedback of the (visually presented) tracking errors – er and eθ for roll and pitch, respectively – as well as physical motion feedback of the controlled system’s roll and pitch attitudes. Finally, crossfeed is accounted for with additional responses – indicated with transfer blocks Hpr, and Hps, that transfer the tracking error in one axis to the operator control input u in the other axis. For the roll axis, the following expression may thus be derived for the total human operator control input ur from Fig. 1:

\[ Ur(jω) = Er(jω)H_{pr}(jω) + Er(jω)H_{ps}(jω) + \Phi(jω)H_{pa}(jω) + Nr(jω) \] (6)

The same derivation method can be applied for pitch axis control to obtain a similar equation.

For identification of the human operator, Eq.(6) would have to be solved for its three unknowns: Hpr, Hps, and Hpa. To achieve this, the objective human operator identification method developed by [12] has been extended. This method is a frequency-domain identification technique that can be used without any prior knowledge about the dynamics of the system to be identified. The objective identification method by [12] uses two independent multisine target and disturbance forcing function signals (e.g., fx and fd, in Fig. 1) to identify two human operator responses (Hpr and Hpa in Fig. 1) in a single-axis task, by interpolating between the frequencies excited by both applied forcing function signals. For the dual-axis task of Fig. 1, a similar method is derived, where for identification of the additional unknown crossfeed response Hps, additional independent forcing function components from the other axis is used. For a successful approach, this requires that all four forcing function signals shown in Fig. 1 be independent, i.e., be composed of sines with different frequencies.

If this requirement is met, following the same procedure as proposed in [12], the following system of equations may be derived by evaluating Eq.(6) at each of the frequencies of fx/ and as well as by interpolating from the frequencies of fd/ and fd/, as indicated by the superscripted symbols in Eq.(7). The interpolation procedure consists of initially removing the forcing function phase from all signals, after which an interpolation of complex numbers is performed.

<table>
<thead>
<tr>
<th>Condition</th>
<th>Axis Configuration</th>
<th>Motion</th>
</tr>
</thead>
<tbody>
<tr>
<td>C1</td>
<td>Single Axis Pitch</td>
<td>No Motion</td>
</tr>
<tr>
<td>C2</td>
<td>Single Axis Roll</td>
<td>No Motion</td>
</tr>
<tr>
<td>C3</td>
<td>Dual Axis</td>
<td>No Motion</td>
</tr>
<tr>
<td>C4</td>
<td>Single Axis Pitch</td>
<td>Motion</td>
</tr>
<tr>
<td>C5</td>
<td>Single Axis Roll</td>
<td>Motion</td>
</tr>
<tr>
<td>C6</td>
<td>Dual Axis</td>
<td>Motion</td>
</tr>
</tbody>
</table>
All variables in Eq.(7) are a function of the roll target forcing function frequency \( (j\omega_r) \), even though this indication is dropped for notation purposes. The system of equations Eq.(7) can be solved for \( H_{p_v} (j\omega_r) \), \( H_{p_p} (j\omega_r) \) and \( H_{p_o} (j\omega_r) \) from inversion of the matrix-vector equation. Furthermore, equivalent frequency response estimates can be obtained at the frequencies of \( f_{dl} \).

To verify the developed method described in this section, human operator simulation data was generated for the dual-axis system of Fig. 1. The simulation was driven by the set of forcing functions also used for the experiment (see Section III) and the remnant \((n_r \text{ and } n_p)\) was omitted. The results of our identification method, as shown in Fig. 4, matches well with the original specified human operator model transfer functions, thereby indicating the efficacy of the proposed method.

2) Parameter Estimation: With the obtained FC of the operator responses, parameter estimation was performed based on the pilot model structure outlined in Section III-C and the candidate crossfeed structure to be outlined in Section V-B. Parameter estimation was performed by minimizing a cost function given in Eq.(9) that includes the FC of the measured data and the frequency response of the pilot model structure with arbitrary parameters:

\[
\epsilon(j\omega|\theta) = \frac{|H(j\omega|\theta) - \hat{H}(j\omega)|}{|\hat{H}(j\omega)|} \tag{8}
\]

\[
J(\theta) = \epsilon(j\omega|\theta)^2 W \epsilon(j\omega|\theta) \tag{9}
\]

Here, \( H(j\omega|\theta) \) is the estimated model as a function of the model parameters \( \theta \) and \( \hat{H}(j\omega) \) the estimated Fourier Coefficients. The complex error is normalized using the Fourier coefficients to avoid the smaller errors from being ignored. The weighting matrix \( W \) was modified such that the outliers can be neglected. These outliers are a consequence of the bias induced during the interpolation of the Fourier Coefficients.

3) Model Validation: The Validation of the model in the time domain. Simulated time domain responses \( u_{mod} \) of the modeled transfer function are compared to experimental time domain data \( u_{exp} \):

\[
\text{VAF} = \left(1 - \frac{\sum_{k=1}^{N}|u_{exp}[k] - u_{mod}[k]|^2}{\sum_{k=1}^{N} u_{exp}[k]^2}\right) \times 100\% \tag{10}
\]

This can be seen as the normalized sum of errors in the time domain subtracted from unity, where \( N \) is the number of time samples. The higher the VAF, the better the model is able to capture the dynamics in the time domain. A VAF of 100% means that 100% of the measured signal is explained by the model.

C. Dependent Measures

The dependent variables consist of performance metrics, parameter estimates, crossfeed metrics and intermittency metrics.

1) Performance metrics: To compare the level task performance between single and dual-axis tracking, the variance of the roll and pitch error signals \( (\sigma^2_c) \) is calculated. Calculation of this variance from spectral analysis of the measured signals \([11]\), allows for separating the individual contributions of the target and disturbance signals, as well those attributable from the target and disturbance signals from the other axis, as all provide power at independent frequencies. Hence, the variance was found by integrating the power spectral density at each forcing function’s set of excitation frequencies. Similarly, the control variance \( (\sigma^2_u) \) is used to quantify differences in control activity between single and dual-axis tasks. To give an indication of the stability of the system, the open loop target phase margin is calculated, whereas to give an indication of how well, and up to which frequency the pilot is able to track the target, the target crossover frequency is calculated. The target crossover frequency, \( \omega_c \), is the frequency at which the magnitude of the open loop response is 1.0, whereas the corresponding phase margin is the phase difference from \(-180\) deg at the crossover frequency. The general open loop function can be obtained using Fourier transferred experimental signals as given in Eq.(11) for roll:

\[
H_{OLr}(j\omega_r) = \frac{\Phi(j\omega_r)}{E_r(j\omega_r)} \tag{11}
\]

2) Parameter Estimates: With the parameter estimation method described in Section IV-B2, the parameters of \( H_{p_v} \), \( H_{p_p}/H_{p_o} \) and \( H_{p_c} \) are estimated. The results of this section can give insight to the underlying principles that define the differences surfaced in the performance measures section.
3) Crossfeed: To detect the presence of crossfeed, a significant component of the error or control variance can be attributed to the off-axis' forcing functions. Whereas to analyze the crossfeed dynamics itself, the identification approach elaborated in Section IV-B1 is applied to obtain frequency response estimates of human operators' visual, motion, and crossfeed responses. To quantify the practical significance of the modelled crossfeed, the modelled output contributions of the visual, vestibular and crossfeed responses, denoted in Fig. 1 by \( u_r, \ u_\varphi \) or \( u_\theta \) and \( u_c \) respectively, are analyzed and compared. This is done with the parametric models of the three operator response functions. The individual output contribution variances are divided by the total contribution to find the percentage contribution of the separate operator responses. Moreover, the time-domain significance of modeled crossfeed is analyzed by comparing the VAF with and without the modeled crossfeed contribution.

To analyze a possible motoric origin of crossfeed, i.e. how crossfeed results from hand geometry, phase plane plots are used as is given by Fig. 5. Here the y axis presents the pitch input \( u_p \) and the x axis presents the roll input \( u_r \). The angle sign-convention is chosen such that a positive input in the principle axis results in a positive input in the off-axis. The relationship between the phase plane input angle and the corresponding crossfeed gain \( K_c \) obtained from the parameter estimates can give insight about the relationship between motoric and identified crossfeed.

4) Intermittency: Intermittent behaviour is not linear and by definition time-variant. Therefore, by comparing the single axis VAF to the dual axis VAF, something can be said about its linear time invariant behaviour, or lack thereof.

Intermittency is defined as the time varying axis prioritization in multi-axis control. When one axis is ignored, error builds up, which can result in an aggressive corrective pilot input, which results in a non-linear peak. Peak time is the time (equal to the number of instances) in which the modelling error (difference between pilot output and simulated model output) is larger than 2\( \sigma \) of the baseline single axis modeling error as illustrated in Fig. 6. To differentiate between pilot noise and intermittency, anything below 2\( \sigma \) is filtered. Here we try to capture the unaccounted-for human operator peaks and see how the occurrences of these peaks may change with each condition. This measure gives a clear indication of intermittency when the modelling accuracy is high.

D. Hypotheses

For this investigation, there are six hypothesis based on previous investigations elaborated in the Background section:

- Performance degrades in dual axis tasks compared to the independent single axis tasks, which can be indicated through an increase in error variance, a decrease in crossover frequency and a decrease in phase margin [7] [13] [4].
- Asymmetrical human control behavior in each axis can be seen from unequal parameters in each axis, as well from differences in error variance, control variance, crossover frequency and phase margin between the roll and pitch axis [10] [4].
- Crossfeed is present in dual axis manual control behavior [5] [7], which can be found through the presence of off-axis frequencies in principle axis and through the developed Fourier Coefficient method.
- Intermittency is present in dual axis [2] which can be indicated through a consistently lower VAF and consistently more occurrences of peaks.
- Performance degradation in dual axis is mitigated with motion [9] [8], which can be indicated by a decrease in error variance, an increase in crossover frequency and an increase in phase margin.
- Intermittency in dual axis is mitigated with motion [9], which can be indicated by a decrease in peak time and an increase in VAF.

V. Results

The results section contains four main parts; performance metrics, crossfeed describing function, parameter estimation, and crossfeed and intermittency. The performance metrics bring forth the higher level distinction between single and dual-axis manual control. The crossfeed describing function presents the crossfeed Fourier Coefficients along with a candidate structure that fits the dynamics of crossfeed. After which the parameter estimation and crossfeed subsections bring about the underlying mechanisms that cause differences between single and dual-axis to occur. Finally, the intermittency section analyzes the linearity of the system and the intensity of intermittent
peaks. Three-way Analyses of Variance (ANOVAs) have been performed with axis type (Pitch or Roll) referred to as “Type”, axis dimension (Single or Dual) referred to as “Dim”, and “Motion” as factors. All ANOVA results are summarized in Table IV. A significant result is denoted by “*” (p ≤ 0.05), a very significant result by “**” (p ≤ 0.01) and no significance by “-”. When the data of one or two conditions are not normally distributed using the Shapiro Wilk test, the ANOVA outcome is superscripted with an ‘a’.

Although two subject groups are tested; Pilot and Non-Pilot, the between subject effect is not significant, therefore only a repeated measure (within subject) ANOVA is presented.

A. Performance Metrics

To evaluate the performance, there are four metrics of interest; error variance, control variance, crossover frequency and phase margin. These are presented in Figs. 7, 8, 9 and 10 respectively.

Figs. 7 and 8 show the average roll and pitch axis error and control signal variances, decomposed in components attributable to the target and disturbance forcing functions of both axes. So, these variances are composed of contributions from the signals of the principle axis, as well as off-axis signal contributions and human operator remnant. Variances are shown for pitch and roll control separately, also indicating the presence of Motion with an (“M”) and No Motion case with (“NM”). Furthermore, the left bar of each set of two corresponds to the single-axis task (“S”), while the right data is from the dual-axis task (“D”).

From Fig. 7, it can be seen that tracking performance was significantly worse for dual axis. The increased $\sigma_e^2$ for the dual-axis case is attributable to three components, as can be seen from Table IV; an increase in the remnant contribution, as well as the added off axis target and disturbance (crossfeed) contributions $\sigma_{f_t}$ and $\sigma_{f_d}$. Although the off-axis target is clearly detected, the off axis disturbance is not as visible, as its contribution is in the same order of magnitude as pilot remnant, illustrated in Fig. 11, which shows an example power spectral density of the roll-axis control signal $u_r$. 

![Fig. 7. Error Variance decomposition](image1)

![Fig. 8. Control Variance decomposition.](image2)

![Fig. 9. Crossover Frequency](image3)

![Fig. 10. Phase Margin](image4)
It can clearly be seen that the performance in roll is worse than that in pitch. This difference is shown through significantly larger target, disturbance, off-target and remnant contributions. The probable reason for such a discrepancy is the nature of the display used. Due to the decreased perceivability of roll errors in the display, the differences between single and dual axis control behavior seem to be enhanced in this axis, which may be a cause for the observed interaction. This can be seen by a significantly larger remnant and off-axis target contribution for dual axis roll than for pitch.

The presence of motion decreases both the target and disturbance contributions significantly, for both axes types and dimensions, however, motion adds more value to the roll axis than to the pitch axis. This interaction stems mainly from the target contribution, as this contribution decreases more when motion is added to the roll axis.

Although the total control variance, see Fig. 8, is not significantly affected by the number of controlled axes or by motion, some of its contributions are. At approximately the same level of total control variance for dual axis, the target contribution decreases, at increased levels of other contributors. For the pitch axis there is significantly larger remnant noise, reflected in a significant interaction. This shows that the dual axis roll axis inputs are noisier than that of dual axis pitch.

The roll axis has a significantly higher control variance than that of the pitch axis which stems from significantly larger target, disturbance and remnant contributions. The reason for such a difference could be due to hand force asymmetry and hand geometry, it could be easier to make larger deflections
in the roll axis of the manipulator stick used. The addition of motion increases the subjects’ reaction to the disturbance signal, moreover the disturbance contribution is slightly higher for dual axis motion than for single axis. The enhancement of disturbance contribution with motion is in line with previous research [22].

Following the open-loop calculation outlined in Section IV, Figs. 9 and 10 show the phase margin and crossover frequency of the open loop system. In the figures, the 'φ' sign stands for the roll axis and 'θ' for pitch.

Fig. 9 shows a significant degradation in crossover frequency in the dual-axis conditions, as expected. It is likely that humans will spend more effort on performing two tasks simultaneously, leaving less attention to optimize the performance of a single axis component. In relation to the phase margin, it seems that the human operators compromise crossover frequency to maintain high stability levels, thereby giving stability a priority. It can also clearly be seen that ωc is higher in the pitch axis than in the roll axis. This inclination towards performing better in pitch indicates axis asymmetry.

The phase margin is not affected by the axis dimension, nor is it consistently different for pitch or roll. It is only significantly affected by motion. This is in line with a previous investigation by [22] which found that for target tracking tasks, the phase margin increases with motion, implying increased stability with motion. Although there is a steady increase in phase margin for all conditions, the increase of dual axis roll from 47 to 63 deg on average, is significantly larger, which is reflected in the significant interaction between axis dimension and motion. With relation to the crossover frequency, it can be said that phase margin is maintained at the cost of crossover frequency. Hence, the dual axis roll without motion seems hard to maintain. Fortunately, the aided value of motion to dual axis roll is greater than to the pitch axis.

B. Crossfeed Describing Function

Using the identification method described in Section IV-B1, the frequency responses of the operator visual, vestibular, and crossfeed responses were estimated. Fig. 12 shows the roll-axis human operator responses identified for Subject 1. The red stars present the identified frequency response, with the errorbars showing the 95% confidence intervals over the five measurement runs.

Fig. 12 shows consistent estimation of the dynamics of all three responses. Furthermore, in partial confirmation of earlier results [5], [7], the dynamics of the crossfeed response appear very similar to those of the visual response, however, with a lower gain and a 180 deg phase shift. Based on these observations, a candidate model structure for the crossfeed response, to complement well-known models for the visual and vestibular responses [1], [16], would be identical to the widely accepted visual response model, as given by:

\[ H_{p_e} = \frac{K_{cp}(1 + T_{L,e}\omega_c^2 + 2\zeta_{nm,e}\omega_{nm,e}\omega_c^2 + \omega_{nm,e}^2)}{\omega_{nm,e}^2 + 2\zeta_{nm,e}\omega_{nm,e}\omega_c^2 + \omega_c^2} e^{-\tau_{pe}} \]  \hspace{1cm} (12)

C. Parameter Estimates

With the parameter estimation method described in IV-B2, the parameters of \( H_{p_v}, H_{p_w}, \) or \( H_{p_{ve}} \) and \( H_{p_{ve}} \) were estimated. In total, 24 parameters could be estimated for a dual axis run with motion. The results of this section can give insight to the underlying human adaptation that cause the differences surfaced in the performance measures section. It will also clarify whether a completely independent crossfeed transfer function is necessary.

Five parameters types are of interest. The gains \( (K_v, K_m \) & \( K_e), \) time delays \( (\tau_v, \tau_m \) & \( \tau_e), \) time constants \( (T_v \) & \( T_m), \) neuro-muscular frequency \( \omega_{nm} \) and \( \omega_{nm,e} \) and neuro-muscular damping \( (\zeta_{nm} \) & \( \zeta_{nm,e})), \) shown in Figs. 13, 14, 15, 16, 17 and 18 respectively. Each plot is analyzed in detail.
1) Gains: The gains are illustrated in Figs. 13 and 14, presenting $K_v$, $K_m$ and $K_c$. Although there is no significant effect of axis dimension on visual gain, for the roll axis, a slight (insignificant) decrease in dual axis gain without motion can be observed. The axis type does have a significant effect on the visual gains, with the pitch axis having a larger gain than roll. Here we can see that due to the higher gain for pitch by default (also for single axis), the pitch errors are corrected more strongly than the roll errors.

The crossfeed gains $K_c$, are presented in Fig. 13. It can be seen that cross-feed gain is significantly affected by axis type, not only in terms of magnitude but also in terms of sign (being negative or positive) as given in Fig. 13. The absolute roll crossfeed gain is higher than the absolute pitch crossfeed gain. This means that there is a stronger component of pitch in the roll axis than vice versa, which is in line with Figs. 7 and 8. In line with the negative roll axis cross-feed gain, the phase of the crossfeed frequency response in Fig. 12 has a -180 deg phase shift. The reasons for the gain’s negative sign in relation to crossfeed is elaborated in Section V-D.

Although there is no consistent significant affect of axis dimension or type on the motion gain, there is a significant motion gain increase for dual axis roll compared to the unaffected dual axis pitch from their baseline single axes conditions. This observation is strengthened by one of the subject comments during experimentation ‘the motion was more useful for roll’.

2) Time Delays: The time delay plot shown in Fig. 15 presents $\tau_v$, $\tau_m$ and $\tau_c$. Parameter $\tau_v$ is significantly different for single and dual-axis tasks, as well as for pitch and roll tracking. This is illustrated by the roll-axis having a clearly higher dual-axis delay, whereas the pitch axis delay is relatively unaltered. A higher delay for dual axis is an expected result, as it takes longer to perceive and process two degrees of freedom simultaneously [7], [13]. Hence the indifference of pitch to axis dimension indicates that the subjects’ preference to give more of their attention to the pitch axis.

On observing the crossfeed time delay $\tau_c$, it can be seen that it is comparable to the visual time delay of the axis that the response is originating from, that is the off-axis visual time delay. Meaning that $\tau_c$ is comparable to $\tau_v$. Given the observed difference in $\tau_c$, the crossfeed time delays of the two axes are also significantly different. This interesting result suggests the possibility of linking the crossfeed time delay parameter with the visual time delay parameter.

3) Time Constants: The time constant plot in Fig. 16 presents $T_{\text{ls}}$ and $T_{\text{lv}}$ which are both unaffected by axis type, axis dimension and motion. From the theory of pilot equalization, it is expected that the pilots lead time constant is at 0.3 rad/s (equivalent to the controlled element break frequency to maintain single integrator dynamics at crossover region), given as a grey reference line in Fig. 16. However the lead time constant value is mostly slightly above the controlled element break frequency, as was the case with previous investigation [2].

The interesting result, that $T_{\text{ls}}$ is unaffected by motion, is unexpected, as the available vestibular lead should facilitate a decrease in the visual lead time constant as observed for similar tasks in earlier investigations [22] [17]. However, this could indicate that this benefit of motion was not needed for this specific task. Moreover the larger variability of $T_{\text{lv}}$ in addition to the large Fourier Coefficient error bars, indicate that there is a possibility for the crossfeed lead time constant to be linked to that of the off-axis $T_{\text{lv}}$. 

4) Neuro-Muscular Frequency: The neuro-muscular frequency plot in Fig. 17 presents $\omega_{\text{nm}}$ and $\omega_{\text{nm},c}$. It can be seen that $\omega_{\text{nm}}$ is consistently and significantly larger for motion cases. This increase in neuromuscular frequency indicates an increased bandwidth of the neuro-muscular actuation response. An increase in neuromuscular frequency also indicates that the subjects are creating larger phase margin, which is in line with Fig. 10. A possible cause could be that the arms increased muscular tension during the runs with motion [17].

The parameter $\omega_{\text{nm},c}$ clearly varies much from person to person, similar to parameter $T_{\text{lv}}$, and can therefore be linked to its off-axis $\omega_{\text{nm}}$. That is, the parameter $\omega_{\text{nm},c}$ can be modeled as its off-axis $\omega_{\text{nm}}$ due to its large variation.

5) Neuro-Muscular Damping: The neuro-muscular damping plot in Fig. 18 shows $\zeta_{\text{nm}}$ and $\zeta_{\text{nm},c}$. Both parameters $\zeta_{\text{nm}}$ and $\zeta_{\text{nm},c}$ are not affected by type, dimension or motion. It is however clearly visible that $\zeta_{\text{nm},c}$ is consistently lower than $\zeta_{\text{nm}}$ which suggests that the parameter $\zeta_{\text{nm},c}$ can not be merged with $\zeta_{\text{nm}}$ for simplification purposes.

D. Crossfeed and its Contribution

The presence of off-axis forcing function contributions in Figs. 7 and 8 is clear evidence of the presence of crossfeed between the roll and pitch tasks. The pronounced peaks in Fig. 11 at the frequencies of the pitch target forcing function (light green markers) in the roll-axis control spectrum are an indication of task interference between both axes.
Crossfeed can have motoric and perceptual origins. Proof that the crossfeed we are considering has a motoric component can be seen in Fig. 19(a), which shows that Subject 1’s single-axis pitch control inputs were not perfectly aligned with the sidestick’s natural pitch axis. Implying that for every pitch input, a coupled negative input in roll was given. Fig. 19(b) shows that this participant showed a similar, yet reduced, crossfeed from roll to pitch. These observations are in line with the differences in the magnitude and sign of $K_c$ shown in Fig. 13. The orientation of the fitted linear regression for the pitch task confirms that for a positive $u_p$, a negative $u_r$ was given. This is highly consistent with the -180 deg phase shift observed for the crossfeed response in Fig. 12 and the negative $K_c$ values obtained for the roll axis. These results prove that participants are unable to fully decouple the pitch and roll-axis tasks at the manipulator level due to hand geometry.

