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1 Abstract

Bimanual coordination is the activation of two limbs in mutual interaction in order to perform tasks, which range from basic tasks such as lifting boxes to complicated tasks such as playing musical instruments. It has been noted that post-stroke, patients lose significant bimanual coordination ability. Research over the years has examined the neural basis behind bimanual coordination, employing it in rehabilitation programs to bring improvement in the paretic limb. Recently, however, studies have pointed to the inefficiency of present bimanual rehabilitation protocols, calling for more systematic investigation to assess their true value. This study was an initial foray into studying a phenomenon associated with bimanual coordination known as motor irradiation, with the application of system identification and physiological control schemes. Motor irradiation is the phenomenon by which intended unilateral activation of one limb causes involuntary activation of homologous muscles on the opposite limb. Measuring position and torque responses, position disturbances were applied to both hands of healthy subjects who were engaged in a force control task with the right wrist. The study sought to find similar patterns of activation and change in physiological parameters across both the task hand and the dormant hand. Significant change in stiffness of the left (dormant) hand have been found upon activation of the right hand, which provides conclusive evidence of motor irradiation. This study thus concludes that humans simultaneously modulate the impedance of contra-lateral joints, even when only one joint is involved in a task.
2 Introduction

Human beings in everyday movements perform tasks which are actually found to be very complex control strategies, executed by the body, involving interaction between limbs. Bimanual movements, involving the use of two limbs, are highly adaptive and context-dependent [31], with both the end-goal and the approach used to accomplish the goal changing from task to task. These tasks can range from being simple and intuitive (lifting boxes, tying shoelaces) to being highly complex and achievable only through extensive training (sports, dancing, playing music). Tasks may demand similar movement of both limbs (pulling or pushing objects) or discrete roles for each limb (opening cans, tying shoelaces). Across these wide segregations, bimanual tasks remain entirely essential to general activities and the independent functioning of human beings.

Bimanual coordination has been studied extensively since the seminal work of Kelso and colleagues [16], which established bimanual coordination as a unique control trait involving a constraint over two limbs to act simultaneously as a single unit, rather than the independent control of both limbs by the body as two single-limb tasks. Behavioural studies have conducted experiments involving external loads [32, 5] and task constraints [28, 31, 1] on rhythmic bimanual tasks involving both ipsilateral [2, 4, 3] and contralateral [33, 16, 15] limbs to develop important frameworks to describe bimanual activity. It is known that humans are able to perform in-phase and anti-phase tasks, i.e. tasks where similar muscles across both limbs are doing the same thing with 0 deg and 180 deg phase relations respectively, with ease. Rhythmic tasks at other phases are involuntarily attracted to either the in-phase or anti-phase pattern with increase in frequency [30]. This is the dual attractor-basin, the basis for the Dynamic Pattern Theory, which is the primary framework to understanding bimanual rhythmic tasks. Of interest to this study is the other important, but mainly theoretical, framework known as Neural Crosstalk, which hypothesizes neural leakage during the execution of unimanual or bimanual tasks from neural pathways of one limb to pathways connected to the opposite, homologous limb [30]. This neural leakage is said to be the cause for both bimanual activity and difficulties in maintaining complex bimanual patterns [5], but remains largely unproven. Models based on the neural crosstalk theory suggest bimanual interaction through various neural connections of the brain, spinal column and muscles [10, 21, 6], but are largely unsophisticated and limited in scope of application. Neuroscientific imaging based studies have been largely successful in correlating task performance and learning over time with brain activity and changes in brain structure. They have proven that bimanual coordination is not the work of a single brain locus but requires activation and participation from several brain areas [12, 30]. The few control engineering based studies in the field [13, 14] focus on phenomenological modelling, with no specific attention to any physiologically-relevant parameters.

These findings are not merely of academic interest. Stroke and brain lesions are found to detrimentally affect the execution of movement tasks and multi-joint coordination, and disruptions in bimanual coordination ability are another handicap for stroke patients [29, 7]. Since bimanual tasks are integral to healthy living, bi-
manual training and rehabilitation is important for stroke rehabilitation \[23, 22, 37\]. However, it has been noted, in an extensive literature study, that very little is known about the degree and nature of influence that the voluntary or involuntary muscle activation of one side has on its contralateral side. The lack of physiologically interpretable parameterisation and poor understanding of such parameters in bimanual task performance is reflected in the conclusions of stroke rehabilitation studies, which call for a more intelligent manipulation of environmental constraints and conditions in bimanual rehabilitation exercises, as well as a better assessment of the true value of such therapy \[29\], which remains unsatisfactorily verified in present research \[29, 18, 7, 36\].