From the full human operator model fits, the percentage of the total modeled control signal’s variance explained by the different human operator responses was calculated for each participant and is shown in Fig. 21. While the modeled contribution of the crossfeed response $\sigma_{uc}^2$ to the total operator input $\sigma_u^2$ is seen to be relatively minor compared to the visual $\sigma_{uv}^2$ and vestibular $\sigma_{um}^2$ contributions, it still can be quite significant with values up to 20-30% for the roll axis with motion. Remarkable is that the addition of motion decreases the relative visual contribution $\sigma_{uv}^2$ by increasing both the vestibular and crossfeed contributions. Moreover, the added value of the modelled crossfeed is clear from the Variance Accounted For data presented in Fig. 20 with a statistically significant contribution of $(F(1,11)=10.8, p \leq 0.01)$. Although the contribution may be small (1-5 % increase), it is consistent, proving a modeling improvement, similar to previous investigations who have also made consistent small improvements with additions to their pilot model [23], [24]. In line with the larger crossfeed contribution in the roll axis, the roll-axis crossfeed has a larger contribution to the VAFF.

Although one may be inclined to postulate such a relation, there is no linear one-to-one correspondence between the motoric single axis phase plane angle as given in Fig. 5 and the crossfeed gain. In Fig. 22 the roll gains are negative and correspond to a negative single axis deviation angle, whereas the positive pitch crossfeed angle corresponds to a positive pitch crossfeed gain. The linear magenta line included in Fig. 22 has a correlation coefficient of 0.81, whereas the non linear hyperbolic tangent function (black line) has a correlation coefficient of 0.89. Although it is difficult to make conclusions about the nature of the relationship, the illustration shows a pattern indicating that up to a certain amount of motoric crossfeed, due to a motoric deflection angle, the crossfeed gain $K_c$ will not further increase, as though there is a saturation limit. Possibly, past the saturation limit, the additional cross-
feed is fully taken as noise. Clearly, more understanding is needed on this topic.

E. Intermittency

The two metrics outlined in Section IV-C, VAF and peak time, indicate the lack of linear time-invariant behavior and intermittency. It can be seen from Fig. 20 that the VAF is significantly lower for dual-axis runs. Although the VAF shows consistently lower values for both roll and pitch dual-axis tasks, the peak time in Fig. 23 only seems to increase for roll dual axis. Using Friedman’s test it is found that there is a statistically significant difference between the conditions for peak time ($\chi^2(7) = 16.69, p = 0.02$), and using Wilcoxon signed rank test it is found the peak time for that dual-axis roll no motion is significantly larger than single-axis roll with ($Z = -2.22, p = 0.026$). An indication of less linear behaviour in the dual-axis roll is also visible in the VAF plot, as dual-axis roll shows the lowest VAF of all conditions.

VI. DISCUSSION

A human-in-the-loop experiment was performed in a moving-base simulator to investigate the presence of four phenomena in dual axis manual control: performance degradation, axis asymmetry, crossfeed and intermittency. The effects of motion on these three phenomena is also studied. Data were collected from twelve participants performing a compensatory roll and pitch tracking task with fully independent target and disturbance forcing functions in each controlled axis. In addition to the dual-axis condition, reference measurements of the corresponding single-axis pitch and roll tracking behavior were collected for direct comparison.

It has been found that dual axis control behavior induces more error and thereby performance degradation, which is in line with previous studies [7] [13]. Proving that the human operator acts as a parallel processor, as when the human has to distribute their attention over multiple channels, the performance in a single channel decreases. Interestingly, this degradation is done at approximately the same total amount
of control variance. However, from the distributed control variance plot it is clear that the operator reacts to other sources; off axis target and noise, thereby decreasing the operators response to the principal axis’ target and disturbance and responding in a more noisy fashion. In fact, in some optimal control models from literature, the modelled human is adapted by only increasing its remnant noise with the number of axis used \([6]\). The performance degradation is also reflected in the decreased crossover frequency. Some studies have indicated an exact degradation ratio in relation to the corresponding single axis \(\omega_c\) such as \(1/\sqrt{2}\) \([9]\). However, a consistent degradation ratio has not been found in this study. With this experimental design, the crossover frequency was reduced as a means to maintain the same level of stability, as phase margin did not significantly change with dual axis. With a greater task difficulty, this may not be the case anymore, however.

Although the control variance of the roll axis is significantly larger than pitch, performance is always less, indicating axis asymmetry. The consistently higher crossover frequency and decreased error variance in pitch for both the dual and single axis cases compared to roll, shows that there is a preference. Earlier experiments \([4], [10]\) state that human operators tend to show markedly worse performance in roll in dual-axis tasks, even for identical task settings. This can be seen in the change of the visual time delay; although the visual time delay of roll increases with dual axis, the delay of pitch stays the same. This effect is also present in the single-axis tasks. For the single-axis roll time delay is significantly larger than that of the single axis pitch delay. A possible cause for such a degradation is the nature of the type of the display used: roll errors tend to be less clearly perceivable than pitch errors which is evident from pitch using a factor of 2.3 pixels more than roll, per degree. Hence, when predicting human-in-the-loop performance for dual axis tasks, awareness of such emphasis on one task dimension is a factor that is important to account for.

Crossfeed has been successfully detected and identified in this paper. The human operator modeling results including crossfeed show that the crossfeed contributes up to 20% of the total human control response, and that the addition of crossfeed improves the accuracy of the time domain modelling by up to 5%, thereby suggesting crossfeed is a key attribute of human multi-axis control. The crossfeed candidate structure used in this paper is similar to that of the visual response structure. If the crossfeed response is purely motoric, one would expect identical parameter settings as found for the off-axis visual response. The results of the parameter estimates suggest that although \(K_c\) and especially \(\zeta_{nm}\) have a different range of values than their principle and off-axes parameters, the time delay parameter \(\tau_c\), time constant \(T_c\) and neuro-muscular frequency \(\omega_{nm}\) could be approximated as its off-axis parameters. This is made possible by the crossfeeds’ Fourier Coefficient error bars being large. Nevertheless, to obtain a firm grasp on the needed parameters for crossfeed modelling, a parameter sensitivity analysis would be beneficial for the future. As not all crossfeed parameters can be simplified, the crossfeed response can be seen as quasi-independent from the off-axes responses, meaning that the crossfeed response is not fully motoric as it can also have a perceptual contribution. This finding of linear time-invariant perceptual crossfeed is in line with \([7]\) who investigated a task that consisted of two separate manipulators for each axis.

As a consequence of hand geometry, we have motoric crossfeed as illustrated in the phase plane plots. However, there also exists crossfeed axis asymmetry which is a consequence of both the nature of the visual display and the hand geometry. The roll crossfeed gain (a contribution from the pitch axis) is larger than the respective pitch crossfeed contribution from the roll axis. This difference in contribution can also be seen from the distributed variance plots and the modelled output crossfeed contribution \(\sigma^2_{u_c}\). Although the control input in the roll axis is larger, which may be due to hand force asymmetry, the crossfeed contribution to the roll axis is found to be larger. The likely reason for a larger roll crossfeed contribution is hand geometry; the average motoric off-axis stick deflection is \(8.5\text{deg}\) for roll and \(17.2\text{deg}\) for pitch as can be seen in Fig. 22. Implying that in our setup the hand naturally tends to give more inputs from pitch to roll.

Intermittency is a type of time-varying axis prioritization, which in combination with crossfeed can be tricky to detect. Previous studies have indicated that the axis with the largest errors is often prioritized \([10], [4]\). This type of time-variant, nonlinear behaviour is traditionally modeled as additional pilot remnant. This study has found larger pilot output remnant for dual axis roll than that for single axis roll, which can be attributable to intermittency, as the peak time for roll dual axis is significantly larger than that for single axis. Furthermore, since the modeling accuracy in the time domain is at an acceptably high level, it can be said that the peak time analysis gives a clear indication of intermittency. The consistently degraded VAF for dual axis tracking indicates that dual axis manual control is less linear-time-invariant. The cause for such intermittent behaviour, especially for the roll axis, could be attributable to the display signals’ perceivability, however this needs more investigation. Therefore, it is recommended to investigate the cause of intermittency to identify its nature and possibly nonlinear task interference effects using more sophisticated non-linear techniques.

Motion was found to significantly improve performance by decreasing error variance and improve stability, which is in line with previous investigations \([17], [22]\). Also for dual-axis tracking, a previous investigation has found a significant decrease in error variance and an increase in crossover frequency with the addition of motion \([9]\). Contrary to previous studies, this investigation has not found a significant effect of motion on crossover frequency, lead time constant or time delay. This unexpected result stems from the controlled element used. The second-order controlled element with a break frequency of 3 \(\text{rad/s}\) ensures that the controlled dynamics is single integrator in the operating bandwidth, meaning that the benefits of motion could not be fully realized. Hence it is possible that the lack of significance of motion on intermittency and crossfeed
could be due to the use of dynamics that doesn’t facilitate any significant benefits of motion for the user. To establish a more distinct difference between single and dual axis manual control and to reveal the potential significant benefits motion, it is recommended to consider a controlled element that requires stronger pilot lead equalization in upcoming work.

VII. CONCLUSIONS

In this paper, the existence of performance degradation, axis asymmetry, crossfeed and intermittency in dual axis tasks and the effect of motion on these occurrences was investigated. It has been found that performance degradation does occur in dual axis tasks, with an increase in error variance and a decrease in crossover frequency, however this degradation is larger for roll than it is for pitch which surfaces evidence for axis asymmetry. Motion is shown to improve stability and error variance for both single and dual axis cases. Crossfeed is successfully detected by finding off-axis excitation frequencies using spectral analysis and was identified using a novel extended Fourier Coefficient method. Moreover with a maximum contribution of 20%, and an improvement of modeled dual-axis behaviour by up to 5%, the crossfeed’s contribution is indeed significant. It is therefore an important phenomenon to consider for future dual-axis manual control modeling. With a consistently lower VAF, dual axis tracking is less linear time-invariant, which, from the increased number of time domain peaks, seems to result from intermittency. Through the authentication of the presence of the four postulated phenomena, the understanding of dual axis manual control behavior is broadened and has become more realistic. This pilot-study also opens doors for future enhanced understanding of underlying human operator dynamics in multi-axis control.

REFERENCES


15
Part II

Preliminary Report
Appendix A

Research Question

The aim of this investigation is to highlight the differences between single and dual-axis manual control behaviour by investigating the presence of performance degradation, asymmetry, crossfeed and intermittency in dual-axis manual control behaviour.

The main research question therefore is:

What are the differences between single and dual axis manual control behaviour?

This rather complicated research question can be split into multiple sub-questions

1. Is there a difference in performance between single and dual-axis tracking manual control behavior?

2. Does axis asymmetry (difference in performance between pitch and roll axis) and prioritization between axis exist in dual axis tracking?

3. Does task interference/crossfeed come into play with dual axis?

4. Is there a change in control structure necessary for modeling human behaviour dual axis tasks?

5. How can task interference/crossfeed be identified?

6. Is time-varying/intermittent behavior present with dual axis?

7. How can this time-varying/intermittent behavior be accurately and reliably captured/detected?

These subquestions form the main challenges of this master thesis. The more simply answered sub questions are presented first. Subquestions 1, 2, 3, 4 and 6 will be looked into from the literature survey in Appendix B. The final answers to these questions are deduced from the experimental results. In appendix C, a summary of all current knowledge of additional dual axis phenomenon is given. This gives way for understanding the needed metrics and
identification techniques that are necessary. Subquestions 5 and 7 will be looked into in appendices D and E which tackles the identification techniques and additional metrics for intermittency detection respectively. In appendix F the chosen experiment task variables are discussed in detail. This preliminary report is concluded with an Experimental Proposal which includes the hypotheses for the experiment. Finally the experimental checkout is elaborated in appendix H.
This chapter will give the background information of dual-axis manual control and previous investigations conducted in the field. As the state-of-the-art of modeling dual-axis control behavior is using two independent single-axis, McRuer-based models (McRuer & Jex, 1967). The fundamentals of single-axis control behavior modeling is elaborated in the first part of this literature survey, whereas the existing investigations conducted dual-axis manual control behavior are elaborated in the second section.

B-1 Introduction to Single Axis Manual Control

Human pilot behavior is adaptive, multimodal and time-varying, capable of variety of behavior depending on the situation. Therefore the human pilot acts differently given a different visual or motion cues. The visual cue considered in this investigation is representative of an attitude indicator. The type of dual axis display used is that of a compensatory display, which is the most basic type of display there is, presenting only the error that needs to be compensated for. In practice, however the attitude indicator acts more like a pursuit display, not giving the error, but rather the attitude and the target, which is imposed by where the human decides to aim to be at. As this investigation will focus on a compensatory type display, the single-axis crossover model is considered. This descriptive human pilot modeling technique has been elaborately developed by McRuer et al. (1965).

As a start the simple case of a uni-modal compensatory display control structure, as given in Fig B-1, is considered. In this figure two transfer functions and five time signals can be seen. The signals that are presented are the target forcing function $f_t(t)$, disturbance forcing function $f_d(t)$, error $e(t)$, human operator output $u(t)$ and controlled element output $x(t)$. Humans apply nonlinear control behavior that can be split into an understandable quasi-linear transfer function $H_{pe}$ and a less-understandable pilot remnant signal $n(t)$, usually modeled as Gaussian white noise. The controlled element $H_c$ encapsulates the dynamics of the vehicle.

Compensatory tracking demands diligent manual minimization of the visually presented error. A good example of compensatory tracking is when performing an instrument landing. The
pilot would have to keep the error between the aircraft’s output and the desired approach path on the glide-slope indicator as small as possible. The figure B-1, presents a combined target following and disturbance rejection task. The source of the disturbance is usually atmospheric turbulence and can be inserted before or after the controlled element dynamics. There is however a clear distinction between the two tasks. A target following task is where the pilot tries to keep the controlled element output as close as possible to the continuous time-varying target signal, whereas a disturbance rejection task is where the pilot has to try and keep the controlled element output to a defined constant at the target, under the influence of a disturbance such as turbulence (Pool et al., 2008).

In compensatory tracking tasks human operators adjusts their control behavior such that the closed-loop characteristics satisfy the demands of a good feedback control system. These include a desired target-response performance, suppression of disturbances and acceptable closed-loop stability (McRuer & Jex, 1967).

These demands of a good feedback control system are satisfied when the open loop transfer function of the compensatory control system given in Fig B-1 is very large in the operator bandwidth and small outside this bandwidth. This can be achieved if the cross-over frequency of the open loop is greater than the input bandwidth. Moreover, the analysis of the cross-over region of the open-loop is important in determining the closed-loop characteristics of the pilot-vehicle system.

\[ |Y_{OL}| = H_{pc}H_c \] (B-1)

This reasoning gives-way to McRuer’s cross-over model which states that around the cross-over region, the pilot applies equalization such that the slope is -20dB/dec. Apart from the resulting open loop integrator dynamics in the crossover region, there is also an additional lag term that originates from the inherent human limitations. A developed human equalization model by (McRuer et al., 1965) models human behavior in the crossover region and has been used in many applications.

\[ H_{pc} = \frac{K_p(T_Lj\omega + 1)}{T_1j\omega + 1}e^{-\tau j\omega} \] (B-2)

This equalization equation has been used as a starting point for many human control models (Pool et al., 2009) (Paassen & Mulder, 2006) and has been validated by objective identification techniques. The objective identification technique consists of obtaining experimental data and obtaining a non-parametric frequency response. After which, a transfer function structure is postulated and fit to the Fourier coefficients using an optimization algorithm (Paassen & Mulder, 2006).
When using a simulator with motion, the human pilot uses this extra input to adjust their control behavior using the vestibular system (Pool et al., 2008). The vestibular input has been found to give lead to the pilot’s response, and is thus in the form of differentiation dynamics. The control structure of the single axis compensatory system with motion changes as given in figure B-2. $H_{pm}$ stands for the operator response function to motion as an input. The remnant signal is added to both the vestibular and visual response.

### B-2 Previous Work on Dual axis Manual Control

This section will give an overview of a total of eight studies conducted in the field of dual axis manual control. In each short overview, the nature of the control task if applicable to elaborated, after which the relevant findings are stated. In some investigations, some details of the control task are missing, therefore are unfortunately not mentioned in the overview.

#### B-2-1 Human Performance in Single and Two-Axis Tracking Systems

In a study by Todosiev et al. (1971), human performance in single and two-axis tracking systems was investigated. Three different conditions were tested with two factors: forcing function input bandwidth and controlled element dynamics, both aiming to adjust the task difficulty. The forcing function used low-pass filtered Gaussian white noise, with frequency $\omega_b$ denoting the bandwidth of the signal. The controlled element dynamics is second order as given in Equation B-3, with a varying time constant value $T$.

$$G(s) = \frac{K}{s(Ts + 1)} \quad (B-3)$$

The conditions or the different tasks tested for is given in Table B-1.

The averaged error variance across all subjects and all axes show that the task difficulty varies, with Task 1 being the easiest and Task 3 the hardest. This indicates that increasing
both forcing function bandwidth $\omega_b$ and controlled element time constant $T$ increases task difficulty.

To form a distinction between single and dual axis performance, human performance was measured in terms of tracking error variance. Moreover, the human parameters of the modeled transfer functions was deduced using a tedious model matching technique. The human transfer function model that was used is given in Equation B-4.

$$H_{pe} = \frac{K(T_1s + 1)}{(T_2s + 1)(T_3s + 1)}$$ (B-4)

The Analysis Of Variance has shown that there is no significant effect of the addition of an axis on the error variance performance metric. It is speculated, however that this is due the fact that the human information processing capacity is not fully loaded, hence the performance is not much affected. As for the change in pilot parameters, it was found that introducing dual axis has a significant effect (of the 5 % level) on the parameter $T_1$. For task 2 and 3 this is clearly visible. The value of $T_1$ increases, meaning that the break frequency of the lead term decreases. In these two tasks the forcing function bandwidth is 1 rad/s (compared to task 1 having a bandwidth of 0.3 rad/s), suggesting that a larger bandwidth can amplify the difference in human control behavior with respect to the addition of an axis.

### B-2-2 Human Performance in a Cross-Coupled Tracking System

In another one of his investigations Todosiev (1967) considers a dual axis tracking task with both controlled element cross-coupling and human operator cross-feed. This can be seen in the electrical engineering framework diagram in Figure B-3. The labels that denote $H_{ij}$ refer to human operator response functions whereas $G_{ij}$ refer to the controlled element dynamics. The human operator output $y_a$ and $y_b$, that is not correlated with the input $r_a$ and $r_b$, is encapsulated in the noise signals $n_a$ and $n_b$.

The display presented two visual errors in the form of dots, that had to be minimized for two axes. The plant dynamics were of second order and are given in Equation B-5. The input signals were filtered Gaussian white noise with a spectrum extending to 10 rad/s. Unfortunately nothing is stated about the amount or type of manipulator used. There were four tasks to be investigated; No coupling, asymmetrical coupling, symmetrical coupling,
and asymmetrical coupling with one forcing function set to zero. Todosiev uses an iterative model-matching technique to identify the human operator response functions. Interestingly, it is said that when there is no coupling in the controlled dynamics, the human cross-feed functions $H_{ab}$ and $H_{ba}$ can be found using open-loop means.

$$G_{aa} = G_{bb} = \frac{5.2}{s(0.3s + 1)}$$

(Todosiev postulates that the cross-coupled dynamics can be decoupled by the human operator as given in Equation B-6. Therefore, when there exists no coupling, Todosiev hypothesized no human cross-feed effects. However, in the absence of coupling, cross-feed was in fact present. Although the parameters and structure of the operator describing functions to the target remained relatively constant for symmetrical coupling, the parameters of the describing functions for each axis were different for asymmetrical coupling. Moreover, the cross-feed parameters and describing function structure with cross-coupled controlled element dynamics were not similar to that of uncoupled controlled element dynamics. Indicating that the amount and type of cross-coupling affects both the cross-feed describing function and target describing function parameters.

$$H_{ab} = \frac{G_{ab}}{G_{aa}}H_{bb}$$


In an investigation done by Bekey et al. (1965), they attempted to make a human mathematical model of dual axis compensatory tasks using differential equations alone. An experiment was conducted consisting of a dual axis display with vertical and horizontal compensatory elements. The two uncorrelated forcing functions were both filtered white noise having constant power between 0 and 100 rad/s. The controlled element dynamics was identical in each axis and was of second order, moreover the two axis were uncoupled. The experiment consisted of three conditions; single axis vertical, single axis horizontal and double axis. This was performed by two subjects and each condition was repeated three times.

The differential equation lacks the time delay element, however this was not an issue as the focus of the study was to develop a modeling technique that encapsulates human crossfeed rather than human performance, hence the time-delay element was ignored, saving computational space.

$$\ddot{z}_v + \alpha_1 \dot{z}_v + \alpha_2 z_v + \alpha_3 \dot{x}_v + \alpha_4 x_v$$

(B-7)

$$\ddot{z}_v + \alpha_1 \dot{z}_v + \alpha_2 \dot{z}_h + \alpha_3 \dot{x}_v + \alpha_4 \dot{x}_h + \alpha_5 x_v + \alpha_6 x_h$$

(B-8)

Equation B-7 refers to the single-axis case and Equation B-8 refers to the dual-axis case. The coefficients $\beta_i$ and $\gamma_i$ describe the cross-feed effects. Here Bekey et. al distinguishes between two different types of cross-feed effects. There is input, or perceptual cross-feed which refers to when the operator can not distinguish between an error in one axis and the other or that
the error in one axis affects the perceived error in the other axis. Mathematically, this means that the input in one axis effects the output in the other axis. The second type is output or motor cross-feed, this is a type of mechanical coupling that results of the controllers inability to give input in purely one axis. Mathematically this means that the output of one axis effects the output of the other axis. These cross-feed effects may appear in a linear and non-linear fashion. Bekey et al. have tried to model the non-linear cross-feed effects with the parameter $\gamma_i$, whereas the linear cross-feed effects are encapsulated in $\beta_i$.

The results of the experiment have shown that the introduction of a second axis decreases the performance of the pilot. The normalized error variance has increased on average between 20 to 67 percent, for each operator per axis. This indicates an increase in task difficulty. For the linear single-axis model without cross-feed effects, 67 % of the horizontal and 78 % of the vertical axis model output is explained. The results of the model matching of Equation B-8 have not been able to show consistent cross-feed effects for the entire run length. The introduction of the cross-feed $\beta_i$ parameters have decreased the accuracy of the model for the entire length of the run. Nevertheless, consistent values of $\beta_i$ were found for smaller time stretches of 20-60 seconds out of the total 5 minutes run time. For small time intervals, the introduction of a constant value parameter $\beta_i$ increases the percentage of the data explained by the model. This indicates that cross-feed effects do exist, however they are time-varying. The non-linear terms $\gamma_i$ were not investigated.

Bekey et. al also found that there is an asymmetry between axes, namely, the vertical axis always has a higher mean squared error that the horizontal axis. Moreover, the normalized model matching error is larger for the horizontal axis than for the vertical axis.

### B-2-4 Two-Dimensional manual control systems with separate displays

In an investigation by W. Levison & Elkind (1967), a two-dimensional control situation in-which there are two separated displays, with two different control sticks, one for each hand, was explored. The angular separation of the two separate displays was altered. Levison & Elkind postulate a model for two-dimensional control with separate displays where the human either uses their foveal or peripheral vision to perform the compensatory control task. They model this concept in an electrical engineering framework with a switch as shown in Figure B-4. The key assumption of the model is that the human controller acts as a two channel processor, one acts upon peripheral inputs, the other on foveal inputs. For our single visual integrated dual axis display, the peripheral input is not applicable, however the fact that the human acts as a dual channel controller is interesting.

The forcing functions are a sum of 17 sinusoids having a square spectrum of bandwidth between 0.5 - 2 rad/s. The controlled elements in both axis were uncoupled. It was found that two axis tracking increases the normalized mean squared error and NMSE increases with increasing input bandwidth. Upon using different controlled element dynamics for each axis, a considerable change in describing functions is found. The human operator has to continuously apply different equalization in each axis, which substantially degrades performance. They also used an eye tracker to see how much time was used to track each axis, it was found that the operator fixates on one axis for 1.4 seconds on average and this dwell time was relatively invariant with forcing function bandwidth. The operator describing function for dual axis is very similar to that of single axis, apart from a decrease in gain, indicating that (McRuer
et al., 1965) models for single axis compensatory control give a very good starting point for modeling dual axis behavior. The models however have to be modified to take interaction between axis into account.

**B-2-5 Identification of Human Operator Describing function in One or Two Inputs closed loop systems**

As part of his Ph.D. dissertation, Van Lunteren (1979) investigated a dual-axis tracking system as given Figure B-5. The aim of the investigation was to measure crossfeed as a consequence of task interference in a configuration with two simultaneous tracking tasks. The two target forcing functions were a summation of 9 sinusoids over a time interval of 102.4
Figure B-6: Table summarizing the found operator response function for different controlled element dynamics

seconds. This signal is also sent through a low-pass filter with a break frequency of 0.43s. The two error signals were presented as two vertically moving moving dots, horizontally 1cm apart. The display was designed such that both signals could be foveally observed such that scanning is not necessary. There were two identical manipulators, one for each hand which could only move in the forward backward direction.

It was found that compared to single axis tracking, dual axis increased the delay terms in both $H_{11}(v)$ and $H_{22}(v)$ by a value of 0.03s. The crossover frequencies, phase margins and performance measures did not differ significantly between single-loop and dual-loop tasks. A summary of the resulting human operator response functions can be found in Figure B-6. An interesting finding is that linear cross-coupling has been found although two manipulators were used.

The crossfeed may have a visual origin, in that the presence of an error in one axis may influence the perception of the error in the other axis and vice versa. This observation is strengthened when looking at the mathematical form of the crossfeed components in Figure B-6, the crossfeed components seems to obey the general equalization rule with a smaller gain than the visual contribution. The crossfeed could also have a motoric origin; if one hand moves rapidly in one direction, the other hand may also tend to move. A third possibility is
that it originates from the brain and cognitive issues. Why there is unsymmetrical crossfeed as given in Figure B-6 with double integrator controlled element dynamics is intriguing and a question that Van Lunteren was puzzled about. Important is that the crossover model is valid for each of the independent axis. The effect of the crossfeed term is small in comparison to the visual response.

B-2-6 The Effects Of Motion Cues and Motion Scaling On One- and Two-Axis Compensatory Control Tasks

In an investigation by Bergeron et al. (1971), the effects of motion on one and two axis compensatory control systems were investigated. The experiment was performed with and without motion and a simulator providing both roll and pitch cues. The display used was an attitude indicator giving visual cues of both roll and pitch. The controlled element was controlled using one manipulator stick with two axis. The computer generated dynamics was first order, however in the presence of the simulator, the combined dynamics was of second order as given in Equation B-9 with a break frequency around 6 rad/s.

$$H = \frac{40}{s^2 + 11s + 40} \quad (B-9)$$

The forcing function used was filtered Gaussian white noise, with a break frequency of 1 rad/s, hence the controlled dynamics were effectively gain dynamics in the given frequency range. The identification was done using an automatic parameter adjusting mathematical model. The type of motion used had two DOF as displayed.

It has been found that when a second axis is added the error variance increases for both axis, however this increase in error is mitigated with the introduction of motion. Moreover, the crossover frequency decreases with an addition of a secondary axis. The time variability of the estimated parameters increased with the addition of a secondary axis, this variability was also mitigated with motion.

B-2-7 Studies of Multivariable Manual Control Systems: A Model for Task Interference

This study by W. H. Levison et al. (1971) explains how task interference was incooperated into the optimal control model framework. Moreover, tests have been done to validate the developed model. However, note that the only validation criteria used is the error variance. Implying that not much insight is given into the underlying mechanisms of human control in dual axis tasks. To begin with, a short introduction to the optimal control model framework is given.

In an optimal control problem there are three main factors that play an important role; dynamic constraints of the system, physical constraints and performance criteria. If applied to an aircraft, the dynamic constraints can be expressed as the equations of motion, the physical constraints could be the maximum flyable altitude. The performance criteria is a criteria that you try to optimize for. There are two main components of the system; a perceptual component and the decision or control component. The perceptual part of the
human control model consists of noise, time delay, a Kalman filter and a predictor. The model implies that the human operator estimates the current state of the system based on noisy delayed observations of the output. The decision or control law is an analytically determined consisting of error variance, control variance and control rate variance. Note that the inclusion of control rate variance denotes the neuro-muscular limitations. The optimal control law weights are derived from the Ricatti equation. The optimal control model is designed to handle multiple inputs and outputs, hence has greater potential for modeling more complex environments.

Levison et al. have found that an equivalent observation or perceptual noise representation of remnant allows them to incorporate task interference in the optimal control framework. The reasoning they used for this is that the more axes are controlled, the more noise is present. Each sensory input variable that the controller wishes to control, is disturbed by white noise. It is known that the human is inherently limited in the amount of motoric and mental effort he/she can give at a certain interval of time. Therefore it is expected that his psychometric performance will decrease when he has to perform more tasks simultaneously. In his model, he considers the human controller as a parallel-channel processor of information. The controller possesses a fixed amount of information processing capability which is shared among the different tasks at hand.

As given in Figure B-7, there is a profound relationship between \(x(t)\) and \(y(t)\) as given in Equation B-10. Here \(r_n(t)\) is gaussian white noise. For each channel used, there is some additional noise contribution.

\[
y_n(t) = x(t) + r_n(t)
\]  

The total amount of power in the noise is given as \(P_n\), that is the noise contribution when all channels are used for one task alone. Now, when there are M perceptual tasks to be done in parallel, the N information channels must be distributed amongst the M tasks. This implies that the human will devote a fraction \(f_m\) to the mth task. Hereby the noise attributed to

\[
\text{Figure B-7: Levison's representation of the humans parallel processing capacity}
\]
that task becomes as given in Equation B-12. That is if there are two tasks at hand with equal priority, the noise contribution doubles.

\[ R^{(1)} = P_o \sigma_x \]  
\[ R^{(M)} = \frac{P_o}{f_m} \sigma_x \]  

Although the controller has a fixed number of information processing channels, it is hard to accurately calculate this number. This investigation has not been able to find it and they consider this as a big limitation to their study, nevertheless, they have experimented with some numbers and have been able to approximate the error variance of the human controller. The investigation conducted was very widespread, investigating up to four axis control with two manipulator sticks. One interesting finding is that although task interference is always present in multi-axis control, the case of two axis with a single manipulator stick has more task interference than when two single axis manipulators are used. Therefore we can expect more task interference than what was found in Van Lunteren’s study. Levison et al. have investigated a case of tracking two foveal axes simultaneously. The controlled element dynamics consisted of a single integrator and the forcing function was a sum of sinusoids with a bandwidth of 2 rad/s. The display was theoretical consisting of two vertical moving dots. Two manipulator sticks were used and four subjects were tested with two trials each. One could say that the nature of the control task was very similar to that of Van Lunteren. The results of the error variance with one axis and two axis show that the error variance increased by 40% for the two axis case. Moreover, the actual data closely matches the predicted error variance from the optimal control model.

### B-2-8 Piloted Simulation Evaluation of Multiple Axis Flying Qualities

In an investigation by Mitchell et al. (1990) dual axis manual control behaviour was compared to that of single axis manual control in order to update the minimum flying qualities, to incorporate the performance degradation that comes with dual axis tasks that require divided attention. The investigation focused on the effect of multiple degradation in two axis, specifically looking into roll and pitch. These tasks were also performed with and without motion. The controlled element dynamics were not identical in each axis, rather, a more realistic approach was taken. The roll axis was characterized by its roll time constant \( T_R \) and the pitch axis by short-period harmonics as given in Equations B-13 and B-14 respectively.

\[ H_\theta = \frac{\omega_{sp}^2/1.25(s + 1.25)e^{-\tau s}}{s(s^2 + 2\zeta_{sp}\omega_{sp}s + \omega_{sp}^2)} \]  
\[ H_\phi = \frac{1/T_Re^{-\tau s}}{s(s + 1/T_R)} \]

Different roll time constants were chosen, making up a total of 87 different configurations that were tested. The mission tasks, were however all representative of low altitude, high
Background

speed flight of a fighter-type aircraft. An attitude indicator display was used with a single manipulator stick. The forcing function consists of a sum of sinusoids with a bandwidth of 2 rad/s. The method of identification used is optimal control model. The investigators (Mitchell et al., 1990) postulated that with the introduction of a second axis, the pilot should not be able to control two axes simultaneously as well as he might control either axis alone. Moreover a shifting of priorities is expected when ones axis has a much larger error than the other.

The results indicate a general reduction in crossover frequency of both roll and pitch with dual axis, nevertheless some pilots have performed better in one axis with dual control. Moreover, pilots tend to prioritize different axis, meaning that performance in one axis is usually better than the other axis, and the type of axis being prioritized varies with the pilot.

When motion is added, pilots tend to control both axis more homogeneously, and with a higher crossover frequency, compared to the case without motion. With motion, the pilots also gave the system 1 more point on the Cooper-Harper scale, than without.

B-3 Conclusions

This chapter has given a good summary and overview of previous investigations and studies conducted in the field of dual axis manual control behavior. The following conclusions of interest to this study can be drawn:

- The single-axis human operator describing functions by McRuer have been successfully in a dual-axis control task.
- Error variance increases with dual axis tasks.
- The system frequency or crossover frequency generally decreases with dual axis.
- The pilot remnant increases with the number of axis he needs to track
- There exists a prioritization between axis, in that the performance in one axis is usually better than the other – Assymetry between axis.
- In the absence of controlled element cross-coupling, still human operator cross-feed effects occur.
- Performance is substantially degraded when the controlled element dynamics is different in each axis.
- Increasing controlled element time constant and forcing function bandwidth increases difficulty.
- A larger input bandwidth could amplify the difference between single and dual axis tracking tasks.
- Both short-duration and full-duration cross-feed effects may occur in dual axis.
- Two types of cross-feed effects; perceptual and motoric.
• Motion mitigates the decrease in error variance
• Motion decreases pilot control variability
S. Barendswaard

Investigating the Difference Between Single and Dual Axis Manual Control
Appendix C

Characteristics of Dual-Axis Control

This section gives an outline of the phenomenon that are expected to occur with the introduction of a second axis according to the information gathered in the literature survey of Chapter 2. There are four main phenomenon that are touched upon; asymmetry, crossfeed, performance degradation, and intermittency. Each will be discussed in relation to what is presented in literature. To start with, a high level representation of dual axis control is firstly looked into.

Looking into modeling the human as a system, the input the system receives is visual, whereas the output is motoric. For the single-axis case the human is a SISO system, that is a single-input-single-output system. Whereas for the dual axis case, the human becomes a MIMO system, as now not only does the human receive more inputs, he also has to produce more outputs. This phenomenon is illustrated in a high level representation of dual-axis in Figure C-1.

Classical control literature claims that dual axis control behavior closely resembles that of two independent single-axis control tasks (Stapleford et al., June 1967). However, other

![Figure C-1: High level structure of Dual-axis tasks](image)

Investigating the Difference Between Single and Dual Axis Manual Control

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literature indicates that due to the divided attention, the human control is considerably different, and may induce intermittent and/or task interference phenomenon (P. M. T. Zaal & Pool, 2014; Van Lunteren, 1979; W. H. Levison et al., 1971). Task interference can be seen as a consequence of MIMO systems, as these systems sometimes have relations between axis, in that the input of one axis affects the output in another axis. These effects can complicate the analysis of dual axis tracking, as the means to detect and monitor both crossfeed and intermittency is still underdeveloped.

In contrast to single axis manual control behavior, there are four main additional phenomenon that come into play with dual axis in literature; crossfeed, assymetricity, intermittency and performance degradation. These phenomena are illustrated in Figure C-2.

### C-0-1 Crossfeed

In realistic piloting tasks, the controlled elements of the two axis being controlled, depend on each other, or are coupled. It was found that, due to the very nature of crosscoupling, the human operator changes his control strategy completely to compensate for the coupling effect (Todosiev, 1967). In the presence and absence of controlled element cross-coupling, a phenomenon called operator crossfeed was detected (Todosiev, 1967). This phenomenon is described as a form of task interference, or the human operators inability to completely decouple the two tasks. Crossfeed can be motoric and can be perceptual, evidence for linear time invariant perceptual crossfeed was found (Van Lunteren, 1979) in a task that consisted
of two separate manipulators for each axis. However, (Bekey et al., 1965) did not find any consistent evidence for crossfeed, rather crossfeed was only found for a short period of time, making the phenomenon time-varying in contrast to it being linear time-invariant. The investigations carried out by (Bekey et al., 1965) and (Todosiev et al., 1971) used subjective time domain iterative model-matching techniques. Whereas (Van Lunteren, 1979) used an objective frequency domain spectral method. His open-loop means of identifying crossfeed however, are mathematically questionable.

C-0-2 Performance degradation

Multiple investigations have clearly found a degradation in performance with dual axis in comparison to single axis (Van Lunteren, 1979; W. Levison & Elkind, 1967; Bekey et al., 1965). In fact, the relation between crossover frequency and the number of axis was postulated to be proportional to the reciprocal of the square-root of the number of axis (Adams et al., 1966). That is, with dual axis, the crossover frequency is \( \frac{1}{\sqrt{2}} \) of that of the single axis case. A similar relation deduced by Hess (2015) states that the crossover frequency is proportional to the reciprocal of the number of axis used. These relations are based on modeling the human brain as a multi-channel processor, the more channels being used, the less amount of continuous attention given to each of the tasks. There are however investigations which do not indicate any statistically significant change in performance with dual axis (Todosiev, 1967; Chernikoff et al., 1960). However, the nature of the control tasks presented to the human were easier than in other investigations, as their forcing functions bandwidth was smaller, implying that the nature of the control task did not fully load the humans information processing capacity. Investigations who have looked into the effect of motion on dual axis have found that the addition of motion improves performance by increasing stability and decreasing error variance (Fourquet, 1989; Bergeron et al., 1971), this however, depends on the difficulty of the task, with the aided value of motion being larger for difficult tasks (Bergeron et al., 1971).

C-0-3 Intermittency

Due to the human having to compensate for two different degrees of freedom, (W. Levison & Elkind, 1967) has modeled a dual axis tracking case with separate displays using a switch. Due to the presence of two separate displays, one can be either perceived foveally or visually, meaning that the human is modelled using two different transfer functions per axis. In an interval in time, one axis uses the foveal response, whereas the other uses the peripheral response. This model assumes, that although both are tracked simultaneously, only one axis is foveally prioritized. Indicating an intermittent prioritization between axis. This phenomenon of prioritization is also found with an integrated display. When one axis has a larger error than the other, the larger error axis is prioritized over the other (Mitchell et al., 1990; Bekey et al., 1965). This type of intermittent behaviour may be mitigated by the use of motion (Bergeron et al., 1971), thereby producing more consistent, linear time invariant pilot behaviour. Intermittency is traditionally lumped up with pilot remnant (McRuer et al., 1965), and has been found to proportionally increase with each additional axis used (W. H. Levison et al., 1971).
C-0-4 Axis Asymmetry

Asymmetry of manual control behaviour in each axis is shown by the performance measures being distinctly different in each axis (Bekey et al., 1965), this can be a consequence of both the different neuromuscular properties in each axis (P. M. T. Zaal & Pool, 2014) as well as the visual means of representing each error being different. Nevertheless, it can also be a consequence of the pilot prioritizing one axis over the other (Mitchell et al., 1990), which is found when the crossover frequency is consistently higher in one axis than in the other.

C-0-5 Summary

Summarizing; crossfeed has been identified, however, using a mathematically questionable manner. Moreover, the origin of crossfeed is unknown, whether perceptual, motoric or both. Most investigations indicate that dual axis degrades pilot performance, which can easily be explained using cognitive multi-tasking models, however this also depends on the nature of the control task experimented with. It is therefore important to consider a realistic, unpredictable piloting task that facilitates frequency domain identification. Some investigations show that dual axis induces pilot intermittent behaviour, the cause for such behavior, or how to model this kind of behavior has also not been investigated yet.

The current state-of-the-art pilot models, based on a combination of independent single axis tracking do not accurately capture pilot control behavior in realistic flying tasks such as landing an aircraft (Beukers et al., 2010). The next sections will focus on finding methods that can successfully identify cross-feed and intermittency.
A fundamental part of understanding the underlying principles of control behavior is done by identification. This way human behavior can be dissembled and analyzed at each frequency. In this investigation there are two main identification techniques that are looked into, the Fourier Coefficient method and Maximum Likelihood Estimation, each which fall into a different identification category; frequency domain and time domain identification. Each identification technique has their own benefits and drawbacks, sometimes they are used separately, other times combined. This chapter will start with a brief comparison of the two general identification techniques. Each control structure that will be analyzed in the experiment is over-viewed using the Fourier Coefficient method. After which, the Maximum likelihood Estimation method is explained and simulated.

D-1 Comparison of Time-Domain and Frequency-Domain Identification

Parameter estimation in the frequency domain is a two step process. It requires an additional step to transform the time domain data to the frequency domain. This is done either by using the Fourier Coefficient method or linear time-invariant models such as auto-regressive exogenous models. The non parametric frequency response is used by the second step to fit a parametric pilot model. Parameter estimation in the time domain, is directly done by either a statistical time domain method such as Maximum Likelihood Estimation or by using Least Squares methods. The fundamental differences are illustrated in Fig D-1.

Although frequency domain techniques require two steps, an advantage is that the first step acts as a data reduction phase making the second optimization step less computationally intensive. Conversely, time domain data has significantly more data points, hence needs more computational power. The non-parametric frequency response resulting form the first step of frequency domain methods, can be used to postulate a good model structure to describe the pilot dynamics. Whereas for time domain identification it is hard to tell if the chosen model is an appropriate model for the data. With two steps involved in the frequency
domain identification, the bias and variance of the parameter estimates are larger than for the direct one step time domain identification method. Furthermore, the number of models that can be identified in frequency domain methods equals the number of forcing functions used. There is a limit to the amount of forcing functions that can be applied as applying multiple forcing functions (more than two) implies an unrealistic piloting task. Moreover the requirements placed on the design of forcing functions are much less stringent for time-domain identification than it is for the frequency domain method (Nieuwenhuizen et al., 2008). Time domain identification allows for more realistic forcing functions that are comparable to real piloting tasks.

In this investigation the Fourier Coefficient, being a frequency domain method, and Maximum Likelihood Estimation, being a time domain method, are used to identify pilot dynamics.

D-2 Fourier Coefficient Method

The Fourier Coefficient Method is a frequency domain identification technique that can be used without any prior knowledge about the structure of the system to be identified. The only aspect that must be known are the amount of inputs and outputs, where each input is assumed to have its own operator response function. After the explanation of the method, there are three different systems or scenarios are considered; manual control with only motion, with only crossfeed and with both motion and crossfeed. All these cases make up MISO systems (Multiple Input Single Output).

To start with a simple example of Fourier Coefficient identification, the most straightforward case is with a SISO system. A good example would be the identification of the human operator describing function in the crossover model as given in Equation D-2.
\[ U(i\omega_t) = H_{pe}(i\omega_t)E(i\omega_t) + N(i\omega_t) \]  
\[ \hat{H}_{pe}(i\omega_t) = \frac{U(i\omega_t)}{E(i\omega_t)} \]

The signal \( U(i\omega_t) \) stands for the pilot output, \( E(i\omega_t) \) the error signal or effective input and the remnant signal \( N(i\omega_t) \) accounts for all the nonlinearities present that can not be modeled using a LTI model. The identification is only done at discrete frequencies of the forcing function, where the signal to noise ratio is high. The estimated linear time invariant model is identified at frequencies where the signal to noise ratio is high and the noise is negligible (Van Paasen & Mulder, 1998). The applied forcing function not only denotes the excitation frequencies at which the identification process may take place but also the nature of the control task, therefore there are stringent requirements placed on the design of forcing functions which are elaborated in Section F.