It is believed that a physiologically-motivated control structure, as opposed to a phenomenologically-motivated control structure, is essential to assess the degree and nature of influence between limbs in bimanual tasks. This study uses a system identification approach based on models of joint impedance \[34, 11, 25\] to test activity in an active hand against a dormant hand during a force task. Evidence for interlimb coupling, and the degree of such coupling, will be explored through static and/or dynamic coupling between the limbs. Static coupling would be seen in lateral cross-over of control settings (i.e. gains and system properties) between the two limbs. Dynamic coupling would be seen in a temporal coupling between variables of the two limbs, to be identified via coherences at the signal level.
3 Methods

3.1 Idea

Bimanual coordination arises from a neural phenomenon of the human body known as motor irradiation - a robust feature by which there is an increase in the excitability of homologous (i.e. same muscle on the other limb) motor pathways when unimanual movements are performed \cite{7}. This coupling of the limbs shall be investigated as static and/or dynamic coupling, as described in Section 2.

This study seeks evidence of motor irradiation with a force task involving just one hand. The varying levels of force demanded of one hand should give rise to motor irradiation in the homologous muscles of the other hand, which would be interpreted as static and/or dynamic coupling based on the nature of results. To achieve this, the neuromuscular system’s passive, active and reflective components must be modelled through an experiment, to obtain the dynamic properties of the ‘system’, by establishing relation of the endpoint torque with the endpoint angle \cite{34,11}. By providing evidence of motor irradiation, the door shall be opened to further studies of active bimanual movements, which can be of direct benefit to rehabilitation therapists and medical researchers.

3.2 Subjects

Ten healthy subjects, six male and four female, participated in the experiments (Mean: 30 years, SD: 8 years).

3.3 Measurement Setup

Two commercially-available MOOG Wristalyzers are used for this experiment, one for each hand. The setup for each consists of a main drive of a vertically positioned servo motor (Parker SMH100 series). The handle of the Wristalyzer has a range of motion of 180 deg with a resolution of 0.35 deg. The nominal motor torque is 6Nm and the maximum angular velocity is 2000 deg/sec.

The arms are fixed to the Wristalyzers and the hands are clamped to the handles. The motor axis is aligned with the rotation axis of the wrist joint before every test. Movement of the motor is therefore directly coupled to flexion/extension of the wrist. The handle has an ellipsoidal shape which, because of its length, prevents flexion of finger muscles. Figure 1 shows a subject engaged in the task.
Figure 1: Left hand clamped in Wristalyzer; Subject in the experiment; Right hand clamped in Wristalyzer

### Data Recording

A data acquisition system from National Instruments, the NI 6221-USB, is used to collect force and angular position readings from each Wristalyzer. Recorded data is sent to a laptop, which also operates the Wristalyzers using Matlab R2010b.

### 3.4 Experimental Protocol

The task designed for the subjects was a force task by which subjects had to maintain a specified torque level for 20 seconds. The test comprised 4 torque levels (0.5Nm, 1Nm, 1.5Nm, 2Nm), and a Rest/‘Do-Nothing’ level. Each torque level was repeated 5 times for every subject, and the order of appearance of torque levels was randomized to evoke unplanned, natural behaviour. The subjects were shown a graphical interface, shown in Figure 2 in which they controlled the horizontal position of a blue bar on the screen by applying force with their right hand against the handle of the Wristalyzer. Flexion force from the right hand would move the blue bar from the right side of the screen towards the left. During each trial of 20 seconds, they were required to move the blue bar to the requested torque level on the screen, and hold it there until the end of the trial. The task was thus a linear, time-invariant (LTI) task.