D-2-1 Parameter Estimation

Given the obtained non parametric Fourier Coefficients, the next step is parameter estimation based on a selected model structure. Parameter estimation is executed by minimizing a cost function that includes the FC of the measured data and a modeled frequency response of the parameters to be estimated. This is an optimization problem. The general form of a cost function, is given in (D-4).

\[ \epsilon(j\omega|\theta) = H(j\omega|\theta) - \hat{H}(j\omega) \]  
\[ J = \epsilon(j\omega|\theta)^T \epsilon(j\omega|\theta) \]  

Where \( H(j\omega|\theta) \) is the estimated model as a function of the model parameters \( \theta \) and \( \hat{H}(j\omega) \) the estimated Fourier Coefficients. Using this cost function, small errors which are magnified in the bode plot, may be ignored. To avoid this problem what is commonly done is to divide the error by the value of the Fourier Coefficients, producing a normalized complex number error. As given in Eq. D-6.

\[ \epsilon(j\omega|\theta) \times \frac{\hat{H}(j\omega|\theta) - H(j\omega)}{H(j\omega)} \]  
\[ J = \epsilon(j\omega|\theta)^T \epsilon(j\omega|\theta) \]  

D-2-2 Forcing Functions

Further in this chapter, there are numerous simulations, each one of these simulations use forcing functions. There are two forcing functions considered on one axis, a target and a disturbance. The forcing functions are designed in accordance with the investigation of
Identification Techniques

Table D-1: Table giving the details of the Target and Disturbance functions in the roll axis

<table>
<thead>
<tr>
<th>n_{d}, ω_d, rad s^{-1}</th>
<th>A_d, deg</th>
<th>φ_{dφ}, rad</th>
<th>n_t, ω_t, rad s^{-1}</th>
<th>A_t, deg</th>
<th>φ_{tφ}, rad</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>0.384</td>
<td>0.396</td>
<td>5</td>
<td>0.460</td>
<td>1.657</td>
</tr>
<tr>
<td>11</td>
<td>0.844</td>
<td>0.299</td>
<td>11</td>
<td>0.997</td>
<td>1.159</td>
</tr>
<tr>
<td>23</td>
<td>1.764</td>
<td>0.149</td>
<td>23</td>
<td>2.071</td>
<td>0.523</td>
</tr>
<tr>
<td>37</td>
<td>2.838</td>
<td>0.076</td>
<td>37</td>
<td>3.145</td>
<td>0.282</td>
</tr>
<tr>
<td>51</td>
<td>3.912</td>
<td>0.046</td>
<td>51</td>
<td>4.065</td>
<td>0.189</td>
</tr>
<tr>
<td>71</td>
<td>5.446</td>
<td>0.028</td>
<td>71</td>
<td>5.599</td>
<td>0.117</td>
</tr>
<tr>
<td>101</td>
<td>7.747</td>
<td>0.018</td>
<td>101</td>
<td>7.9</td>
<td>0.074</td>
</tr>
<tr>
<td>137</td>
<td>10.508</td>
<td>0.013</td>
<td>137</td>
<td>10.661</td>
<td>0.054</td>
</tr>
<tr>
<td>171</td>
<td>13.116</td>
<td>0.011</td>
<td>171</td>
<td>14.880</td>
<td>0.0423</td>
</tr>
<tr>
<td>226</td>
<td>17.334</td>
<td>0.009</td>
<td>226</td>
<td>17.564</td>
<td>0.039</td>
</tr>
</tbody>
</table>

Table D-2: Table giving the details of the Target and Disturbance functions in the pitch axis

<table>
<thead>
<tr>
<th>n_{d}, ω_d, rad s^{-1}</th>
<th>A_d, deg</th>
<th>φ_{dφ}, rad</th>
<th>n_t, ω_t, rad s^{-1}</th>
<th>A_t, deg</th>
<th>φ_{tφ}, rad</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>0.614</td>
<td>0.417</td>
<td>8</td>
<td>0.690</td>
<td>1.681</td>
</tr>
<tr>
<td>15</td>
<td>1.150</td>
<td>0.283</td>
<td>15</td>
<td>1.227</td>
<td>1.129</td>
</tr>
<tr>
<td>30</td>
<td>2.301</td>
<td>0.124</td>
<td>30</td>
<td>2.378</td>
<td>0.499</td>
</tr>
<tr>
<td>44</td>
<td>3.375</td>
<td>0.069</td>
<td>44</td>
<td>3.451</td>
<td>0.283</td>
</tr>
<tr>
<td>55</td>
<td>4.218</td>
<td>0.049</td>
<td>55</td>
<td>4.295</td>
<td>0.202</td>
</tr>
<tr>
<td>75</td>
<td>5.752</td>
<td>0.031</td>
<td>75</td>
<td>5.829</td>
<td>0.129</td>
</tr>
<tr>
<td>105</td>
<td>8.053</td>
<td>0.020</td>
<td>105</td>
<td>8.130</td>
<td>0.084</td>
</tr>
<tr>
<td>141</td>
<td>10.815</td>
<td>0.015</td>
<td>141</td>
<td>10.891</td>
<td>0.062</td>
</tr>
<tr>
<td>172</td>
<td>13.192</td>
<td>0.013</td>
<td>172</td>
<td>14.956</td>
<td>0.049</td>
</tr>
<tr>
<td>232</td>
<td>17.794</td>
<td>0.011</td>
<td>232</td>
<td>17.871</td>
<td>0.045</td>
</tr>
</tbody>
</table>

(P. M. T. Zaal & Pool, 2014). However, in this investigation the excitation frequencies in each axis are different to facilitate the identification of task interference. The forcing functions are designed such that they have an appropriate crest factor, not making the signal have rapid fluctuations, but also not very smooth and monotonic. Moreover, the forcing functions are designed such that the target has a variance of 2\(25\)deg\(^2\) and the disturbance a variance of 0.139deg\(^2\). The forcing functions defined in Table D-1 and D-2 are used in the identification chapter. For Maximum Likelihood estimation, these and a set of two other forcing functions with different phases are used to create other realizations of the time signals. The excitation frequencies however, are kept constant. The forcing function requirements outlined in Section F are applied to all forcing functions.

D-2-3 Case: Compensatory Tracking with Motion

This case requires two forcing functions and is not exclusive to dual axis identification. The forcing functions used are target and disturbance. There are three signals being measured,
they are the pilot output \( u_r(t) \), controlled element output \( \phi(t) \) and error \( e_r(t) \) as can be seen in Figure D-4.

The pilot’s output equation is one equation with two unknown operator response functions. Making the case with motion more challenging to solve. To solve this, firstly all measured signals are split with respect to sets of excitation frequencies. The signal \( U(i\omega) \) is split into \( U(i\omega_l) \) and \( U(i\omega_d) \). Through this splitting, we can automatically write two equations. However, we want two equations based on the same set of excitation frequencies, so we can solve for the operator response functions as a function of a certain set of excitation frequencies. To solve this problem, the signals \( U(i\omega_d) \) are interpolated to frequencies \( \omega_l \).

Before the interpolation process the initially induced phases into the forcing functions are removed from all signals. This brings about a new interpolated signal \( \tilde{U}(i\omega_l) \).

\[
U_r(i\omega_l) = \Phi(i\omega_l)H_p\phi + E_r(i\omega_l)H_p\phi \tag{D-7}
\]

\[
\tilde{U}_r(i\omega_l) = \tilde{\Phi}(i\omega_l)H_p\phi + \tilde{E}_r(i\omega_l)H_p\phi \tag{D-8}
\]

The terms \( \tilde{U}_r(i\omega_l) \), \( \tilde{\Phi}(i\omega_l) \) and \( \tilde{E}_r(i\omega_l) \) are the signals that were interpolated from the disturbance frequencies to the target frequencies. For the sake of simplicity, the term \( (i\omega_l) \) will be left out. When these simultaneous equations are solved, Equations D-10 & D-9 result. These equations produce the non-parametric frequency response functions.

\[
\hat{H}_{p\phi} = \frac{U_r\tilde{E}_r - E_r\tilde{U}_r}{\Phi E_r - E_r\Phi} \tag{D-9}
\]

\[
\hat{H}_{p\phi} = \frac{\Phi\tilde{U}_r - U_r\tilde{\Phi}}{\Phi E_r - E_r\Phi} \tag{D-10}
\]

**Simulation**

The structure of the models \( H_{p\phi} \) and \( H_{p\phi} \) are given in Equations D-31 and D-28. After the Fourier coefficients are obtained, parameter estimation is done based on the model structure.

\[
H_{p\phi} = K_{e_r}(1 + T_{Lr}s)e^{-s\tau_{er}}\frac{\omega_m^2}{\omega_m^2 + 2\xi_m\omega_ms + s^2} \tag{D-11}
\]
$H_{p\phi} = sK_{p\phi}e^{-s\tau_{\phi}} \frac{\omega_{nmr}^2}{\omega_{nmr}^2 + 2\zeta_{nmr}\omega_{nmr}s + s^2}$  \hspace{1cm} (D-12)

A simulation run was performed to test the Fourier Coefficient and parameter estimation method. This simulation run is performed without any noise calculation.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|c|
\hline
 - & $K_{tr}$ & $T_{tr}$ & $\tau_{tr}$ & $\omega_{nmr}$ & $\zeta_{r}$ & $K_{m_{r}}$ & $\tau_{m_{r}}$ & VAF \\
\hline
True value & 0.08 & 0.48 & 0.32 & 10 & 0.21 & 0.07 & 0.15 & \\
Parameter estimate & 0.08 & 0.47 & 0.32 & 10 & 0.19 & 0.06 & 0.15 & 96 % \\
\hline
\end{tabular}
\caption{Parameter values and VAF}
\end{table}

Figure D-3: $H_{p\phi}$ operator response function using the Fourier coefficient method and parameter estimation technique

S. Barendswaard Investigating the Difference Between Single and Dual Axis Manual Control
Figure D-4: $H_{p_x}$ operator response function using the Fourier coefficient method and parameter estimation technique.
Identification Techniques

D-2-4 Case: Compensatory Tracking Without Motion and with Crossfeed

The second case is one where crossfeed is present without motion, which is similar to the case with only motion in that the system has two inputs and one output. Here we can see that the output of one signal is affected by both the error in that axis and the error in the other axis. The Fourier Coefficient method is particularly useful and interesting for identifying experimental crossfeed, as a pilot structure can be postulated from the frequency response function. The investigation by (Van Lunteren, 1979) used open-loop means to calculate the crossfeed frequency response. This investigation however, will consider the identification of crossfeed in a simultaneous manner using the Fourier Coefficient method.

Due to the presence of crossfeed as given in Figure D-5, in one axis, there are effectively four different sets of forcing functions and thereby excitation frequencies present. This means that to identify crossfeed without motion, only two different forcing functions are required. However, for the experiment, four forcing functions are kept such that a fair comparison can be made, the subtraction of forcing functions will change the nature of the task. The non parametric operator response functions are given in Equation D-14.

\[
\begin{pmatrix}
U_r
\nU_r
\end{pmatrix} =
\begin{pmatrix}
E_r & E_p
E_r & E_p
\end{pmatrix}
\begin{pmatrix}
H_{pre}
H_{pdp}
\end{pmatrix}
\]

(D-13)

\[
H_{pre} = \frac{U_r \hat{E}_p - \hat{U}_r E_p}{E_r \hat{E}_p - E_r E_p}
\]

\[
H_{pdp} = \frac{\hat{U}_r E_r - U_r \hat{E}_r}{E_r \hat{E}_p - E_r E_p}
\]

(D-14)
Simulation

With the presence of crossfeed, properties of one axis can be transferred to the other axis. The crossfeed operator response function needed for the roll axis includes the neuro-muscular properties of the pitch axis. Implying that unlike the case with motion and no crossfeed, the parameter optimization needs to be done simultaneously. Due to this interesting phenomenon, the optimization is more complex, resulting in a simultaneous optimization of 14 parameters.

According to the investigation by (Van Lunteren, 1979), it was found that for double integrator controlled element dynamics without motion, the pilot applies pure lead with an exclusive crossfeed time delay. This found model structure will be used as given in Equations D-15 and D-16. The visual operator response model structure used is same as in the previous case and is given in Equation D-31.

$$H_{p_{crp}} = K_{crp} s + \frac{\omega_{nmr}^2}{1 + 2\zeta_r \omega_{nmr} + \omega_{nmr}^2} e^{-\tau_{crp}}$$ (D-15)

$$H_{p_{crp}} = K_{crp} s + \frac{\omega_{nmp}^2}{1 + 2\zeta_p \omega_{nmp} + \omega_{nmp}^2} e^{-\tau_{crp}}$$ (D-16)

It can be seen from the parameter estimates that the values are close to the true parameter values and the VAF is high. This is expected however, as this simulation is performed without noise. Nevertheless it proves that the Fourier Coefficient method developed for crossfeed can be applied theoretically.

Table D-4: Parameter values and VAF for the roll axis

<table>
<thead>
<tr>
<th>Parameter</th>
<th>True value</th>
<th>Parameter estimate</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_{vr}$</td>
<td>0.08</td>
<td>0.08</td>
<td>100%</td>
</tr>
<tr>
<td>$T_{vl}$</td>
<td>0.48</td>
<td>0.48</td>
<td>100%</td>
</tr>
<tr>
<td>$\tau_{vr}$</td>
<td>0.32</td>
<td>0.32</td>
<td>100%</td>
</tr>
<tr>
<td>$\omega_{nmr}$</td>
<td>0.21</td>
<td>0.21</td>
<td>100%</td>
</tr>
<tr>
<td>$\zeta_r$</td>
<td>0.0007</td>
<td>0.0007</td>
<td>100%</td>
</tr>
<tr>
<td>$\tau_{cr}$</td>
<td>0.25</td>
<td>0.25</td>
<td>100%</td>
</tr>
<tr>
<td>$\omega_{nmr}$</td>
<td>0.25</td>
<td>0.25</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table D-5: Parameter values and VAF for the pitch axis

<table>
<thead>
<tr>
<th>Parameter</th>
<th>True value</th>
<th>Parameter estimate</th>
<th>VAF</th>
</tr>
</thead>
<tbody>
<tr>
<td>$K_{vp}$</td>
<td>0.07</td>
<td>0.07</td>
<td>100%</td>
</tr>
<tr>
<td>$T_{lp}$</td>
<td>0.85</td>
<td>0.87</td>
<td>100%</td>
</tr>
<tr>
<td>$\tau_{vp}$</td>
<td>0.24</td>
<td>0.24</td>
<td>100%</td>
</tr>
<tr>
<td>$\omega_{nmp}$</td>
<td>11.24</td>
<td>11.25</td>
<td>100%</td>
</tr>
<tr>
<td>$\zeta_p$</td>
<td>0.27</td>
<td>0.27</td>
<td>100%</td>
</tr>
<tr>
<td>$\omega_{nmp}$</td>
<td>0.0007</td>
<td>0.0007</td>
<td>100%</td>
</tr>
<tr>
<td>$\tau_{cr}$</td>
<td>0.25</td>
<td>0.25</td>
<td>100%</td>
</tr>
<tr>
<td>$\omega_{nmp}$</td>
<td>0.25</td>
<td>0.25</td>
<td>100%</td>
</tr>
</tbody>
</table>

Investigating the Difference Between Single and Dual Axis Manual Control
S. Barendswaard
Figure D-6: $H_{pe_r}$ and $H_{pe_c}$ Frequency response functions with their Parameter Estimates

Figure D-7: $H_{pe_p}$ and $H_{pe_p}$ Frequency response functions with their Parameter Estimates
D-2-5 Case: Compensatory Tracking with Motion and Crossfeed

The third case includes all possible operator response functions. Therefore there are three operator response functions to be identified per axis as given in Figure D-8. Normally, without crossfeed, it is not possible to realistically identify three operator response functions in one axis, given the limitation of the amount of forcing functions that can be applied per axis to maintain a realistic task. However this is made possible given the nature of crossfeed, all the signals in one axis are transferred to the other axis. In fact, since four different forcing functions are used, four different operator response functions per axis, meaning eight different operator response functions can be identified.

The pilots output equation consists of the summation of three operator response functions multiplied with their consecutive time signals as given in Equation D-17.

\[
U_r = E_r H_{pc_r} + E_p H_{pc_p} + \Phi H_{\phi}
\]  

Using the interpolated Fourier Coefficients from two other forcing functions, the matrix in Equation D-18 can be obtained.

\[
\begin{pmatrix}
U_r^1 \\
\tilde{U}_r^2 \\
\tilde{U}_r^3 \\
\end{pmatrix} = \begin{pmatrix}
E_r^1 & E_p^1 & \Phi^1 \\
\tilde{E}_r^2 & \tilde{E}_p^2 & \tilde{\Phi}^2 \\
\tilde{E}_r^3 & \tilde{E}_p^3 & \tilde{\Phi}^3 \\
\end{pmatrix} \begin{pmatrix}
H_{pc_r} \\
H_{pc_p} \\
H_{\phi} \\
\end{pmatrix} 
\]

For multi-channel identification, where the pilot’s output is dependent on two or more transfer functions, simultaneous equations are created and solved. Note that any signal with a tilde is an interpolated signal, moreover, the number associated with the signal is the number of the forcing function or set of original excitation frequencies the signal adheres to (before interpolation). The solution to Equation D-18 is given in Equation D-19.
<table>
<thead>
<tr>
<th>$-$</th>
<th>$K_{vr}$</th>
<th>$T_{lv}$</th>
<th>$\tau_{vr}$</th>
<th>$\omega_{nmv}$</th>
<th>$\zeta_{r}$</th>
<th>$K_{mr}$</th>
<th>$\tau_{mr}$</th>
<th>$K_{pr}$</th>
<th>$\tau_{pr}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>True value</td>
<td>0.08</td>
<td>0.48</td>
<td>0.32</td>
<td>10</td>
<td>0.21</td>
<td>0.07</td>
<td>0.15</td>
<td>0.008</td>
<td>0.25</td>
</tr>
<tr>
<td>Parameter estimate</td>
<td>0.085</td>
<td>0.436</td>
<td>0.312</td>
<td>9.888</td>
<td>0.22</td>
<td>0.07</td>
<td>0.148</td>
<td>0.008</td>
<td>0.24</td>
</tr>
<tr>
<td>Parameter estimate with noise</td>
<td>0.029</td>
<td>0.923</td>
<td>0.335</td>
<td>10.36</td>
<td>0.15</td>
<td>0.04</td>
<td>0.171</td>
<td>0.013</td>
<td>0.000</td>
</tr>
</tbody>
</table>

**Table D-6:** Parameter values for the roll axis

\[
\begin{align*}
H_{pv e} &= \frac{U_r^1 \bar{E}_p^2 \bar{\Phi}^3 - U_r^1 \bar{E}_p^3 \bar{\Phi}^2 - \bar{U}_r^2 E_p^1 \bar{\Phi} + \bar{U}_r^2 E_p^1 \bar{\Phi} + \bar{U}_r^3 E_p^1 \bar{\Phi} - \bar{U}_r^3 E_p^1 \bar{\Phi}}{E_r^1 E_p^2 \bar{\Phi}^3 - E_r^1 E_p^3 \bar{\Phi}^2 - E_r^1 E_p^1 \Phi + E_r^2 E_p^1 \Phi + E_r^3 E_p^1 \Phi - E_r^3 E_p^1 \Phi} \\
H_{pv pr} &= \frac{U_r^1 \bar{E}_p^2 \bar{\Phi}^3 - U_r^1 \bar{E}_p^3 \bar{\Phi}^2 - \bar{U}_r^2 E_p^1 \bar{\Phi} + \bar{U}_r^2 E_p^1 \bar{\Phi} + \bar{U}_r^3 E_p^1 \bar{\Phi} - \bar{U}_r^3 E_p^1 \Phi}{E_r^1 E_p^2 \Phi^3 - E_r^1 E_p^3 \Phi^2 - E_r^1 E_p^1 \Phi^3 + E_r^2 E_p^1 \Phi^3 + E_r^3 E_p^1 \Phi^2 - E_r^3 E_p^1 \Phi} \\
H_{pv e} &= \frac{U_r^1 \bar{E}_p^2 \bar{\Phi}^3 - U_r^1 \bar{E}_p^3 \bar{\Phi}^2 - \bar{U}_r^2 E_p^1 \bar{\Phi} + \bar{U}_r^2 E_p^1 \bar{\Phi} + \bar{U}_r^3 E_p^1 \bar{\Phi} - \bar{U}_r^3 E_p^1 \Phi}{E_r^1 E_p^2 \Phi^3 - E_r^1 E_p^3 \Phi^2 - E_r^1 E_p^1 \Phi^3 + E_r^2 E_p^1 \Phi^3 + E_r^3 E_p^1 \Phi^2 - E_r^3 E_p^1 \Phi} \\
\end{align*}
\]

**Simulation**

In the investigation by (Van Lunteren, 1979), the operator response function for crossfeed was identified to be a lead term coupled with an exclusive crossfeed time delay for a case without motion. Although the introduction of motion presents itself with readily available vestibular lead, meaning that the crossfeed structure term may alter, for this simulation the structure will stay the same. This is because the aim of this simulation is not necessarily to replicate what happens in reality, as that itself is what the next experimentation phase aims to discover, but to validate that the developed Fourier Coefficient method works. The crossfeed model structure is is given in the previous case in Equations D-15 and D-16. The motion and visual model structures used are identical to that described in the first case given in Equations D-28 and D-31.

Due to the crossfeed neuromuscular parameters being equal to the neuromuscular properties of the axis it originated from (the other axis), parameter estimation of 18 parameters is done simultaneously. With very noisy datasets, the parameter estimation may become challenging. Therefore, to check this methods pragmatic validity, the pilots remnant is simulated as Gaussian Mean White Noise. The variance of this noise is assumed to be 10% of the variance of the presented signal.

It can be seen from Tables D-6 and D-7 that the parameter estimate deviates from the true parameter value with the introduction of noise, as one would expect. The difference between the Fourier Coefficients with and without noise can be visually inspected in Figures D-9, D-10, D-11 and D-12. Although the presence of noise has a negative affect on the Fourier Coefficients and thereby the parameter estimate, the parameter estimate still fall close to the original function.
Investigating the Difference Between Single and Dual Axis Manual Control

S. Barendswaard

D-2 Fourier Coefficient Method

<table>
<thead>
<tr>
<th>Parameter</th>
<th>( K_{tp} )</th>
<th>( T_{tp} )</th>
<th>( \tau_{tp} )</th>
<th>( \omega_{nm,p} )</th>
<th>( \zeta_p )</th>
<th>( K_{mp} )</th>
<th>( \tau_{mp} )</th>
<th>( K_{crp} )</th>
<th>( \tau_{crp} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>True value</td>
<td>0.12</td>
<td>0.85</td>
<td>0.24</td>
<td>11.25</td>
<td>0.27</td>
<td>0.04</td>
<td>0.16</td>
<td>0.008</td>
<td>0.25</td>
</tr>
<tr>
<td>Parameter estimate</td>
<td>0.125</td>
<td>0.86</td>
<td>0.23</td>
<td>10.760</td>
<td>0.290</td>
<td>0.047</td>
<td>0.161</td>
<td>0.007</td>
<td>0.245</td>
</tr>
<tr>
<td>Parameter estimate with noise</td>
<td>0.032</td>
<td>2.74</td>
<td>0.202</td>
<td>11.05</td>
<td>0.168</td>
<td>0.047</td>
<td>0.245</td>
<td>0.000</td>
<td>0.305</td>
</tr>
</tbody>
</table>

Table D-7: Parameter values for the roll axis

Figure D-9: \( H_{per} \), \( H_{pcr} \) and \( H_{ pxr} \) Frequency response functions with their Parameter Estimates result
Figure D-10: $H_{pep}$, $H_{pec}$ and $H_{pex}$ Frequency response functions with their Parameter Estimates
Figure D-11: $H_{p_{cr}}$, $H_{p_{cr}}$, and $H_{p_{cr}}$. Frequency response functions with their Parameter Estimates result in the presence of noise.
Figure D-12: $H_{pep}$, $H_{pdp}$, and $H_{pdp}$, Frequency response functions with their Parameter Estimates in the presence of noise.
This section first provides a short introduction on what maximum likelihood estimation is and how it is applied to the dual axis problem. Note that the specific method used is identical to the method developed by (P. Zaal et al., 2009).

Maximum likelihood estimation is a statistical time domain parameter estimation technique that has been successfully used for multi-modal pilot model identification (P. Zaal et al., 2009). Parameter estimation of a multi-modal multi-channel quasi-linear pilot model from measurement data is a nonlinear optimization problem. This is because a quasi-linear pilot model is fit to inherently non-linear measurement data. The inherently nonlinear data could be perfectly simulated using a model that is nonlinear in the parameters. The non-linear optimization may become even more challenging when effects such as intermittency become more dominant due to increased task complexity. The nonlinear optimization problem has many local minimums, to cope with these, a genetic algorithm is added to find a a good starting parameter set. This section consists of the identification technique explained in detail, and an application of this technique.

D-3-1 Identification Theory

Maximum likelihood estimation aims to find a parameter set that maximizes a likelihood function. The likelihood function is a conditional probability density function of the prediction error for m measurements of $u(t)$ as given in Equation D-20.

$$L(\Theta) = f(\epsilon(1), \epsilon(2), ..., \epsilon(m)|\Theta)$$  \hspace{1cm} (D-20)

The discrete error $\epsilon(k)$ is defined as the difference between the modeled output, given a set of parameters $\Theta$ and the measured pilot output. Given the pilot remnant is assumed to be zero mean Gaussian white noise, the variance is defined as $\sigma_n^2$. The conditional probability density function for one measurement is defined as given in Equation D-21.

$$f(\epsilon(k)|\Theta) = \frac{1}{\sqrt{2\pi}\sigma_n^2}e^{-\frac{\epsilon^2(k)}{2\sigma_n^2}}$$  \hspace{1cm} (D-21)

Note that maximizing the likelihood function implies trying to minimize the error. When taking the logarithm of this formula, the problem can be converted to an minimization problem which presents an easier optimization problem. By combining Equations D-20 and D-21, an easy maximum likelihood expression is obtained in Equation D-22

$$\hat{\Theta}_{ML} = \arg\min_{\Theta} \left[ -\ln L(\Theta) \right] = \arg\min_{\Theta} \left[ \frac{m}{2} \ln \sigma_n^2 + \frac{1}{2\sigma_n^2} \sum_{k=1}^{m} \epsilon^2(k) \right]$$  \hspace{1cm} (D-22)

Equation D-22 summarizes the optimization problem in maximum likelihood estimation. It is interesting to note that if one ignores the first term, the problem becomes one of trying to find a parameter set that minimizes each discrete error point over the whole measurement.
set. This optimization problem is highly non-linear, for this reason a genetic algorithm is used to find a starting parameter set that has a high probability of being close to the global minimum.

The starting parameter set is used as an input to the more common Gauss-Newton optimization. The iterative parameter update equation is given in Equation D-23.

\[
\hat{\Theta}(i + 1) = \hat{\Theta}(i) - \alpha(i) M_{\Theta\Theta}^{-1}(\hat{\Theta}(i)) \frac{\delta L(\hat{\Theta}(i))}{\delta \Theta}
\]

The gradients of the likelihood functions \(\frac{\delta L(\hat{\Theta}(i))}{\delta \Theta}\) are found using the Jacobians of the state space matrices. The line search parameter \(\alpha(i)\) is updated in each iteration before the parameter update to ensure the most rapid minimization of the likelihood function. The Fisher information matrix denoted by \(M_{\Theta\Theta}\) is defined by Equation D-24.

\[
M_{\Theta\Theta} = \frac{1}{\sigma^2} \frac{1}{n} \sum_{k=1}^{m} \left( \frac{\delta \epsilon(k)}{\delta \Theta} \right)^2
\]

This matrix is inverted for the iterative parameter update. Note that the inverse of the Fisher matrix is equivalent to the Cramer-Rao lower bound. That is the minimum achievable variance of the parameter update. As the sample size increases, the parameter set converges to the true parameter set and the parameter variances converge to the Cramer Rao lower bound. (P. Zaal et al., 2009).

**D-3-2 MLE for single axis with motion**

The pilot model considered is multi-channeled, meaning that the output signal \(u(t)\) is dependent on the summation of two operator responses. Maximum likelihood estimation requires that the pilot model be written in a state space form. That is in the form shown in Equation D-29 and D-30.

\[
\dot{x}(t) = \begin{bmatrix} A_{ce,(\Theta)} & 0 \\ 0 & A_{c\phi,(\Theta)} \end{bmatrix} x(t) + \begin{bmatrix} B_{ce,(\Theta)} & 0 \\ 0 & B_{c\phi,(\Theta)} \end{bmatrix} \begin{bmatrix} e_r(t) \\ \phi(t) \end{bmatrix}
\]

\[
u(t) = [C_{e_r,(\Theta)} - C_{\phi,(\Theta)}] x(t) + [D_{e_r,(\Theta)} - D_{\phi,(\Theta)}] \begin{bmatrix} e_r(t) \\ \phi(t) \end{bmatrix} + n(t)
\]
Parameter estimation problem

The pilot model considered in this MLE test simulation is independent with no interference from one axis onto the other, meaning no crossfeed. In fact, only one axis is considered with motion included, making it a multi-modal pilot model. This pilot model is illustrated in Figure D-13.

\[
H_{pe} = K_{es} (1 + T_{Lr}s)e^{-s\tau_{er}} \frac{\omega^2_{nmr}}{\omega^2_{nmr} + 2\zeta_{nmr}\omega_{nmr}s + s^2} \quad (D-27)
\]

\[
H_{p\phi} = sK_{\phi}e^{-s\tau_{\phi}} \frac{\omega^2_{nmr}}{\omega^2_{nmr} + 2\zeta_{nmr}\omega_{nmr}s + s^2} \quad (D-28)
\]

Eq D-31 describes the operator's response to a visually illustrated error signal; \(K_{es}\) is the visual-perception gain, \(T_{Lr}\) is the visual-lead time constant and \(\tau_{er}\) is the visual-perception time delay. The human sensors that detect rotational roll motion are the semicircular canals which make part of the vestibular system. The roll motion operator response Eq D-28 is summarized by a lead term, a motion gain \(K_{\phi}\) and a motion-perception time delay \(\tau_{\phi}\).

Simulation

In this simulation subsection, two different time divisions are tested. A full time window MLE is performed along with a windowed MLE. For the full time window MLE three different sets of time realizations of the same pilot system are made using different forcing functions to test the identification method. The Maximum likelihood estimation was performed multiple times to ensure that the estimation technique has fallen in its global minimum. It can be seen in Table D-8 that for all runs, the VAF is very high, even if the parameter values may deviate from their true value. This could originate from the fact that the MLE method focuses on trying to minimize time-domain error, hence the large Variance Accounted For. However, this may not mean that when the estimated parameters are fed with another forcing function of different phases, the high VAF is maintained.

The windowed MLE divides the full time window of 81.92s into 8 consecutive parts. A windowed MLE can be performed due to the nature of MLE being a time-domain identification technique, which is done to test time varying behavior in a system (Dobbe, 2014). However, as less information or signal is available, less information is available to make a good estimate. A measure of how good the parameter estimate can get is given by the Cramer Rao Lower Bound. That is the minimum attainable variance of the parameter estimate, this minimum
Identification Techniques

Variance is attained when the length of the time signal considered becomes infinite. It can be seen in Figure D-14, that different time windows produce different parameter values although maintaining a high VAF for all estimates. One could claim that we have a time varying parameters, however this is not the case as the time signal was produced in the absence of noise with a LTI model. Therefore, the issue lies in the information that is available in the time signal. It can be said, that when using the windowed MLE, only the relative time variability of parameters can give an indication of time varying behavior.

D-3-3 MLE for Dual axis with Crossfeed

The pilot model considered for dual axis with crossfeed has three inputs and one output. \( u(t) \) is dependent on the summation of three operator responses. Maximum likelihood estimation requires that the pilot model be written in a state space form. That is in the form shown in Equation D-29 and D-30.

\[
\dot{x}(t) = \begin{bmatrix} A_c(\Theta) & 0 & 0 \\ 0 & A_\phi(\Theta) & 0 \\ 0 & 0 & A_{ep}(\Theta) \end{bmatrix} x(t) + \begin{bmatrix} B_c(\Theta) & 0 & 0 \\ 0 & B_\phi(\Theta) & 0 \\ 0 & 0 & B_{ep}(\Theta) \end{bmatrix} \begin{bmatrix} e_r(t) \\ \phi(t) \\ e_p(t) \end{bmatrix} \tag{D-29}
\]

\[
u(t) = [C_c(\Theta) - C_\phi(\theta) + C_{ep}(\Theta)] \ddot{x}(t) + [D_c(\Theta) - D_\phi(\theta) + C_{ep}(\Theta)] \begin{bmatrix} e_r(t) \\ \phi(t) \\ e_p(t) \end{bmatrix} + n(t) \tag{D-30}
\]

Parameter estimation problem

The pilot model structure considered in this MLE test simulation is same as the previous section, with exception to the added crossfeed dynamics \( H_{pcr} \). The dynamics of the crossfeed contribution has the same structure as the visual response \( H_{pcr} \). The control diagram is given in Fig D-15.

\[
H_{pcr} = K_{pcr} (1 + T_{rcr} s) e^{-s \tau_{r}} \frac{\omega_{nm,cr}^2}{\omega_{nm,cr}^2 + 2\zeta_{nm,cr} \omega_{nm,cr} s + s^2} \tag{D-31}
\]
Figure D-14: The variance accounted for of the resulting parameter estimates given different levels of dead time threshold

Figure D-15: Pilot structure considered for Maximum Likelihood Estimation with crossfeed contribution
Simulation

In this simulation a full time window MLE is performed with crossfeed contribution. The same procedure as the previous section is chosen for this simulation. It can be seen from table D-9 and D-10 that although the VAF is considerably high (above 90) the crossfeed contribution is very badly modelled. This is due to the fact that it has a very small contribution in the time domain, so is hard to detect. Moreover, although it is falsely modelled, the VAF is still relatively high, as the false crossfeed contribution is still low. Therefore it is not possible to model the crossfeed using maximum likelihood estimation.
This chapter consists of an overview of different metrics that are tested as a means to detect measure intermittency and crossfeed. Intermittency could be detected using; coherence, VAF and recurrence plots. Here, an analytical approach to the operators crossover frequency is looked into. To start with, the method of implementing intermittency in simulations is elaborated.

**E-1 Simulation of intermittent manual control**

Intermittent signals, are a type of non-linear signal. The type simulated in this investigation is that of dead-time. The dead time depends on whether the error signal is below a certain threshold value so, we assume operators respond to errors above a certain threshold magnitude. That is when; the error is below a certain percentage of the maximum of the signal, the output of the pilot is zero. This is summarized in the algorithm presented in Equation E-1. An illustration of this phenomenon is shown in Figure E-1.

\[
\text{if abs}(e(t)) > \text{Threshold} \\
\begin{align*}
    u(t) &= u(t) \\
    \text{else} \\
    u(t) &= 0 \\
    \text{end}
\end{align*}
\]

\text{(E-1)}
E-2 Coherence testing

The aim of this section is to deduce whether the Coherence metric successfully gives an indication of non-linearity in terms of dead time. Intuitively, a drop in coherence may be expected for intermittent control. This section is divided into explaining the coherence metric, describing the double-band forcing functions used, the simulation setup and the results.

E-2-1 Coherence definition

The coherence is a measure for the linearity between two time-domain signals. A high coherence gives justification to be able to model the human operator with a quasi-linear operator model. The coherence has a value between zero and one, perfectly linear relation between signals means a coherence of one and totally unrelated signals translate into a coherence of zero. The coherence between the target forcing function and the operators control of input signal u, is given by:

\[ \Gamma(\tilde{\omega}_f) = \sqrt{\frac{|\tilde{S}_{fu}(\tilde{\omega}_f)|^2}{\tilde{S}_{ff}(\tilde{\omega}_f)\tilde{S}_{uu}(\tilde{\omega}_f)}} \]  

(E-2)

With S the power-spectral density function of the respective subscripted signals. A tilde denotes the average over the double frequency bands of the input frequencies, which is only possible with double frequencies. This means that per forcing function, ten coherence values are estimated.
**E-2-2 Simulation setup**

The simulation uses the control structure given in Fig. E-2. This control structure does not include motion feedback. This is due to the fact that motion is not required for the purpose of coherence calculation.

**E-2-3 Forcing function**

A target signal with a period of 81.92s and frequency resolution of \( \frac{2\pi}{T} = 0.0767 \text{ rad/s} \), is constructed to be sums of sinusoids, defined by E-3.

\[
f(t) = \sum_{i=1}^{N} A_i \sin(\omega_i t + \phi_i) \quad \text{with} \quad \omega_i = \omega_m n_i
\]  

(E-3)

The forcing function has an amplitude \( A_i \), frequency \( \omega_i \) and phase \( \phi_i \). Twenty excitation frequencies are chosen such that there is an even logarithmic separation and a set of twenty-five different phase sets were selected to produce 25 different forcing functions and 10 different double-banded frequencies. The phases were kept at a value such that the overall signal is homogeneous. The power distribution is identical to that of the target forcing function in the investigation by (P. M. T. Zaal & Pool, 2014), elaborated in Section F and has a variance of 2.25 deg². To calculate the coherence, double input frequency bands were used. The excitation indexes are given in Equation E-4. The amplitude spectrum of the forcing function is illustrated in Figure E-3.

\[
n_t = [2 \ 3 \ 8 \ 9 \ 14 \ 15 \ 26 \ 27 \ 40 \ 41 \ 78 \ 79 \ 110 \ 111 \ 148 \ 149 \ 177 \ 178 \ 220 \ 221]
\]  

(E-4)

**E-2-4 Results**

The SISO pilot system was used to generate pilot output signals with different levels of deadtime as a percentage of the maximum value of the error signal. This was done only for the roll axis. This analysis focused on intermittency so two axes would be redundant. The coherence was calculated on basis of the target forcing function and the pilot output. It can be seen that the coherence is affected by the percentage of deadtime as one would expect. The greater the amount of nonlinearity in a signal, the lower the coherence. However, the
difference is very small and with the presence of human remnant in the real experiment, this small decrease in coherence can easily be obscured by noise. Therefore, the coherence metric most likely does not give a distinct indication of intermittent pilot behavior, meaning that double frequencies are not needed for the forcing function.

Figure E-4: Coherence values vs degree of dead time threshold
E-3 Variance Accounted For

A common metric to express the quality of fit of an identified LTI model is the Variance Accounted For. It is a time-domain validation metric and compares a simulated pilot output with a measured signal. The measured signal in this case is the simulated pilot output with different levels of deadtime.

\[
VAF = \left(1 - \frac{\sum_{k=1}^{N} |u_{exp}(k) - u_{mod}(k)|^2}{\sum_{k=1}^{N} u_{exp}^2(k)}\right) \times 100\% \tag{E-5}
\]

Equation E-5 can be seen as the normalized sum of errors in the time domain subtracted from unity. \(N\) is the number of data points in the time domain. The experimental or measured output signal is given as \(u_{exp}\) and the modeled response is given as \(u_{mod}\). The higher the VAF, the better the model is able to capture the dynamics in the time domain. If a VAF of 100% is achieved it means that 100% of the measured signal is explained by the model.

The purpose using this metric here is to give an indication of how well an LTI model can be fit to an intermittent data set. The more intermittent, the greater the non-linearity is in the output signal meaning that it will be harder to fit a parametric LTI model to the data, so a reduced VAF would be expected.

E-3-1 Simulation Setup

The simulation setup is illustrated in Figure E-2. Twenty five different sets (target and disturbance) forcing functions which abide to the requirements set in Section F were fed into a simulation with motion and an intermittent operator block. The forcing function excitation frequencies are described in Table D-1. The intermittent operator block is as described in Section E-1. The means of identification used is Maximum likelihood estimation which is a better option than the Fourier Coefficient method as the structure of the operator response functions are known and the estimation technique is unbiased.

E-3-2 Results

The VAF is calculated for different sets of homogeneous forcing functions and different levels of dead time threshold. On observing Figure E-5 there is a clear effect of deadtime or intermittency on the VAF metric. As one would expect, the more non-linear the pilot output signal, the harder it is to model the pilot using a Linear Time Invariant model. In the experimentation phase, if the VAF decreases as the task changes from single to dual axis control, then it may be stated that the degree of nonlinearity in the signals has increased. That is, a type of behaviour that is harder to model using LTI models. Even for a 10% increase in dead time threshold, we see a decrease of 15% which makes the VAF seem like a very good metric to detect this type of intermittency.
E-4 Recurrence Plots

Recurrence plots analysis is a graphical approach created by (Eckmann et al., 1987) to illustrate hidden recurring patterns, nonstationarity and structural changes in measured signals. Using the method of time delays (Eckmann et al., 1987), it is possible to reconstruct the output signal of a system into a characteristic phase-space plot. Whenever the phase space trajectory meets approximately the same place in the phase-space plot, a dark spot appears on the recurrence plot. Recurrence is a phenomenon that occurs much more frequently in nonlinear systems. As the theory of recurrence states that non-linear systems recur to their initial state much more than linear systems. This advanced illustration technique can reveal properties of a time signal that are otherwise not visible.

Recurrence plots of two different signals were calculated for application to dual axis control: that of a sum of sinusoids and that of an intermittent pilot output signal in Figures E-6 and E-7 respectively. It can be seen that the sum of sinusoids has a characteristic periodic pattern and the intermittent signal can easily be seen by its blocks. This visual illustration can give an initial illustration whether intermittency is present. If the differences are distinct, an indication of intermittency can be deduced.
Figure E-6: Recurrence plot of a sum of sinusoids
Figure E-7: Recurrence plot of an intermittent pilot output signal
The crossover frequency gives an indication of how good the pilot is tracking the target signal, that is, up to which frequency of the signal the pilot is able to track. It has been concluded by Hess (2015) that with the introduction of more controlled axes, the crossover frequency decreases. This section will investigate whether crosfeed may be detected from a decreased crossover frequency. The control structure with crosfeed considered is given in Figure E-8.

The following six equations can be readily deduced from the control structure given in Figure E-8:

\[
U_r = E_r H_{pr} + \Phi H_{p\phi} + E_p H_{pe} \quad (E-6)
\]
\[
E_r = F_{tr} - \Phi \quad (E-7)
\]
\[
\Phi = U_r K_s H_c \quad (E-8)
\]
\[
U_p = E_p H_{pe} + \Theta H_{pg} + E_r H_{pr} \quad (E-9)
\]
\[
E_p = F_{tp} - \Theta \quad (E-10)
\]
\[
\Theta = U_p K_s H_c \quad (E-11)
\]

Rearranging these equations to form a system of equations is necessary for an easy calculation process. Starting with the first three equations relating to the roll axis, the unknown variables \(E_r, U_r\) and \(\Phi\) are placed in the left hand side of the equation, whereas the known variables \(F_{tr}\) and \(F_{dt}\) are on the right hand side.
\[ U_r - E_r H_{\phi r} + \Phi H_{\phi o} + \Theta H_{\phi p} = F_{t_p} H_{\phi p} \]  
(E-12)

\[ E_r + \Phi = F_{t_r} \]  
(E-13)

\[ \Phi - U_r K_s H_c = 0 \]  
(E-14)

\[ U_p - E_p H_{\phi p} + \Theta H_{\phi o} + \Phi H_{\phi r} = F_{t_r} H_{\phi r} \]  
(E-15)

\[ E_p + \Theta = F_{t_p} \]  
(E-16)

\[ \Theta - U_p K_s H_c = 0 \]  
(E-17)

\[
\begin{pmatrix}
1 & -H_{\phi r} & H_{\phi o} & 0 & 0 & H_{\phi p} \\
0 & 1 & 1 & 0 & 0 & 0 \\
-1 & K_s H_c & 0 & 1 & 0 & 0 \\
0 & 0 & H_{\phi r} & 1 & -H_{\phi p} & H_{\phi o} \\
0 & 0 & 0 & 0 & 1 & 1 \\
0 & 0 & 0 & -K_s H_c & 0 & 1
\end{pmatrix}
\begin{pmatrix}
U_r \\
E_r \\
\Phi \\
U_p \\
E_p \\
\Theta
\end{pmatrix}
=
\begin{pmatrix}
F_{t_p} H_{\phi p} \\
F_{t_r} \\
0 \\
F_{t_p} H_{\phi r} \\
F_{t_p}
\end{pmatrix}
\]  
(E-18)

When solving the system of equations for \(E_r, U_r, \Phi, E_p, U_p\) and \(\Theta\), it can be seen that these variables are found in terms of both \(F_{t_r}\) and \(F_{t_p}\). However, these signals have a large magnitude at their respective excitation frequencies. Moreover, the open loop transfer functions are defined separately for each axes, in terms of the excitation frequency of that axis as given in Equations E-19 and E-20.

\[ H_{OL_r}(j\omega_r) = \frac{\Phi(j\omega_r)}{E_r(j\omega_r)} \]  
(E-19)

\[ H_{OL_p}(j\omega_p) = \frac{\Theta(j\omega_p)}{E_p(j\omega_p)} \]  
(E-20)

The component \(\Phi(j\omega_r)\) is the Fourier transformed time signal \(\phi(t)\) at the excitation frequencies \(\omega_r\). This means that the components of \(\Phi\) from the solutions of the system of equations that relate to \(F_{t_p}\) are not considered in \(\Phi(j\omega_r)\). The open loop transfer function for the roll axis is given in Equation E-21.

\[ H_{OL_r}(j\omega_r) = \frac{K_s H_c (H_{\phi r} + K_s H_c H_{\phi o} H_{\phi p} - K_s H_c H_{\phi r} H_{\phi p} + K_s H_c H_{\phi r} H_{\phi o} H_{\phi p})}{1 + K_s H_c (H_{\phi p} + H_{\phi o} + H_{\phi p} + K_s H_c H_{\phi p} H_{\phi o} + K_s H_c H_{\phi o} H_{\phi p})} \]  
(E-21)

To check the validity of this open-loop function, we can equate \(H_{\phi r} = H_{\phi o} = H_{\phi p} = 0\) and compare it to that of the simple case single axis compensatory open loop given in (Wasicko et al., 1966).

\[ H_{OL_r}(j\omega_r) = \frac{K_s H_c H_{\phi r}}{1 + K_s H_c H_{\phi o}} \]  
(E-22)
The simplified transfer function is in accordance with the findings of (Wasicko et al., 1966). Note that the open loop transfer function for pitch is similar to that of for roll and is given in Equation E-23.

$$H_{OLp}(j\omega_p) = \frac{K_c H_c (H_{per} + K_c H_{per} H_{per} - K_c H_c H_{per} H_{per} + K_c H_c H_{per} H_{per})}{1 + K_c H_c (H_{per} + H_{p\phi} + K_c H_c H_{per} H_{p\phi} + K_c H_c H_{per} H_{p\phi})} \quad (E-23)$$

**E-5-1 Simulation**

The simulation was done to test how the crossover frequency, a measure of how good the pilots tracking behaviour is, which can be retrieved from the open-loop function, is affected by different levels of crossfeed. This was done by using the equations set for $H_{per}$, $H_{p\phi}$ and $H_{per}$ was set to be a equal to $K_c H_{per}$, in this way the variable $K_c$ could be experimented with. The result is illustrated in Figure E-9. It can be seen that despite the fact that the closed loop control doesn’t change, we see a decrease in crossover frequency simply because of the presence of crossfeed.

![Figure E-9: Crossover Frequency for different values of $K_c$](image-url)
The objective of the experimental considerations chapter is to discuss the relevant variables important for formulating an experiment performed to measure the differences between single and dual-axis manual control tasks. As given in Section C, there are a couple of additional phenomena related to dual axis when compared to single axis tracking.

The experiment should be designed to explore different task difficulty levels such that the different phenomena; intermittency, crossfeed, performance degradation and asymmetry can be detected. According to McRuer & Jex (1967), when designing a Manual control experiment, there are a couple of variables that influence its outcome. These factors can influence the nature of human control behavior and therefore need to be thought of and set appropriately. They are:

- Task variables
- Environmental variables
- Operator-centered variables
- Procedural variables

The task variables are illustrated in Figure F-1 (McRuer & Jex, 1967). The task variables are all the inputs and system properties. The inputs consist of visual and vestibular inputs, the latter indicating the use of motion. The task variables are that which need most attention as they have a direct influence over the nature of the resulting human control behavior. The choice of the different task variables will be elaborated in this chapter. The environmental variables encapsulate the choice whether to perform a fixed base, moving or in flight experiment. Other factors such as vibration, G-level and temperature also come under environmental variables. The operator centered variables are sometimes hard to control and may vary from person to person. These include motivation, stress, workload, training and fatigue. Procedural variables consist of instructions, amount of practice given, experimental design and order of task presentation.
F-1 Task variables

This section will cover the design of the Task variables for this experiment. The task variables are the forcing function, controlled element dynamics, perceived inputs, manipulator and display.