The requested torque level is indicated when a white bar on the screen turns red, each white bar representing one of the 4 torque levels. During the force-control task, position perturbations are applied on both the handles through the laptop in order to allow system identification. These disturbance signals constitute the inputs with the measured force on the handles as the outputs, both necessary to identify the wrist systems in between them.
At the start of the experiment, the subject is instructed that the blue bar on the screen can only be controlled by the right hand, and that the left hand will be useless in completing the task successfully. The subject is also explained how a force task with position perturbations works, because maintaining a torque level is inherently non-intuitive and subjects tend to focus on trying to control the position of the handle, which is detrimental to task performance here. About the ‘Do Nothing’ trial, the subject is told to ‘relax and not react to the perturbations in any way’.

The subject is given one of two instructions at the start of each trial. For the 4 force levels, the instruction says - “Reach and hold at red box”. For the ‘Do Nothing’ case, the instruction says - “Relax and do nothing”. The subject is given information about the trials, as is summarized in Table 1.

<table>
<thead>
<tr>
<th>Force Level</th>
<th>Required Torque (Nm)</th>
<th>Time/trial (sec)</th>
<th># trials</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 (Do Nothing)</td>
<td>0</td>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>1</td>
<td>0.5</td>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>3</td>
<td>1.5</td>
<td>20</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>2</td>
<td>20</td>
<td>5</td>
</tr>
</tbody>
</table>

**Perturbation Signal**

Wide bandwith multisine signals are generated offline in the frequency domain and used for the position perturbations. Each perturbation signal has constant power while the phase is chosen at random (crested afterwards to remove outliers) with a
uniform distribution between 0 and $2\pi$ radians, and frequency range from 1 Hz to 20 Hz. Power is applied to alternate frequency points - even frequency indices for the right hand signal and odd for the left hand. This is done with the aim of being able to differentiate easily on the frequency spectrum the effects due to left hand and right hand perturbation. The signals are passed through a second order filter to mimic the 2nd order response of the wrist with cut-off frequency at 4 Hz, which helped to create a power spectrum comparable to previous single-wrist studies [9, 26] as well as reduce the suppression of reflexes due to high frequency displacements. Inverse Fourier transform of the multisine signals yield unpredictable time signals with a duration of 20 seconds.

### 3.5 Data processing

**Non-Parametric Analysis**

Non-parametric estimations of the wrist FRF were calculated using two approaches, each for their own benefits. Cross-spectral densities of fast-fourier transforms (FFT) of the measured angular displacement and torque signals were used to calculate coherences, which would indicate cross-coherence between the limbs. However, to overcome the deficiencies of spectral data in a Multiple Input Multiple Output (MIMO) system, as well as to ensure reliable identification using short observation periods, subspace identification techniques were used as well. Subspace techniques are introduced in the next portion on ‘Parametric Analysis’ since they were directly used to calculate parametric values. This subsection will deal with spectral estimation.

Since we are working with a two-wrist system, it is modelled as a MIMO system. The admittance transfer function estimator was therefore selected to account for input coupling as well, shown in Equation 1

$$H_{u1y1}(f) = \frac{G_{u1y1}(f) \ast G_{u2u2}(f) - G_{u2y1}(f) \ast G_{u1u2}(f)}{G_{u1u1}(f) \ast G_{u2u2}(f) - G_{u2u1}(f) \ast G_{u1u2}(f)}$$  \hspace{1cm} (1)$$

where $u_1$ refers to torque measured from right hand, $u_2$ refers to torque measured from left hand, $y_1$ refers to angular displacement of the right hand and $y_2$ refers to angular displacement of the left hand.

Admittance (the inverse of impedance) defines the causal, dynamic relation between wrist rotation and applied torque/force, describing the wrist as a position controller and giving us insight into the dynamic properties of the neuro-muscular system. It is the measure of displacement due to a force and roughly resembles a second-order system [24]. At low frequencies, elastic properties dominate behaviour while at high frequencies, admittance shows a 2nd order decline due to inertial influence. In general, the lower the admittance, the stiffer the system and thus the greater the resistance to disturbing forces. Similarly, high admittance means low stiffness and greater displacement to a given torque/force.
Multiple and partial coherences were calculated from the spectral data, varying between 0 and 1, to indicate the degree of linearity between the torque and angular displacement data. The coherence plots were expected to be strong indications of dynamic coupling between the limbs. Since dynamic coupling is seen at the signal level between the two hands over time, the partial coherences offer a chance to see the linearity between the torque data of one hand against the perturbations applied on the other hand. Low coherence here would suggest poor temporal coupling, non-linearities or low signal-to-noise ratio whereas high coherence would point to an active dynamic coupling between the limbs throughout the duration of the task.