F-1-1 Display & Manipulator

There will be three different displays used, that for single axis roll, single axis pitch and dual axis. The dual axis display is an integrated display and is the same display as that used for the investigation by P. M. T. Zaal & Pool (2014). All displays presented are compensatory, limiting the visual input to the error. This is done to facilitate comparison between the results of this investigation to those of P. M. T. Zaal & Pool (2014); Bergeron et al. (1971); Mitchell et al. (1990). A more realistic approach would be to use a pursuit display. That is a display resembling an attitude indicator, with a reference point, the target given as an ILS indicator along with the aircraft’s output. However, with the current known and accepted identification procedure this is not possible for a case with motion. There are a maximum two forcing functions per axis, so three operator response functions cannot be identified, which is needed for pursuit with motion. Identification is only possible for the dual axis case, as a maximum of 8 operator describing functions can be identified. However Single/Dual comparison with a pursuit display can only be done without motion. The identification limitations restrict the comparison of single/dual with motion to only compensatory displays.

Unfortunately, a downside of using a compensatory display with motion is that the visually presented error would not correspond to the physically felt controlled element output, as the motion is based on the controlled element output \( m(t) \) and not on the visually presented \( e(t) \). Nevertheless, compensatory tracking tasks have an advantage in that there are elaborate agreed upon developed models to describe the resulting human operator response namely; McRuer’s crossover model (McRuer & Jex, 1967).

Motoric crossfeed in a dual-axis task, can be heavily influenced by the the way in which the manipulator stick is set. If the manipulator base is circular, then the maximum deflection possible at 45° angle would be only \( \sqrt{2}/2 \) of the maximum value. For all deflections to be possible at all stances, the manipulator base should be a square. The independent motoric...
control authority of a two-axis stick is illustrated in Figure F-3. Note the maximum deflection from the vertical is $15^\circ$ for the current experiment with a square manipulator base.

### F-1-2 Perceived inputs

As this experiment considers a compensatory display, the human perceives an error on the display. Extra modes of input such as motion and peripheral inputs can be considered. For peripheral inputs, it is challenging to present a peripheral display that acts for two axis. A peripheral display is known to work only for single-axis tracking. Furthermore, motion cues affect performance more than a peripheral display (Pool et al., 2008).

An elaborate study (Vaart, 1992) has found that adding motion for single axis, compensatory systems with double integrator controlled element dynamics, increases tracking performance. Moreover, (Pool et al., 2008) verifies this result for when using different forcing functions. Two main clusters of tracking tasks related to forcing functions were investigated: disturbance rejection and target following. It was found that motion increases the crossover frequency of disturbance rejection tasks, whereas only slightly decreases the crossover frequency of target following tasks. The phase margin of target following tasks showed a significant increase whereas that of the disturbance rejection task remained constant. Interestingly, the visual time delay for all forcing function types have decreased. Concluding that for the single axis case, motion improves performance.
For the dual-axis case it has been shown that the use of motion improved performance by decreasing the error variance to about a half of its original value, this already at only 25% of the full motion output (Bergeron, 1970). It has also been found that with the addition of motion, the time variability of the human pilot parameters decreased (Bergeron et al., 1971). With motion for dual axis, performance improves, brings the experiment closer to a realistic situation and the investigation by Bergeron et al. (1971) suggests that pilot intermittent behavior may decrease with the presence of motion. Therefore to investigate the effect of motion on dual axis phenomena (performance degradation, axis asymmetry, crossfeed and intermittency) is of interest.

F-1-3 Controlled Element Dynamics

This subsection will elaborate on the nature of the controlled element dynamics, the different possibilities will be discussed. It is important to note that in dual-axis tasks, there are two different controlled elements, which introduces more possibilities in terms of the interaction between the controlled element dynamics in each axis.

On basis of the investigation by Todosiev (1967), the degree and type of controlled element dynamics can effect both the human operator describing function and the crossfeed describing function. A thorough investigation on how cross-coupling affects crossfeed and operator describing functions in dual axis tracking has not been done. Changing the nature of cross-coupling may increase the task difficulty and facilitate a wider range of conditions, however including cross-coupling will add another dimension and complication to the experiment. Adding cross-coupling may obscure the plain difference between single and double axis tracking. To keep the investigation unadulterated, cross-coupling will not be included.

Using different controlled elements in each axis decreases performance by increasing the normalized mean squared error (W. Levison & Elkind, 1967) (Chernikoff et al., 1960). Although W. Levison & Elkind (1967) have not included crossfeed in their model, they have concluded that using different controlled element dynamics in each axis changes the human operator describing functions. This makes sense as the equalization in each axis should be different. However, this implies that not much is known about the structure of the crossfeed response functions when using different controlled element dynamics. Since the aim of this investigation is to examine the difference between single and dual-axis control, looking into using different controlled element dynamics may scatter the focus of this investigation.

In simplified aircraft aileron to roll or elevator to pitch dynamics, there is a smooth transition from single to double integrator dynamics around a characteristic frequency. In the realistic situation, both characteristic frequencies are in practice not identical, but for the purpose of this investigation, they are set equal. Pure double integrator dynamics represent the limit for what a human can manually control, higher orders can not be successfully controlled.

Second order controlled element dynamics as given in Equation F-1 can facilitate changes the in manual control difficulty level by using the break frequency \( \omega_b \) as a variable. Note that \( K \) is the gain of the controlled element.

\[
H_{c\theta}(s) = H_{c\phi} = H_c = \frac{K}{s(s + \omega_b)} \quad (F-1)
\]
At frequencies below the break frequency the controlled element approximates integrator dynamics $\frac{1}{s}$, whereas above the break frequency the controlled element acts as double integrator $\frac{1}{s^2}$. Note the lower the value of $\omega_b$, the greater the frequency range of second order controlled element dynamics. Depending on the value of the controlled element break frequency $\omega_b$ and the open loop cross-over frequency $\omega_c$, the operator will have to adjust their own dynamics to equalize with either gain or lead (McRuer et al., 1965). When lead is to be generated, the pilot has to apprehend the derivative of the signal. The use of motion substantially helps due to the readily available vestibular lead. In a previous investigation with single axis, it is found that decreasing $\omega_b$ will decrease $\omega_c$ and gradually increase both control effort and error variance (Zollner et al., 2010). Indicating that the variable $\omega_b$ can provide a means to adjust task difficulty. Note that when adjusting the break frequency $\omega_b$, the controlled element gain needs to be adjusted to yield approximately equal control authority. The pilot model is affected by the change in break frequency of the controlled element, this is through McRuer et al’s crossover model. The pilot’s crossover frequency is kept constant to $3.25\text{rad/s}$ which is the average crossover frequency for a second order system (McRuer & Jex, 1967) and time delay to 0.25.

Figure F-4 gives a representation of the control output when using the controlled element
gain given in Table F-1. All three controlled elements were tested during the checkout experimentation phase. It was shown that the break frequency $0.2 \text{rad/s}$ was too hard especially for the case with no motion, $10 \text{rad/s}$ was easy and $3 \text{rad/s}$ was not too hard and not too easy. It is very important that the tracking task not be too hard, as the subjects will be more likely to suffer from fatigue effects.

### F-1-4 Forcing Function

Forcing functions are used as a means to excite the human operators control behavior. The design of forcing functions is challenging however, as it is difficult to anticipate the effects of choosing a certain forcing function on human control behavior. Different forcing functions can change the task difficulty and even the nature in which the human performs the control task. Moreover, the design of forcing functions is crucial for identification in the frequency domain, as what is done in this investigation (Dammveld et al., 2010). For the Fourier Coefficient identification method to be possible, the forcing function should be a sum of sinusoids. Previous investigations on the identification of manual control have used the sum of sinusoids as a forcing function (McRuer et al., 1965), (Pool et al., 2008). The general form of a sum of sinusoids is given in Equation F-2.

$$f_i(t) = \sum_{k=1}^{N} A_k \sin(\omega_k t + \phi_k)$$

Each excitation frequency $\omega_k$ is related to an amplitude $A_k$ and a phase $\phi_k$ which all make up the $k^{th}$ sinusoid. When designing a forcing function, all three variables must be tackled. To facilitate accurate pilot identification in the frequency domain, they should satisfy a few requirements (Dammveld et al., 2010):

- The forcing function must be random-appearing, the pilot must think that he/she is controlling a random process to prevent the operator from memorizing parts of the signal, otherwise the forcing function can change the form of the control structure of the operator by introducing feed-forward behavior.

- The forcing function should be stimulating such that the operator does not get bored. This is to ensure relatively constant control strategy and motivation to obtain accurate describing functions.

- The forcing function must have a high signal-to-noise ratio at frequencies of interest, to maximize identification accuracy.

- The forcing function must have a Gaussian magnitude distribution, to obtain describing functions that resemble real-life control behavior as closely as possible.

The signals should not be too easy or predictable as the human should be fully engaged, nevertheless not suffer from fatigue due to high workload. According to McRuer et al. (1965) a sufficiently unpredictable and random forcing function can be designed with at least five excitation frequencies. When a forcing function’s bandwidth increases up to around the crossover
Bandwidth is not the only variable that affects the difficulty of a forcing function. The function should be homogeneous to prevent sudden peaks which cause sudden high-workload instances. That is the forcing function should have a Gaussian magnitude distribution. This is defined by something called a crest factor which is dependent on the choice of the respective phase $\phi_k$ of each of the sinusoids. The crest factor of the resulting signal is given in Equation F-3. The crest factor must be kept to a median value, that is not too high or too low. In the case of Figure F-5, we want to keep the crest factor around 2.3.

\[
C = \frac{|x|_{\text{max}}}{x_{\text{rms}}} \tag{F-3}
\]

Fourier Coefficient identification method poses extra requirements on the forcing function, namely:

- There must be a limited amount of excitation frequencies to prevent the power to be spread out over too many excitation frequencies, causing a lower signal to noise ratio.
- It is preferred that they be equally spaced on a logarithmic scale.
- When identifying multi-channel operator models, each channel needs a forcing function.

Figure F-5: Crest factor histogram for a 1000 randomly generated phases.
For one axis three operator describing functions are defined for a dual axis with motion case. Therefore, the complete control structure results in 6 operator describing functions to be identified, for which 4 independent forcing functions are required. Whereas for the case without motion, 4 operator describing functions are to be identified, implying that only 2 forcing functions are required, the nature of all tasks must not change with respect to the forcing functions applied. Hence a fixed amount of 4 forcing functions will be constantly applied in all situations. For the design of these forcing functions, both axes should be equivalent to avoid inherent asymmetry in the task, hence there are some requirements to be met (Damveld et al., 2010).

- equivalent power
- equivalent bandwidth
- equal variances

The variances of the forcing functions have to be equivalent up to the fourth derivative of the forcing function. This however is physically impossible as the forcing functions in each axis must have different excitation frequencies to maintain accurate identification results. Given the equations F-4 and F-5 for the variance of a sum of sinusoids signal and its derivative, it is not possible to maintain both constant variances with different excitation frequencies and signals with the same power. Therefore what is done instead is to keep the values of the variances close as possible in value.

\[
\sigma^2_{f_k} = \sum_{i=1}^{N} \frac{A_i^2}{2} \quad (F-4)
\]

\[
\sigma^2_{f_k'} = \sum_{i=1}^{N} \omega_i^2 \frac{A_i^2}{2} \quad (F-5)
\]

According to (McRuer & Jex, 1967), with increasing controlled element order, the cross-over frequency decreases. Moreover, the frequency at which crossover regression occurs decreases, making the system more vulnerable to this phenomenon. With the introduction of an axis, issues such as divided attention come into play. This occurrence can introduce extra time delays as verified by the investigations done by (Van Lunteren, 1979) and (W. Levison & Elkind, 1967) who both found an increase of 0.03s. Note, however, that both investigations had separate manipulators for each axis. This, however, is only valid to a situation without motion, as the addition of motion decreases the inherent human time delay (Pool et al., 2008). Using the verbal adjustment rules that were developed for single axis tracking tasks, it can be postulated that with extra inherent human time delay, cross-over regression may occur at an even lower frequencies than normal (Beerens et al., 2009). The first verbal adjustment rule given in Equation F-6 states that the input forcing function crossover frequency, or bandwidth should be lower than 80% of the pilot-vehicles open loop cross-over frequency. The second verbal adjustment rule of interest is Equation F-7 stating that the phase margin \( \phi_m \) can be related to the operators cross-over frequency \( \omega_c \) and inherent operator time delay \( \tau_e \).
Keeping the phase margin constant, these relations imply that the input forcing function bandwidth should decrease. From relation F-7, with constant phase margin, \( \omega_c \) is inversely proportional to time delay \( \tau_e \). From relation F-6, with decreased \( \omega_c \), there is a decrease in the maximum bandwidth possible without introducing crossover regression effects. However if the cross-over frequency does not change, the phase margin will decrease with a dual axis display.

Changing the bandwidth can facilitate a change in difficulty level of tracking for the human operator, this is verified by (Zollner et al., 2010). The conducted experiment explored two different forcing function bandwidths; 1.5 and 2.5 rad/s. The second bandwidth is on the verge of crossover regression according to (McRuer & Jex, 1967). Interestingly the higher forcing function bandwidth increases both the error variance and control input, the phase margin increased for all controlled element dynamics, indicating a greater required effort, deteriorated performance but improved stability (Zollner et al., 2010) (McRuer et al., 1965). The cross-over frequency increases with increasing forcing function bandwidth as a consequence of the human being an adaptive controller. Hence in experiments that change the forcing function bandwidth, changes in cross-over frequency are not an indication of performance.

The amplitude spectrum determines the power in the signal and the variance of the signal. The amplitude spectrum has a low pass filter shape as given in Equation F-8. The constant \( T_{A1} \) and \( T_{A2} \) are 0.1 and 0.8 respectively. This means that the forcing function input bandwidth is 1.25 rad/s. The gain of the amplitude filter was tuned such that the variance of the target signals is 2.25 deg\(^2\) and of the disturbance 0.1390 deg\(^2\). This is done to replicate the signals used in the investigation by (P. M. T. Zaal & Pool, 2014).

\[
A(k) = \left| \frac{1 + T_{A1} j\omega(k)}{1 + T_{A2} j\omega(k)} \right| \quad (F-8)
\]

In contrast to the forcing functions used by McRuer, which have a rectangular amplitude spectrum shape, this type of low pass filter spectrum is used. This is because when using motion, what is used as input for motion cueing is the acceleration or second order derivative of the resulting controlled element output. If we consider both a rectangular spectrum and a low pass filter spectrum with the same resulting variance and power, to illustrate the second order derivative, both are multiplied by \( s^2 \). At high frequencies, the amplitude of the acceleration of the rectangular forcing function is much higher than that of the low pass filter, creating larger motion deflections at higher frequencies which is unnatural. The acceleration spectrum of the low pass filter is similar to that of the Dryden spectrum which is very realistic for a disturbance signal as it replicates turbulence. The Amplitude spectrum of the resulting forcing functions designed to adhere to an appropriate crest factor and set variances is given F-6. The forcing functions are not only designed at different excitation frequencies, the frequencies are chosen such no two frequencies are subsequently next to each other. This is done to avoid obscuring the noise, especially at low frequencies. The forcing functions used in the experiment for the
Figure F-6: The amplitude spectrum of all four forcing function signals

roll and pitch axis are given in tables R-19 and F-3 respectively. These forcing functions are tailored for second order controlled element dynamics with a break frequency of 3 rad/s.
F-1 Task variables

<table>
<thead>
<tr>
<th>disturbance, $f_d$</th>
<th>target, $f_t$</th>
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<tbody>
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<td>$A_d$, deg</td>
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<tr>
<td>5</td>
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</tr>
<tr>
<td>11</td>
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<td>23</td>
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<td>37</td>
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<tr>
<td>51</td>
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</tr>
<tr>
<td>71</td>
<td>5.446</td>
</tr>
<tr>
<td>101</td>
<td>7.747</td>
</tr>
<tr>
<td>137</td>
<td>10.508</td>
</tr>
<tr>
<td>171</td>
<td>13.116</td>
</tr>
<tr>
<td>226</td>
<td>17.334</td>
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</tbody>
</table>

Table F-2: Table giving the details of the forcing functions in the roll axis

<table>
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<th>target, $f_t$</th>
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</thead>
<tbody>
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<tr>
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<td>105</td>
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<tr>
<td>172</td>
<td>13.192</td>
</tr>
<tr>
<td>232</td>
<td>17.794</td>
</tr>
</tbody>
</table>

Table F-3: Table giving the details of the forcing functions in the pitch axis
F-2 Concluding remarks

This chapter has touched upon many points, therefore to summarize, the following concluding remarks are made:

- Motion is used for the purpose of bringing the experiment closer to reality and analyzing how motion may affect the differences between single and dual axis manual control behavior.

- The display used is a compensatory display due to the identification limitations when motion is used. Moreover this display is identical to the previously done experiment by (P. M. T. Zaal & Pool, 2014), making it in line with previous investigations.

- Although changing the forcing function bandwidth would facilitate change in the task difficulty, there is a risk that it could lead to crossover regression, as this phenomenon is more likely to occur at earlier frequencies with dual axis tracking.

- Due to the nature of dual axis tasks having two controlled element dynamics, it is possible to introduce controlled element crosscouplings, be symmetric or assymetric. However this will complicate the analysis of the data and even obscure the plain differences between single and dual axis manual control behavior, therefore crosscoupling, although it is realistic and present in aircraft, should be left to another investigation.

- Although changing the second order controlled element break frequency facilitates a change in task difficulty, it would introduce too many independent variables. The results of the checkout experimentation phase has shown that a fixed controlled element break frequency of $3\,\text{rad/s}$ shows a distinction between single and dual axis manual control, however does not induce fatigue without motion.
Figure F-7: Tree summarizing the possible experimental factors for dual-axis tracking tasks
Appendix G

Experiment Proposal

With dual axis manual control behavior classically being modelled as two independent single-axis controllers, the main goal of this study is to investigate whether this customary modelling practice is valid. To achieve this goal, the differences between single and dual-axis manual control behavior are analyzed to establish the additional phenomenon possibly being overlooked. This investigation is performed with and without motion, which is done both to simulate a situation that is closer to reality and also to analyze experimental evidence showing that motion may affect the differences between single and dual-axis control behavior. The experiment consists of 6 experimental conditions, containing two factors namely motion and the axis type. This experimental proposal consists of two main sections; the experiment itself and the hypothesis to be tested.

G-1 Experiment

This section will describe the conditions tested and the reasoning behind their choice. Moreover the apparatus used to perform the experiment is explained, the type of forcing function used is explained and the experimental procedure is elaborated.

G-1-1 Conditions

To investigate the differences between single and dual axis manual control, both the number of axes and the presence of motion feedback will be varied during the experiment. This means that there are two independent variables. To satisfy the current identification limitations and to stay in line with previous researchers (P. M. T. Zaal & Pool, 2014) three different axes settings are to be presented. That is single axis roll, single axis pitch and an integrated dual axis case as illustrated in Figure F-2 in the previous chapter. The integrated display is equal to that used in (P. M. T. Zaal & Pool, 2014).

The motion component is introduced for two main reasons; it has been found that it not only improves performance due to the readily available vestibular lead (Pool et al., 2008) (Fourquet,
1989), it also reduces the time-variability of the identified human parameters (Bergeron, 1970). Moreover motion brings the control task closer to reality. To make the experiment more realistic, the next step would be to include controlled element crosscoupling, however, this investigation aims to extract the fundamental differences between single and dual axis control, which will be obscured if cross-coupling is included. The total amount of conditions are six, as illustrated in Figure G-1.

![Figure G-1: Overview illustrating the different conditions to be tested](image)

### G-1-2 Apparatus

The experiment will be performed in the SIMONA Research Simulator. The hydraulic six-degree of freedom hexapod motion system, will be used to give the pilot pitch and roll motion cues. Such that the pilot is not disturbed by the noise made by the hydraulic system, they will wear noise-canceling headphones. The motion simulator has a delay of 30ms. The right pilot seat in the simulator is used and a Moog FCS Ecol-8000 electrical sidestick for giving pitch and roll control inputs. The characteristics of this control loaded manipulator is adjusted such that there is a linear force-displacement characteristic with a stiffness of 1.5 N/deg with no added mass, damping, or breakout force. For both axes, the input can be given in an independent manner, such that giving an input in one axis will not affect the output of the other axis. The maximum manipulator deflection is $\pm 15^\circ$ and the manipulator gains are set to 0.08, for each axis.

### G-1-3 Forcing Functions

The forcing functions will consist of sums-of-sinusoids. To successfully identify frequency components of each axis separately, the excitation frequencies in each axis are set differently. The task is both a target following and disturbance rejection task, however the variance of the disturbance is designed to be only 25% of that of the target. Due to the display being a compensatory display, meaning that the illustrated visual signal is an error, the predictability of the signal will not be a problem. The forcing functions used in the experiment for the roll and pitch axis are given in tables R-19 and F-3 respectively.
Twelve subjects will participate in the experiment. They will be instructed to minimize the presented error as good as they can. For each condition, each subject will be trained until a stable performance is reached. After which, five runs are recorded. The experiment is 90 seconds per run, of which, the first 8 seconds are taken as run-in time. For a single subject including breaks, the experiment will take approximately 3 hours.

G-2 Hypothesis

Since knowledge on dual axis phenomena is still limited, firstly the basic hypothesis is tested. The following hypotheses are formulated based on the literature survey:

- The performance degrades in dual-axis tasks.
  - The error variance increases in dual axis
  - The crossover frequency decreases in dual axis
  - The phase margin decreases in dual axis
- Pitch/Roll human behavior is not identical.
  - Pitch/Roll error variance are consistently different
  - Pitch/Roll crossover frequency are consistently different
  - Pitch/Roll phase margin are consistently different
  - Pitch/Roll Modeling parameters are consistently different
- Crossfeed is present in dual-axis manual control behavior.
- Intermittent behavior present in dual axis is mitigated with motion.
  - The VAF increases with motion
- Performance degradation in dual axis is mitigated with motion.
  - Error variance decreases with motion
  - Phase margin increases with motion

The first hypothesis can be verified by comparing the error variance, crossover frequency and phase margin of both single and dual-axis control. If the differences are significant, it proves that indeed performance does degrade in dual-axis tasks. It may be the case, however, that not all of the three metrics show a significant effect. Nevertheless if any one of the three does show a significant effect it means that the hypothesis is proved.

The second hypothesis can be tested by two main ways. Comparing the performance metrics in pitch and roll separately and see how they differ and comparing the estimated parameters of both axis. It is expected that the asymmetry stems from either the difference in how the error is illustrated for each axis, or that the humans response is different in each axis.
The third hypothesis can be verified using the tailored Fourier Coefficient method that was developed to detect frequency components coming from the adjacent axis. Moreover, the spectral error variance and control variance can also indicate whether there are components coming from the adjacent axis. This can serve as immediate evidence for crossfeed.

The fourth and fifth hypotheses are based on the study by Bergeon et al. The intermittent component of dual axis tracking can be found by comparing the linear time invariant single axis responses to the dual axis response. Since the target forcing function is kept constant, it is interesting to see how the linearity of the behavior may change when involving another axis. If crossfeed is present, it may although, be challenging to discretely identify intermittency aswell. Nevertheless, the fourth hypothesis can be tested using the VAF and a time domain comparison of peaks. The fifth hypothesis can be tested by comparing the performance measures with and without motion.
Appendix H

Experimental checkout

This appendix gives a summary of the experimental checkout results and reasoning for why certain conditions were taken through to the actual experimentation phase. The experimental checkout reviewed 18 conditions as given in Table 1. The purpose of the checkout experiment are twofold; to setup the data processing code and to choose the most suitable controlled element dynamics.

The initial phase of this investigation has chosen the controlled element break frequencies $0.2\text{rad/s}$ and $10\text{rad/s}$. The reason for the latter is to achieve effective second order controlled element dynamics in the frequency band being controlled and to be in line with the previous investigation by (P. M. T. Zaal & Pool, 2014). The controlled element break frequency $10\text{rad/s}$ was chosen as an easier controlled element as the system would effectively be a single integrator in the frequency range being controlled. The slope of the forcing function starts the decrease at $1.2\text{rad/s}$ and levels at around $10\text{rad/s}$, this means that a controlled element break frequency of $3\text{rad/s}$ will make part of the dynamics second order, however most will be of first order dynamics, as the crossover frequency is usually around $3\text{rad/s}$. This extra controlled element break frequency was added to provide as an intermediary between the two (relatively) extreme controlled element dynamics. Note that in the plots the first letter stands

<table>
<thead>
<tr>
<th>Controlled Element $\omega_b$</th>
<th>Axis Type</th>
<th>Motion</th>
<th>No Motion</th>
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<tbody>
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<td>pitch</td>
<td>C1</td>
<td>C2</td>
</tr>
<tr>
<td>0.2</td>
<td>roll</td>
<td>C3</td>
<td>C5</td>
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<td>C6</td>
<td>C7</td>
</tr>
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<td>3</td>
<td>pitch</td>
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<td>C9</td>
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<td>C10</td>
<td>C11</td>
</tr>
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<td>C12</td>
<td>C13</td>
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<tr>
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<td>C17</td>
<td>C18</td>
</tr>
</tbody>
</table>

Table H-1: Conditions tested in the checkout experiment
for the axis, be it P - pitch or R- roll, the second letter stands for the controlled element break frequency, it can be H - high 10rad/s, M- med 3rad/s and L- low 0.2rad/s.

H-1 Results and analysis

The relevant metrics chosen to analyze the checkout results and thereby to decide upon the final break frequency are the error variance, control variance, crossover frequency and coherence. Note that the coherence is calculated by using the average of the taken five runs and not using double frequency bands.

The error variance plot with motion is figure H-1 shows that there is a general increase in error with a decrease in controlled element break frequency $\omega_B$. Moreover, the error of roll is larger than that of pitch. This may stem from both prioritization and the way that the error is presented on the screen. The dual axis case generally has a worse performance than the single axis case as is expected, the only exception is for the 0.2rad/s pitch. This is due to the presentation of conditions.

Unfortunately, the error variance plot without motion in figure H-2, shows that the error goes out of order for the dual axis roll at 0.2rad/s. Without the available vestibular lead, it seems to be very hard to control this task. In fact this type of condition was not tested before, therefore it may be too hard and possibly induce fatigue, like the subject has subjectively stated. This drastic increase in error is complemented with a drastic increase in control variance. The case without motion, shows a control variance that is double the amount of with motion in Figures H-4 and H-3 respectively.

The Figures H-5 and H-6 illustrating the crossover frequency show an interesting result, namely that the crossover frequency for the 0.2rad/s break frequency roll axis shows a higher value than that for pitch. This result can only be explained by the order of conditions presented. Apart from this result the only other significant pattern to be seen is a decrease in crossover frequency with dual axis. Moreover, the added motion seems to homogenize the crossover frequencies between axes.

The coherence metric could give an indication of intermittent behaviour present. Unfortunately, the coherence does not seem to give any visible pattern or difference between the different controlled element break frequencies.

Summarizing; the purpose of this analysis was to choose a break frequency. It is clear from the error variance and control variance that the break frequency of 0.2rad/s seems to be too difficult, especially in the absence of motion. This is reflected by the large errors and the distinctly large control variance for all the runs with that break frequency. This leaves us with either 10rad/s or 3rad/s. The break frequency of 10rad/s has shown that it is easy to control, whereas the intermediary break frequency was more challenging. These results are also backed by the subjective opinion of the subject. Therefore the chosen break frequency for the final experiment is 3rad/s.
Figure H-1: Error variance values with motion

Figure H-2: Error variance values without motion
Figure H-3: Control variance values with motion

Figure H-4: Control variance values without motion
Investigating the Difference Between Single and Dual Axis Manual Control

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Experimental checkout

Figure H-7: Coherence values for pitch axis

Figure H-8: Coherence values for roll axis

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Investigating the Difference Between Single and Dual Axis Manual Control
Part III

Experiment
Once agreeing to participate in the experiment, subjects received a briefing that includes instructions for the experiment. It gives a short goal of the experiment, the task at hand, the hardware used, experimental conditions tested and the procedures. The experimental briefing is given in the coming page.
Human Manual control behaviour is commonly modeled using McRuer’s crossover model. This model was developed for single axis tracking tasks, which are tasks with only one variable or degree of freedom to track. However, most practical tracking tasks, such as a landing an airplane using an attitude indicator (which illustrates both roll and pitch attitudes), are dual-axis tracking tasks. Here, the pilot has to track two signals or variables simultaneously. Therefore, as a first step to properly model dual axis manual control; the aim of this study is to investigate the differences, if any, between single and dual axis manual control.

The experiment will be performed in the SIMONA Research Simulator. Your assignment will be to actively minimize the aircraft roll and/or pitch errors in a combined target-following and disturbance rejection task. The experiment consists of six conditions; the controlled axes being a factor with three levels and motion being another factor with two levels (on and off). The displays used are given in Fig. I-1 and each illustrate a different tested controlled axes setting.

Figure I-1: The three displays used

In the experiment you will control the roll and or pitch attitude with a sidestick from the right pilot seat in the simulator cab. Roll is controlled by left-right movements, and pitch is controlled by fore-aft stick movements. The display is positioned in front of you. Your main objective is to keep the errors on the display as close to zero as possible. Two scores are calculated after each run to indicate your performance in roll and pitch, respectively. A lower score indicates a better performance.

At the start of the experiment, you will be allowed to familiarize yourself with the task. After that, each condition will be trained until a constant level of performance is observed by your experiment supervisor. You will be notified of your scores after each run. During the training phase, your goal should be to constantly attempt to improve your score. Finally, the measurement runs will be performed, where each condition is repeated five times. The order of presentation of the six experimental conditions is random. It is important to adopt a consistent control strategy throughout the experiment once the training runs are completed. Each experiment run takes 90 seconds to complete.

Breaks will be taken regularly to alleviate any discomfort that might occur after sitting in a fixed position for a prolonged period of time. The total duration of the experiment is approximately three hours, including breaks.

Thank you for participating!
When conducting human-in-the-loop experiments, one confounding factor may be the order in which the conditions are presented. Therefore to get rid of this possible confound, the conditions are presented to each subject differently, such that if there is an effect, it is canceled out through the changing order of presentation. These orders were such that each condition was performed first, second, third, fourth, fifth and sixth once in each group of six subjects. This is called a balanced Latin-square design of the experimental conditions. The order of the conditions for all twelve subjects is given in Table J-1. Note that Subject 8 was taken out due to motion sickness and substituted by Subject 13. There were two different groups of participants tested; pilots and non-pilot good manual controllers (people who are also good in gaming), which are indicted in Table J-1 as P and NP respectively. Roll, Pitch and Dual axis are denoted by R, P and D respectively. Whereas Motion and No Motion are denoted by the sub-scripted M and NM respectively.
Table J-1: Balanced Latin Square Design

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Part IV

Data Analysis
This chapter gives an overview of the distributed control variance separated for pilot and non-pilot. Each participant group has completed their own latin square, therefore an ANOVA can be performed to test for the between subject significance in section R. Although the results of the ANOVA show no significant effect, the plots are still presented to see visual differences. First the error variance is presented in Fig K-1 and K-2, after which the control variance is illustrated and K-4. It can be seen that the pilot error variance is less than the non pilot error variance on average. Moreover the difference between single and dual axis seems more distinct for non-pilots than for pilots. Moreover, off-axis contributions are only present for dual axis cases which is clearly visible by the green bands. Nevertheless, the increase in dual axis comes mainly from an increase in remnant noise. The roll axis has much higher error than that of pitch and the addition of motion decreases error, thereby improving performance.

On average it seems that the non pilot subjects use less control variance for dual axis case, this is intuitive as the more axes you have, the less effort you spend per axis, as the effort is being distributed to a certain extent. Due to the fact that pilots are used to performing multi-axis tasks, here we can see larger control variance for dual axis. However this difference is not significant. Possibly if the controlled element is more challenging, the differences between single and dual axis will be significant for both pilot and non pilot, thereby also creating a between subjects effect. For the pitch axis, not much can be said, however for roll, it can be said that the remnant contribution increases with dual axis, consequently the pilots response to target decreases which in turn increases the error.
Distributed Variance

Figure K-1: non pilot error variance

Figure K-2: pilot error variance

Figure K-3: non pilot control variance

Figure K-4: pilot control variance

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This section shows the average cumulative variance separated for with and without motion, however grouping all subject groups together as there was no significance found in the ANOVA. For the roll axis, the largest jumps in error variance are made at 0.69 rad/s, 1.22 rad/s and 2.37 rad/s. Whereas for pitch the largest jumps are made at 0.997 rad/s and 2.071 rad/s. The consecutive pitch frequency at 3.145 rad/s does not show a large jump. It can be said that the largest contribution to error is made by frequencies between 0.69 till 2.37 rad/s. Motion does not seem to affect the cumulative error variance. Moreover, although there are jumps in error variance at certain frequencies, this is not done with corresponding jumps in control variance. Rather the changes in control variance are more homogeneous, with exception to the high frequencies. They do not seem to be reacted upon much. However this also comes from the fact that their amplitude in the frequency domain is also much smaller.
Figure L-1: Cumulative error variance plot without motion

Figure L-2: Cumulative error variance plot with motion

Figure L-3: Cumulative control variance plot without motion

Figure L-4: Cumulative control variance plot with motion

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The crossover frequency gives an indication of how well the operator can track the target signal (target crossover frequency). Moreover, the phase margin gives an indication of stable the system is. For pilots, we do not see a consistent increase or decrease for dual axis. However, for non-pilot subjects there is a clear decrease in crossover frequency. It can mean that due to the expertise level of the pilots, their performance does not seem to degrade. The crossover frequency for pitch is consistently higher than for roll for both subject groups. As a consequence, similar patterns are observed for the phase margin. Not much change exists for pilots, however, for non-pilots, there is a clear decrease in phase margin for dual axis. Moreover, the pitch axis has a larger phase margin than that of roll.
Figure M-1: pilot crossover frequency

Figure M-2: nonpilot crossover frequency

Figure M-3: pilot Phase Margin

Figure M-4: nonpilot Phase Margin

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Appendix N

Relative Crossover Frequency

The relative crossover frequency is the dual axis crossover frequency divided by the corresponding single axis crossover frequency. It can be seen that except for subject 11 and 12, dual axis crossover frequency degrades for at least one axis. For the non-pilots, more subjects degrade in both axis, whereas for pilots, the degradation is more commonly only in one axis. As the spread seems quite large, a single degradation factor can not be deduced. The degradation or change in crossover frequency changes from person to person.
Relative Crossover Frequency

Figure N-1: Relative pilot crossover frequency **without motion**

Figure N-2: Relative pilot crossover frequency **with motion**

Figure N-3: Relative non pilot crossover frequency **without motion**

Figure N-4: Relative non pilot crossover frequency **with motion**
The relative error variance is the error variance of dual-axis divided by the error variance of single axis. This has been done for both pilot and non-pilot subjects. It can be seen that the ratio for roll is worse than for pitch for both pilot and non-pilot. Although the pilot relative error variance seems slightly lower, there is no significant subject group affect.
Figure O-1: Relative pilot error variance

Figure O-2: Relative nonpilot error variance
Appendix P

Crossfeed Contribution plots

This section illustrates the absolute value of motoric single axis crossfeed as given in P-1 and that of the modelled dual axis crossfeed relative contribution in P-2. It can be seen that there is consistently more roll axis motoric and dual axis roll modelled crossfeed, in comparison to pitch crossfeed. However, the difference between roll and pitch is much larger for the modelled dual axis crossfeed. The reason for such differences is most likely hand geometry and hand force axis asymmetry.
Figure P-1: Motoric crossfeed control variance addition

Figure P-2: Relative control contribution of the Visual, Vestibular and Crossfeed transfer blocks
Peak time is defined as the time the operator participates in unaccounted for peaks. Meaning that the peaks are not part of the model. A peak is defined as a modelling error that is larger than two standard deviations of the the corresponding single axis modelling error. In figure Q-1, it can be seen that the peak time is larger for roll dual axis than for the pitch single axis. Indicating more non-linear behaviour in roll. To give a deeper insight into the peak time analysis, the total number of peak instances for all subjects is given in Figs. Q-2 & Q-3 respectively. If there are clear instances at which many peaks occur, a pattern is detected, meaning the peaks have a strong correlation with the forcing function. However this is clearly not the case.

Figure Q-1: Peak time
Figure Q-2: peak instances for roll axis over full time $T$ for all subjects
Figure Q-3: peak instances for pitch axis over full time T for all subjects
120

Peak Time Analysis

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Investigating the Difference Between Single and Dual Axis Manual Control
The Analysis of Variance (ANOVA) can tell which metrics show a statistically significant result. The type of ANOVA analysis that is to be tested at hand is both a three-way mixed (split-plot) ANOVA and a three way repeated measures ANOVA. The first ANOVA is to test for between subjects effects. Since between subjects ANOVA was found to be not significant a repeated measures ANOVA is also performed. Firstly, the underlying assumptions for a (mixed) ANOVA are stated:

- The dependent variable is measured at a continuous level (i.e., they are either interval or ratio variables).
- The within-subjects factors should consist of at least two related groups, meaning that the same subjects have tested each factor.
- The between-subjects factor has to consist of at least two independent groups.
- There should be no significant outliers in the between Subjects or within subjects groups.
- The dependent variables should be approximately normally distributed for each combination of group and factor. This can be done using a Shapiro-Wilk normality test.
- For between subjects, there needs to be a homogeneity of variances for each combination of the groups and factors. This can be tested using Levene’s test of homogeneity of variances.
- The sphericity, that is the variances of the differences between the related groups of within and between subjects factors must be equal. This can be tested using Mauchly’s test of sphericity.

It can be said that the first 4 assumptions are already met. Both the normality and homogeneity of variances of each set of data is can be tested, whereas the sphericity can not be tested as there is only 2 levels within each factor.
R-1  Between Subjects Tests

The between subjects ANOVA is mixed as the group of 12 subjects are split in terms of being a pilot or not. Hence there is a between subject effect being whether or not the Subjects are a pilot.

R-1-1  Normality Test for Performance and Modeling Metrics

Table R-1: Shapiro Wilk’s test of Normality for performance metrics

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Table R-2: Shapiro Wilk’s test of Normality for Visual operator response parameters

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Table R-3: Shapiro Wilk’s test of Normality for motion operator response parameters

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<tr>
<th>Factors</th>
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<th>$K_m$</th>
<th>$\tau_m$</th>
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</thead>
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<td>PitchSingle</td>
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<td>Non Pilot</td>
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<td>Pilot</td>
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Table R-4: Shapiro Wilk’s test of Normality for crossfeed operator response parameters

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<th>$T_{lc}$</th>
<th>$\omega_{nm_c}$</th>
<th>$\zeta_{nm_c}$</th>
<th>$\tau_c$</th>
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<tr>
<td>PitchMotion</td>
<td>Non Pilot</td>
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<td>0.553</td>
<td>0.313</td>
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<td>0.251</td>
<td>0.897</td>
<td>0.858</td>
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<td>RollMotion</td>
<td>Non Pilot</td>
<td>0.248</td>
<td>0.739</td>
<td>0.237</td>
<td>0.500</td>
<td>0.860</td>
</tr>
<tr>
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<td>Pilot</td>
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<td>0.727</td>
<td>0.605</td>
<td>0.943</td>
<td>0.326</td>
</tr>
<tr>
<td>PitchNoMotion</td>
<td>Non Pilot</td>
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<td>0.417</td>
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<tr>
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<td>0.668</td>
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R-1-2 Levene’s Equality of Variances Test for Performance and Modeling Metrics

Table R-5: Levene’s Equality of Variances

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<th>σ²c</th>
<th>σ²u</th>
<th>VAF</th>
<th>σme</th>
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<td></td>
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<td>0.549</td>
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<td>0.123</td>
<td>0.238</td>
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<td>Motion</td>
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<td></td>
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<td>0.689</td>
<td>0.011</td>
<td>0.892</td>
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<td>Motion</td>
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Table R-6: Levene’s Equality of Variances

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<th>Kv</th>
<th>Tw</th>
<th>ωnm</th>
<th>ζnm</th>
<th>τv</th>
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<td>0.440</td>
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<td></td>
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<td>0.521</td>
<td>0.492</td>
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<td>Motion</td>
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<td></td>
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<td>0.651</td>
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<td>0.045</td>
<td>0.127</td>
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<td>Motion</td>
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<td>0.079</td>
<td>0.852</td>
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<td>Motion</td>
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<td>0.081</td>
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<td>Motion</td>
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Table R-7: Levene’s Equality of Variances

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Table R-8: Levene’s Equality of Variances

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<th>Tl</th>
<th>ωnm</th>
<th>ζnm</th>
<th>τc</th>
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<td>0.088</td>
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<td>Motion</td>
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<td>0.237</td>
<td>0.336</td>
<td>0.09</td>
<td>0.889</td>
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<td>0.791</td>
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<td>Motion</td>
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<td>0.012</td>
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S. Barendswaard Investigating the Difference Between Single and Dual Axis Manual Control
### R-1-3 ANOVA

#### Table R-9: ANOVA for factors and group interaction

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<th>Axis Dim * G</th>
<th>Motion</th>
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<td>7.18</td>
<td>0.032</td>
<td>1</td>
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<td>0.002</td>
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<tr>
<td>$\tau$</td>
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<td>4.14</td>
<td>0.004</td>
<td>1</td>
<td>9.44</td>
<td>0.001</td>
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<td>4.14</td>
<td>0.004</td>
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<td>9.44</td>
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<td>$\rho_{\text{error}}$</td>
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<td>0.004</td>
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#### Table R-10: ANOVA for interaction between two factors and group interaction

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<td>F</td>
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</tr>
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<td>0.913</td>
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<tr>
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</table>

S. Barendswaard
Table R-11: ANOVA for interaction between three factors and group interaction

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<th>Type<em>Dim</em>Motion*G</th>
<th>Group</th>
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<td>1</td>
<td>0.335</td>
<td>0.57</td>
</tr>
<tr>
<td>$\phi_m$</td>
<td>1</td>
<td>2.07</td>
<td>0.180</td>
</tr>
<tr>
<td>$\sigma_c^2$</td>
<td>1</td>
<td>1.689</td>
<td>0.223</td>
</tr>
<tr>
<td>$\sigma_y^2$</td>
<td>1</td>
<td>0.487</td>
<td>0.501</td>
</tr>
<tr>
<td>VAF</td>
<td>1</td>
<td>0.068</td>
<td>0.799</td>
</tr>
<tr>
<td>$\sigma_{peak}$</td>
<td>1</td>
<td>0.029</td>
<td>0.868</td>
</tr>
<tr>
<td>$K_v$</td>
<td>1</td>
<td>91.213</td>
<td><strong>0.000</strong></td>
</tr>
<tr>
<td>$T_{Iv}$</td>
<td>1</td>
<td>0.686</td>
<td>0.427</td>
</tr>
<tr>
<td>$\tau_v$</td>
<td>1</td>
<td>0.254</td>
<td>0.625</td>
</tr>
<tr>
<td>$\omega_{nm}$</td>
<td>1</td>
<td>0.718</td>
<td>0.417</td>
</tr>
<tr>
<td>$\zeta_{nm}$</td>
<td>1</td>
<td>5.176</td>
<td>0.049</td>
</tr>
<tr>
<td>$K_m$</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\tau_m$</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$K_c$</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$T_{Ic}$</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\omega_{nmC}$</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\zeta_{nmC}$</td>
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</tr>
<tr>
<td>$\tau_c$</td>
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</tr>
</tbody>
</table>
R-2 Within Subjects Tests

Since the between subjects ANOVA has shown that the between subjects factor has no significant effect, the ANOVA is repeated as a repeated measures within subject experimental design. Note that for the within subjects tests, there is no need for Levene’s equality of variances test.