**Parametric Analysis**

As a first step in identification of the limited set of parameters we intended to fit to the model, subspace techniques were used to extract the subsystems to be fitted. Subspace identification is a method which uses time-domain data to construct state-space systems, similar to that shown in Equation 2, which describe the input/output behaviour of a system. Here, $u_k$ and $y_k$ are measured input and output data ($k$ referring to time instant) while $v_k$ is the noise source.

\[
\begin{align*}
    x_{k+1} &= Ax_k + Bu_k \\
    y_k &= Cx_k + Du_k + v_k
\end{align*}
\]  

(2)

Subspace identification can be easily applied to MIMO systems analysis. They are more suitable than spectral estimators since they are more efficient over limited timespans of data, and are not affected by poor realizations of the frequency spectrum (which can occur with MIMO systems), using the state $x(t)$ (of order $n$) as a memory vector for simulation and other purposes, which is an efficient organization of variables and information [19]. By simply selecting the order of the system to be identified, the algorithm first reconstructs an extended observability matrix, like one shown in Equation 3, and then uses singular value decomposition to determine state-space matrices $C$ and $A$. This leads to estimation of states $x_k$ and noise contributions, and then the matrices $B$ and $D$ and initial state $x_0$ as well.

\[
O_r = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{r-1} \end{bmatrix}
\]  

(3)

The raw data is first re-sampled by a reduction factor of 8, to allow the identification process to pay greater attention to lower frequency behaviour. The first 2 seconds of the sample data were removed from the identification process, to eliminate the effects of initial adaptation to the task, i.e. time variant behaviour. Modeling the wrist as a position controller, the torque data was given as input data and the position perturbations as output data (also shown in Figure 4), while the subspace
identification process, with an order of 8, returned a state-space model for the controller in between.

Usually, a ‘gap’ between singular values is detected to select subspace model order. However, in biological systems, due to the noise and non-linearities, this gap can be difficult to find. Hence, to select the subspace model order, VAFs of the subspace model outputs against measured datasets were considered. Because every subject performed at a torque level for 5 trials, for each of these 5 data-sets, 2 were used for subspace identification. The two models obtained were validated against the other 3 data-sets, measuring VAFs of the model-estimated output against the measured output, to gauge model accuracy. This was carried out for different selected orders for the subspace model, \( n = 6, 8, 10, 12, 14 \). The results, shown in Figure 3, indicate insignificant difference between the VAFs. The plot suggests that a 6th order model was almost as good as the 8th order model in estimating the output (angular displacement) of the system, and that after the 8th order, estimates reduced in quality. Allowing for a 3rd order time delay, 2nd order activation dynamics and the 2nd order intrinsic IBK system, we get a final value of 7, so the order of 8 was finally chosen for the subspace identification.

The state-space model can be decomposed into 4 subsystems, relating each input to each output, as shown in Equation 4. It should be kept in mind that torque data is given as input to the subspace model to generate angular displacement as output. Hence, \( H_{11} \) refers to torque input from right hand for position output of right hand, \( H_{12} \) refers to torque input from right hand for position output of left hand and so

![Figure 3: VAFs of subspace model output against measured outputs. VAFs of data-sets identified (ID-sets) are in blue, and VAFs of datasets compared after sending torque data into models obtained from ID-sets are in red (validation-sets). Bars indicate mean VAF values and numbers on top are standard deviations over trials. Results shown are of one typical subject.](image-url)
After subspace identification, it was found that the gains for the off-diagonal sub-systems, i.e. $H_{12}$ and $H_{21}$, were almost zero, indicating that no cross-lateral effects could be found from signal data. Thus, only the sub-systems $H_{11}$ and $H_{22}$ were used for parameterization. The frequency responses of these non-parameterised state-space sub-systems over the relevant frequency spectrum are used for parameterization.

A method of validation was employed before a particular data-set’s subspace model was parameterized. Since every subject repeated each torque level 5 times, each repetition (trial) data-set was modelled and the subspace model validated on the basis of VAF readings against the other 4 trials at that torque level. The VAF was calculated with the measured angular displacement of the validation trial against the model’s estimated angular displacement when given the validation trial’s measured torque as input. If the VAFs obtained of 2 or more validation trials out of the 4 were below 50%, that subspace model was rejected as incapable of predicting control behaviour.