R-2-1 Normality Test for Performance and Modeling Metrics

Table R-12: Shapiro Wilk’s test of Normality for distributed error variance metrics

<table>
<thead>
<tr>
<th>Factors</th>
<th>$\sigma^2_{e_{na}}$</th>
<th>$\sigma^2_{e_{lv}}$</th>
<th>$\sigma^2_{e_{ld}}$</th>
<th>$\sigma^2_{e_{ldo}}$</th>
<th>$\sigma^2_{e_{ldo}}$</th>
<th>$\sigma^2_{e_{ldo}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PitchSingleNoMotion</td>
<td>0.034</td>
<td>0.002</td>
<td>0.267</td>
<td>0.003</td>
<td>0.001</td>
<td>0.000</td>
</tr>
<tr>
<td>PitchDualNoMotion</td>
<td>0.426</td>
<td>0.377</td>
<td>0.368</td>
<td>0.164</td>
<td>0.283</td>
<td>0.070</td>
</tr>
<tr>
<td>PitchSingleMotion</td>
<td>0.434</td>
<td>0.340</td>
<td>0.095</td>
<td>0.409</td>
<td>0.002</td>
<td>0.010</td>
</tr>
<tr>
<td>PitchDualMotion</td>
<td>0.301</td>
<td>0.773</td>
<td>0.567</td>
<td>0.112</td>
<td>0.002</td>
<td>0.735</td>
</tr>
<tr>
<td>RollSingleNoMotion</td>
<td>0.542</td>
<td>0.068</td>
<td>0.696</td>
<td>0.201</td>
<td>0.110</td>
<td>0.068</td>
</tr>
<tr>
<td>RollDualNoMotion</td>
<td>0.238</td>
<td>0.072</td>
<td>0.287</td>
<td>0.197</td>
<td>0.541</td>
<td>0.043</td>
</tr>
<tr>
<td>RollSingleMotion</td>
<td>0.330</td>
<td>0.388</td>
<td>0.357</td>
<td>0.002</td>
<td>0.695</td>
<td>0.817</td>
</tr>
<tr>
<td>RollDualMotion</td>
<td>0.325</td>
<td>0.001</td>
<td>0.081</td>
<td>0.000</td>
<td>0.000</td>
<td>0.197</td>
</tr>
</tbody>
</table>

Table R-13: Shapiro Wilk’s test of Normality for distributed control variance metrics

<table>
<thead>
<tr>
<th>Factors</th>
<th>$\sigma^2_{u_{na}}$</th>
<th>$\sigma^2_{u_{lv}}$</th>
<th>$\sigma^2_{u_{ld}}$</th>
<th>$\sigma^2_{u_{ldo}}$</th>
<th>$\sigma^2_{u_{ldo}}$</th>
<th>$\sigma^2_{u_{ldo}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>PitchSingleNoMotion</td>
<td>0.034</td>
<td>0.531</td>
<td>0.967</td>
<td>0.526</td>
<td>0.298</td>
<td>0.148</td>
</tr>
<tr>
<td>PitchDualNoMotion</td>
<td>0.184</td>
<td>0.413</td>
<td>0.376</td>
<td>0.112</td>
<td>0.222</td>
<td>0.316</td>
</tr>
<tr>
<td>PitchSingleMotion</td>
<td>0.434</td>
<td>0.863</td>
<td>0.242</td>
<td>0.040</td>
<td>0.230</td>
<td>0.191</td>
</tr>
<tr>
<td>PitchDualMotion</td>
<td>0.301</td>
<td>0.833</td>
<td>0.984</td>
<td>0.621</td>
<td>0.137</td>
<td>0.358</td>
</tr>
<tr>
<td>RollSingleNoMotion</td>
<td>0.710</td>
<td>0.052</td>
<td>0.067</td>
<td>0.166</td>
<td>0.735</td>
<td>0.006</td>
</tr>
<tr>
<td>RollDualNoMotion</td>
<td>0.228</td>
<td>0.236</td>
<td>0.196</td>
<td>0.179</td>
<td>0.414</td>
<td>0.117</td>
</tr>
<tr>
<td>RollSingleMotion</td>
<td>0.033</td>
<td>0.180</td>
<td>0.970</td>
<td>0.081</td>
<td>0.875</td>
<td>0.102</td>
</tr>
<tr>
<td>RollDualMotion</td>
<td>0.325</td>
<td>0.677</td>
<td>0.356</td>
<td>0.131</td>
<td>0.302</td>
<td>0.312</td>
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Table R-14: Shapiro Wilk’s test of Normality for intermittency metrics

<table>
<thead>
<tr>
<th>Factors</th>
<th>$\text{Peaktime (s)}$</th>
<th>$\text{VAF}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RollSingleNoMotion</td>
<td>0.003</td>
<td>0.001</td>
</tr>
<tr>
<td>RollDualNoMotion</td>
<td>0.027</td>
<td>0.316</td>
</tr>
<tr>
<td>PitchSingleNoMotion</td>
<td>0.000</td>
<td>0.377</td>
</tr>
<tr>
<td>PitchDualNoMotion</td>
<td>0.046</td>
<td>0.796</td>
</tr>
<tr>
<td>RollSingleMotion</td>
<td>0.000</td>
<td>0.096</td>
</tr>
<tr>
<td>RollDualMotion</td>
<td>0.160</td>
<td>0.603</td>
</tr>
<tr>
<td>PitchSingleMotion</td>
<td>0.000</td>
<td>0.003</td>
</tr>
<tr>
<td>PitchDualMotion</td>
<td>0.000</td>
<td>0.047</td>
</tr>
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</table>
## Table R-15: Shapiro Wilk’s test of Normality for performance metrics

<table>
<thead>
<tr>
<th>Factors</th>
<th>$\omega_c$</th>
<th>$\phi_m$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RollSingleNoMotion</td>
<td>0.049</td>
<td>0.196</td>
</tr>
<tr>
<td>RollDualNoMotion</td>
<td>0.881</td>
<td>0.592</td>
</tr>
<tr>
<td>PitchSingleNoMotion</td>
<td>0.369</td>
<td>0.999</td>
</tr>
<tr>
<td>PitchDualNoMotion</td>
<td>0.400</td>
<td>0.348</td>
</tr>
<tr>
<td>RollSingleMotion</td>
<td>0.055</td>
<td>0.136</td>
</tr>
<tr>
<td>RollDualMotion</td>
<td>0.971</td>
<td>0.380</td>
</tr>
<tr>
<td>PitchSingleMotion</td>
<td>0.425</td>
<td>0.232</td>
</tr>
<tr>
<td>PitchDualMotion</td>
<td>0.963</td>
<td>0.632</td>
</tr>
</tbody>
</table>

## Table R-16: Shapiro Wilk’s test of Normality for visual parameters

<table>
<thead>
<tr>
<th>Factors</th>
<th>$K_v$</th>
<th>$T_l$</th>
<th>$\tau_v$</th>
<th>$\omega_{nm}$</th>
<th>$\zeta_{nm}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RollSingleNoMotion</td>
<td>0.979</td>
<td>0.221</td>
<td>0.346</td>
<td>0.986</td>
<td>0.095</td>
</tr>
<tr>
<td>RollDualNoMotion</td>
<td>0.932</td>
<td>0.268</td>
<td>0.944</td>
<td>0.333</td>
<td>0.812</td>
</tr>
<tr>
<td>PitchSingleNoMotion</td>
<td>0.504</td>
<td>0.006</td>
<td>0.101</td>
<td>0.492</td>
<td>0.587</td>
</tr>
<tr>
<td>PitchDualNoMotion</td>
<td>0.131</td>
<td>0.053</td>
<td>0.070</td>
<td>0.566</td>
<td>0.405</td>
</tr>
<tr>
<td>RollSingleMotion</td>
<td>0.215</td>
<td>0.603</td>
<td>0.824</td>
<td>0.050</td>
<td>0.692</td>
</tr>
<tr>
<td>RollDualMotion</td>
<td>0.648</td>
<td>0.222</td>
<td>0.767</td>
<td>0.132</td>
<td>0.771</td>
</tr>
<tr>
<td>PitchSingleMotion</td>
<td>0.076</td>
<td>0.610</td>
<td>0.081</td>
<td>0.297</td>
<td>0.983</td>
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<tr>
<td>PitchDualMotion</td>
<td>0.079</td>
<td>0.277</td>
<td>0.387</td>
<td>0.261</td>
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## Table R-17: Shapiro Wilk’s test of Normality for motion parameters

<table>
<thead>
<tr>
<th>Factors</th>
<th>$K_m$</th>
<th>$\tau_m$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RollSingle</td>
<td>0.145</td>
<td>0.031</td>
</tr>
<tr>
<td>RollDual</td>
<td>0.961</td>
<td>0.302</td>
</tr>
<tr>
<td>PitchSingle</td>
<td>0.289</td>
<td>0.160</td>
</tr>
<tr>
<td>PitchDual</td>
<td>0.018</td>
<td>0.018</td>
</tr>
</tbody>
</table>

## Table R-18: Shapiro Wilk’s test of Normality for crossfeed parameters

<table>
<thead>
<tr>
<th>Factors</th>
<th>$K_c$</th>
<th>$T_{lc}$</th>
<th>$\tau_c$</th>
<th>$\omega_{nm_c}$</th>
<th>$\zeta_{nm_c}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>RollNoMotion</td>
<td>0.336</td>
<td>0.523</td>
<td>0.010</td>
<td>0.013</td>
<td>0.090</td>
</tr>
<tr>
<td>PitchNoMotion</td>
<td>0.276</td>
<td>0.659</td>
<td>0.001</td>
<td>0.144</td>
<td>0.008</td>
</tr>
<tr>
<td>RollMotion</td>
<td>0.354</td>
<td>0.015</td>
<td>0.264</td>
<td>0.005</td>
<td>0.020</td>
</tr>
<tr>
<td>PitchMotion</td>
<td>0.007</td>
<td>0.012</td>
<td>0.046</td>
<td>0.154</td>
<td>0.984</td>
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### Table R-19: ANOVA for factors and group interaction

<table>
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<tr>
<th>Metric</th>
<th>Axis Dim</th>
<th>Axis Type</th>
<th>Motion</th>
<th>Axis Type</th>
<th>Axis Dim</th>
<th>Motion</th>
<th>Axis Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>$σ^2_i$</td>
<td>3.59</td>
<td>0.046</td>
<td>1</td>
<td>9.84</td>
<td>0.012</td>
<td>1</td>
<td>1.24</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>2.257</td>
<td>0.115</td>
<td>1</td>
<td>9.84</td>
<td>0.012</td>
<td>1</td>
<td>1.24</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>26.576</td>
<td>0.000</td>
<td>1</td>
<td>11.39</td>
<td>0.005</td>
<td>1</td>
<td>0.95</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>6.210</td>
<td>0.036</td>
<td>1</td>
<td>4.063</td>
<td>0.069</td>
<td>1</td>
<td>0.004</td>
</tr>
<tr>
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<td>0.044</td>
<td>1</td>
<td>7.11</td>
<td>0.080</td>
<td>1</td>
<td>0.001</td>
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<tr>
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<tr>
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<td>7.710</td>
<td>0.018</td>
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<td>9.85</td>
<td>0.009</td>
<td>1</td>
<td>0.29</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>0.290</td>
<td>0.097</td>
<td>1</td>
<td>24.69</td>
<td>0.050</td>
<td>1</td>
<td>30.09</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>43.33</td>
<td>0.000</td>
<td>1</td>
<td>9.19</td>
<td>0.024</td>
<td>1</td>
<td>0.008</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>6.43</td>
<td>0.028</td>
<td>1</td>
<td>2.46</td>
<td>0.149</td>
<td>1</td>
<td>0.001</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>0.290</td>
<td>0.097</td>
<td>1</td>
<td>24.69</td>
<td>0.050</td>
<td>1</td>
<td>30.09</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>43.33</td>
<td>0.000</td>
<td>1</td>
<td>9.19</td>
<td>0.024</td>
<td>1</td>
<td>0.008</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>6.43</td>
<td>0.028</td>
<td>1</td>
<td>2.46</td>
<td>0.149</td>
<td>1</td>
<td>0.001</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>0.290</td>
<td>0.097</td>
<td>1</td>
<td>24.69</td>
<td>0.050</td>
<td>1</td>
<td>30.09</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>43.33</td>
<td>0.000</td>
<td>1</td>
<td>9.19</td>
<td>0.024</td>
<td>1</td>
<td>0.008</td>
</tr>
<tr>
<td>$σ^2_{i,j}$</td>
<td>6.43</td>
<td>0.028</td>
<td>1</td>
<td>2.46</td>
<td>0.149</td>
<td>1</td>
<td>0.001</td>
</tr>
</tbody>
</table>

*Investigating the Difference Between Single and Dual Axis Manual Control*  
S. Barendswaard
Parameter Estimates

This Chapter gives the illustrations of all the parameter estimates and their corresponding Fourier Coefficients. The method on how the Fourier Coefficients and the parameter estimates are elaborated in Section D

S-1  Subject 1
Figure S-1: Parameter estimate plot of Subject 1, dual axis motion pitch axis

Figure S-2: Parameter estimate plot of Subject 1, dual axis motion roll axis
Figure S-3: Parameter estimate plot of Subject 1, single axis motion pitch axis

Figure S-4: Parameter estimate plot of Subject 1, single axis motion roll axis

Figure S-5: Parameter estimate plot of Subject 1, dual axis no motion pitch axis

Figure S-6: Parameter estimate plot of Subject 1, dual axis no motion roll axis
Figure S-7: Parameter estimate plot of Subject 1, single axis no motion pitch axis

Figure S-8: Parameter estimate plot of Subject 1, single axis no motion roll axis
Figure S-9: Parameter estimate plot of Subject 2, dual axis motion pitch axis
Figure S-10: Parameter estimate plot of Subject 2, dual axis motion roll axis

Figure S-11: Parameter estimate plot of Subject 2, single axis motion pitch axis

Figure S-12: Parameter estimate plot of Subject 2, single axis motion roll axis
Figure S-13: Parameter estimate plot of Subject 2, dual axis no motion pitch axis

Figure S-14: Parameter estimate plot of Subject 2, dual axis no motion roll axis

Figure S-15: Parameter estimate plot of Subject 2, single axis no motion pitch axis

Figure S-16: Parameter estimate plot of Subject 2, single axis no motion roll axis
S-3 Subject 3

Figure S-17: Parameter estimate plot of Subject 3, dual axis motion pitch axis
Figure S-18: Parameter estimate plot of Subject 3, dual axis motion roll axis

Figure S-19: Parameter estimate plot of Subject 3, single axis motion pitch axis

Figure S-20: Parameter estimate plot of Subject 3, single axis motion roll axis
Figure S-21: Parameter estimate plot of Subject 3, dual axis no motion pitch axis

Figure S-22: Parameter estimate plot of Subject 3, dual axis no motion roll axis

Figure S-23: Parameter estimate plot of Subject 3, single axis no motion pitch axis

Figure S-24: Parameter estimate plot of Subject 3, single axis no motion roll axis
Figure S-25: Parameter estimate plot of Subject 4, dual axis motion pitch axis
Figure S-26: Parameter estimate plot of Subject 4, dual axis motion roll axis

Figure S-27: Parameter estimate plot of Subject 4, single axis motion pitch axis

Figure S-28: Parameter estimate plot of Subject 4, single axis motion roll axis
Figure S-29: Parameter estimate plot of Subject 4, dual axis no motion pitch axis

Figure S-30: Parameter estimate plot of Subject 4, dual axis no motion roll axis

Figure S-31: Parameter estimate plot of Subject 4, single axis no motion pitch axis

Figure S-32: Parameter estimate plot of Subject 4, single axis no motion roll axis
S-5  Subject 5

Figure S-33: Parameter estimate plot of Subject 5, dual axis motion pitch axis
Figure S-34: Parameter estimate plot of Subject 5, dual axis motion roll axis

Figure S-35: Parameter estimate plot of Subject 5, single axis motion pitch axis

Figure S-36: Parameter estimate plot of Subject 5, single axis motion roll axis
| Figure S-37: Parameter estimate plot of Subject 5, dual axis no motion pitch axis |
| Figure S-38: Parameter estimate plot of Subject 5, dual axis no motion roll axis |

| Figure S-39: Parameter estimate plot of Subject 5, single axis no motion pitch axis |
| Figure S-40: Parameter estimate plot of Subject 5, single axis no motion roll axis |
Figure S-41: Parameter estimate plot of Subject 6, dual axis motion pitch axis
**Figure S-42:** Parameter estimate plot of Subject 6, dual axis motion roll axis

**Figure S-43:** Parameter estimate plot of Subject 6, single axis motion pitch axis

**Figure S-44:** Parameter estimate plot of Subject 6, single axis motion roll axis
Figure S-45: Parameter estimate plot of Subject 6, dual axis no motion pitch axis

Figure S-46: Parameter estimate plot of Subject 6, dual axis no motion roll axis

Figure S-47: Parameter estimate plot of Subject 6, single axis no motion pitch axis

Figure S-48: Parameter estimate plot of Subject 6, single axis no motion roll axis
Figure S-49: Parameter estimate plot of Subject 7, dual axis motion pitch axis
Figure S-50: Parameter estimate plot of Subject 7, dual axis motion roll axis

Figure S-51: Parameter estimate plot of Subject 7, single axis motion pitch axis

Figure S-52: Parameter estimate plot of Subject 7, single axis motion roll axis
Figure S-53: Parameter estimate plot of Subject 7, dual axis no motion pitch axis

Figure S-54: Parameter estimate plot of Subject 7, dual axis no motion roll axis

Figure S-55: Parameter estimate plot of Subject 7, single axis no motion pitch axis

Figure S-56: Parameter estimate plot of Subject 7, single axis no motion roll axis
Figure S-57: Parameter estimate plot of Subject 9, dual axis motion pitch axis
Figure S-58: Parameter estimate plot of Subject 9, dual axis motion roll axis

Figure S-59: Parameter estimate plot of Subject 9, single axis motion pitch axis

Figure S-60: Parameter estimate plot of Subject 9, single axis motion roll axis
Figure S-61: Parameter estimate plot of Subject 9, dual axis no motion pitch axis

Figure S-62: Parameter estimate plot of Subject 9, dual axis no motion roll axis

Figure S-63: Parameter estimate plot of Subject 9, single axis no motion pitch axis

Figure S-64: Parameter estimate plot of Subject 9, single axis no motion roll axis
S-9  Subject 10

Figure S-65: Parameter estimate plot of Subject 10, dual axis motion pitch axis
Figure S-66: Parameter estimate plot of Subject 10, dual axis motion roll axis

Figure S-67: Parameter estimate plot of Subject 10, single axis motion pitch axis

Figure S-68: Parameter estimate plot of Subject 10, single axis motion roll axis
**Figure S-69**: Parameter estimate plot of Subject 10, dual axis no motion pitch axis

**Figure S-70**: Parameter estimate plot of Subject 10, dual axis no motion roll axis

**Figure S-71**: Parameter estimate plot of Subject 10, single axis no motion pitch axis

**Figure S-72**: Parameter estimate plot of Subject 10, single axis no motion roll axis
Figure S-73: Parameter estimate plot of Subject 11, dual axis motion pitch axis
Figure S-74: Parameter estimate plot of Subject 11, dual axis motion roll axis

Figure S-75: Parameter estimate plot of Subject 11, single axis motion pitch axis

Figure S-76: Parameter estimate plot of Subject 11, single axis motion roll axis
Figure S-77: Parameter estimate plot of Subject 11, dual axis no motion pitch axis

Figure S-78: Parameter estimate plot of Subject 11, dual axis no motion roll axis

Figure S-79: Parameter estimate plot of Subject 11, single axis no motion pitch axis

Figure S-80: Parameter estimate plot of Subject 11, single axis no motion roll axis
S-11  Subject 12

Figure S-81: Parameter estimate plot of Subject 12, dual axis motion pitch axis
Figure S-82: Parameter estimate plot of Subject 12, dual axis motion roll axis

Figure S-83: Parameter estimate plot of Subject 12, single axis motion pitch axis

Figure S-84: Parameter estimate plot of Subject 12, single axis motion roll axis
Figure S-85: Parameter estimate plot of Subject 12, dual axis no motion pitch axis

Figure S-86: Parameter estimate plot of Subject 12, dual axis no motion roll axis

Figure S-87: Parameter estimate plot of Subject 12, single axis no motion pitch axis

Figure S-88: Parameter estimate plot of Subject 12, single axis no motion roll axis
Figure S-89: Parameter estimate plot of Subject 13, dual axis motion pitch axis
Figure S-90: Parameter estimate plot of Subject 13, dual axis motion roll axis

Figure S-91: Parameter estimate plot of Subject 13, single axis motion pitch axis

Figure S-92: Parameter estimate plot of Subject 13, single axis motion roll axis
Figure S-93: Parameter estimate plot of Subject 13, dual axis no motion pitch axis

Figure S-94: Parameter estimate plot of Subject 13, dual axis no motion roll axis

Figure S-95: Parameter estimate plot of Subject 13, single axis no motion pitch axis

Figure S-96: Parameter estimate plot of Subject 13, single axis no motion roll axis
Appendix T

Phase-Plane Plots

This section gives the illustration of the single-axis phase plane plots giving evidence for
motoric crossfeed. The red line gives the least squares best fit of the human operators phase
plane behaviour.

Figure T-1: Phase plane plots without motion for Subject 1

Figure T-2: Phase plane plots with motion for Subject 1

Figure T-3: Phase plane plots without motion for Subject 2

Figure T-4: Phase plane plots with motion for Subject 2
Figure T-5: Phase plane plots without motion for Subject 3

Figure T-6: Phase plane plots with motion for Subject 3

Figure T-7: Phase plane plots without motion for Subject 4

Figure T-8: Phase plane plots with motion for Subject 4

Figure T-9: Phase plane plots without motion for Subject 5

Figure T-10: Phase plane plots with motion for Subject 5

Figure T-11: Phase plane plots without motion for Subject 6

Figure T-12: Phase plane plots with motion for Subject 6
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Figure T-13: Phase plane plots without motion for Subject 7

Figure T-14: Phase plane plots with motion for Subject 7

Figure T-15: Phase plane plots without motion for Subject 9

Figure T-16: Phase plane plots with motion for Subject 9

Figure T-17: Phase plane plots without motion for Subject 10

Figure T-18: Phase plane plots with motion for Subject 10

Figure T-19: Phase plane plots without motion for Subject 11

Figure T-20: Phase plane plots with motion for Subject 11
Figure T-21: Phase plane plots without motion for Subject 12

Figure T-22: Phase plane plots with motion for Subject 12

Figure T-23: Phase plane plots without motion for Subject 13

Figure T-24: Phase plane plots with motion for Subject 13
Single axis Motoric Crossfeed Frequency Response

The single-axis motoric crossfeed response is plotted with the dual axis crossfeed response. The single-axis crossfeed response is obtained by equation U-1. The off axis pilot output (which should be zero) is divided by the principal axis error signal.

\[ H_{c_{\text{single}}} = \frac{U_{\text{offaxis}}(j\omega t)}{E(j\omega)} \]  

(U-1)

The dual-axis crossfeed response is found using the extended Fourier coefficient method, however the dual axis crossfeed response illustrated in this section is modified. It is modified because when a response enters another loop it gets attenuated. Therefore the dual axis crossfeed response is multiplied by the inverse of the openloop of the loop that it contributed to. This is done to facilitate a fair comparison to the single-axis (open-loop) crossfeed, as this response is not affected by any sort of attenuation. For dual axis with motion the correction is given in (U-2), whereas without motion correction is given in (U-3).

\[ H_{c_{\text{dual}}}^* = H_{c_{\text{dual}}}(1 + (H_{p_u} - H_{p_x})H_{\text{sys}}) \]  

(U-2)

\[ H_{c_{\text{dual}}}^* = H_{c_{\text{dual}}}(1 + H_{p_u}H_{\text{sys}}) \]  

(U-3)

It can be seen from the plots, that even with the corrected crossfeed, the dual axis crossfeed has a lower magnitude than that of single axis pure motoric crossfeed. This serves as proof that in dual axis control, there is more than only motoric crossfeed, as there may be perceptual factors that also play a role. It could also mean that the human operator is more careful with their off-axis inputs during dual axis control, as they are aware of the consequences.
Figure U-1: Motoric single axis crossfeed frequency response without motion for Subject 1

Figure U-2: Motoric single axis crossfeed frequency response with motion for Subject 1

Figure U-3: Motoric single axis crossfeed frequency response without motion for Subject 2
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Figure U-4: Motoric single axis crossfeed frequency response with motion for Subject 2
Figure U-5: Motoric single axis crossfeed frequency response without motion for Subject 3

Figure U-6: Motoric single axis crossfeed frequency response with motion for Subject 3

Figure U-7: Motoric single axis crossfeed frequency response without motion for Subject 4
Figure U-8: Motoric single axis crossfeed frequency response with motion for Subject 4

Figure U-9: Motoric single axis crossfeed frequency response without motion for Subject 5

Figure U-10: Motoric single axis crossfeed frequency response with motion for Subject 5
Figure U-11: Motoric single axis crossfeed frequency response without motion for Subject 6

Figure U-12: Motoric single axis crossfeed frequency response with motion for Subject 6

Figure U-13: Motoric single axis crossfeed frequency response without motion for Subject 7
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Figure U-14: Motoric single axis crossfeed frequency response with motion for Subject 7

Figure U-15: Motoric single axis crossfeed frequency response without motion for Subject 9

Figure U-16: Motoric single axis crossfeed frequency response with motion for Subject 9
Figure U-17: Motoric single axis crossfeed frequency response without motion for Subject 10

Figure U-18: Motoric single axis crossfeed frequency response with motion for Subject 10

Figure U-19: Motoric single axis crossfeed frequency response without motion for Subject 11
Figure U-20: Motoric single axis crossfeed frequency response with motion for Subject 11

Figure U-21: Motoric single axis crossfeed frequency response without motion for Subject 12

Figure U-22: Motoric single axis crossfeed frequency response with motion for Subject 12
Single axis Motoric Crossfeed Frequency Response

Figure U-23: Motoric single axis crossfeed frequency response without motion for Subject 13

Figure U-24: Motoric single axis crossfeed frequency response with motion for Subject 13