Parameterization of the suitable subspace models was done using the non-linear least squares function in MatLab. The subspace model, with frequencies over 10Hz removed to eliminate grip dynamics, was parameterized over two runs of the function, the second run with the values obtained from the first. Initial parameter values were tuned within bounds to obtain accurate SEM values.

A neuromuscular system (NMS) model, shown in Figure 4, incorporates inertia ($I$), spring stiffness ($k$) and damping ($b$) as intrinsic parameters (in $H_{\text{int}}$), eigen-frequency of 2nd order muscle activation filter ($F_a$) as activation parameter (in $H_{\text{act}}$), and velocity dependent 1st order reflex gain ($k_v$) with time delay ($T_d$) as reflexive parameters (in $H_{\text{ref}}$) for each hand, as per previous studies [20, 34]. Position and acceleration dependent components of the reflex gain have been ignored, in accordance with recent, previous studies [17, 20].

These parameter values are later examined for evidence of static coupling between the two hands. To find static coupling, we expected the change in parametric values due to varying force levels of the right hand to be matched by change in parametric values in the left hand.

The muscle dynamics can be described by the equation shown in Equation 5.
Figure 4: Block diagram of the human two-hand setup, showing blocks for activation dynamics $H_{act}$, reflexive feedback $H_{ref}$ and intrinsic muscle properties $H_{int}$. The individual hand models are based on previous studies \cite{34, 20}. The dotted lines indicate the systems being identified as the left and right hands. Static coupling of the left and right hand is indicated in blue. $N_R$, the neural input to the active right hand, is shown to affect the parameters of the left hand subsystems, exhibiting cross-lateral influence of parametric values. Dynamic coupling is indicated through the red line, the signal from the right hand contributing to the signals in the left hand. $T_R$ and $T_L$ indicate torque data which was measured against the Wristalyzer handle, during position perturbations $Y_R$ and $Y_L$ respectively. A stiff controller ensured no deviations between measured position and actual position values.

\begin{align*}
H_{wrist}(s) &= \frac{H_{int}(s)}{1 + H_{int}(s)H_{ref}(s)H_{act}(s)} \quad (5)
\end{align*}

where $H_{int}(s) = \frac{1}{Ts^2 + bs + k}$

$H_{ref}(s) = (kv) e^{-T_d s}$

$H_{act}(s) = \frac{1}{\frac{1}{\omega_0^2} s^2 + \frac{2\beta}{\omega_0} s + 1}; \quad \omega_0 = 2\pi F_a \text{ and } \beta = 0.7$

The model was fitted onto the frequency response of the state-space system at the frequencies which were given power in the perturbation signal. The following
criterion function was used to minimize errors as per [25, 27], shown in Equation 6:

\[
E = \sqrt{\frac{1}{f}} \left| \ln(H_{ss}) - \ln(H_{wrist}) \right|
\]  

(6)

Here, \( f \) represents the vector of frequencies which contain power in the perturbation signal, \( H_{ss} \) is the non-parameterized FRF of the subspace identification and \( H_{wrist} \) is the FRF of the parameterized, NMS model.

**Statistical Analysis**

Repeated measures ANOVA was used to compare changes in values of the parameters for the different force levels and the 'do nothing' case. This was done for both the left and the right hand.
4 Results

4.1 Subspace System Identification

Subspace identification with measured force data as input yielded estimated position data for both hands, a sample of which is shown in Figure 5.

![Angular Displacement, Measured vs Subspace](image)

Figure 5: Comparison of measured angular displacement data vs displacement estimated from subspace techniques with torque input. Data presented is of a single, typical sample.

4.2 Spectral Estimations

Plots for the multiple coherence and partial coherences were obtained, as shown in Figures 6 and 7 for a typical sample.

![Multiple Coherence across subjects](image)

Figure 6: Multiple coherence for both hands. Red line indicates the median multiple coherence. Grey region represents the confidence region within the interquartile range, the upper boundary as 75th percentile and lower as 25th percentile.
Multiple coherence, which shows the influence of position perturbations from both hands on the torque output of one hand, remains consistently high for the left hand, dropping in the higher frequencies. A significant drop in coherence of the right hand occurs close to 4 Hz in the frequency averaged x-axis, which is the cut-off frequency of the 2nd order butterworth filter used in design of the perturbation signal. The drop is also attributed to non-linear behaviours occurring in the right hand due to the active tasks. Coherence rises to high values again for the high frequencies, as expected during active tasks.

![Partial coherence across subjects](image)

Figure 7: Partial coherence for both hands. The red line indicates the median partial coherence. The grey region represents the confidence region within the interquartile range, the upper boundary being the 75th percentile and the lower the 25th percentile.

Partial coherence values remain high within-hand, i.e. force response against the position perturbation of the same hand. This is seen in the plots along the diagonal in Figure 7, which represent within-hand coherence. The right hand’s partial coherence shows a significant drop in coherence at the same frequencies as the multiple coherence plot (Figure 6) for the same reasons.

Very low values are seen in the between-hand cross-coherences, in comparison to the within-hand coherences, which indicates negligible dynamic coupling between the limbs.

### 4.3 Parameterization

The FRFs of the individual hand admittances for a typical sample are shown in Figure 8. It can be seen that the parameterized NMS response fits the state-space model well.

VAFs were calculated in time domain for the physical, NMS model versus the meas-
4 RESULTS

Figure 8: FRFs of wrist admittance of a single, typical sample. The red, dashed line indicates the state-space system frequency response to which the parameterized model response (in blue) is fitted. In black is the spectral estimation.

Figure 9: Histogram of VAFs in time domain for both left and right hands, for all datasets.

It can be seen that VAFs for the left hand are generally higher than those of the right hand. This is as expected because the left hand is dormant and behaves more linearly during the task.

4.4 Parameter Values and Reliability

Parameters are obtained for all the NMS models, across all subjects, and plotted against torque levels. Figure 10 shows the distribution of intrinsic parameter values.
across the 4 force levels and the ‘Do-Nothing’ condition (0 Nm).

Figure 10: Box-plots of intrinsic parameters - inertia, stiffness and damping - indicating median, 25th percentile, 75th percentile and outer boundaries of parameter values across all trials and subjects, segregated according to the force level of the particular trial.

Values were also tested for significant within-subject differences across the five torque levels. This was done to find evidence of static coupling between the limbs, in the form of significant parameter changes across both hands.

Right hand stiffness rises significantly with activation as seen in Figure 10 from Torque Level 0 Nm to 0.5 Nm, and proceeds to rise almost linearly after that, each torque level (0 – 2 Nm) differing significantly from the other levels (p < 0.05). The left hand stiffness, in contrast, is of lower overall magnitude, but also shows significant change in value due to activation, i.e. ‘Do Nothing’ level compared with all other torque levels (p < 0.05).
Inertial values for the right hand can be seen to change upon activation as well, changing significantly for the ‘Do Nothing’ condition versus all other torque levels ($p < 0.05$).

The other 3 parameters - reflex velocity gain, time delay for reflexes and the cut-off frequency of muscle activation dynamics - are represented in box-plots in Figure 11. The reflexive time delay ($T_d$) for the right hand varied significantly with activation, the ‘Do Nothing’ condition shows significant difference from the 1.5Nm and 2Nm conditions. Similarly, cut-off frequency of activation dynamics in the right hand varied significantly for the ‘Do Nothing’ condition versus all other torque conditions.

Figure 11: Box-plots of reflexive and activation parameters - reflex velocity gain, time delay and cut-off frequency of muscle activation dynamics - indicating median, 25th percentile, 75th percentile and outer boundaries of parameter values across all trials and subjects, segregated according to the force level of the particular trial.
Apart from significant changes \((p < 0.05)\) in activation frequency of the right hand for ‘Do Nothing’ condition versus all other conditions, no changes can be seen in any of these parameter values, probably due to natural suppression of reflexive action in the force task [34, 11].

SEM values were obtained to indicate the level of reliability of the parameters. Parameter values were judged as reliable, with most parameters deviating not more than 5%. Reflexive time delay, \(T_d\), shows highest SEM values, going up to almost 3 times the mean on occasion.
5 Discussion

The goal of this study was to find evidence of interlimb coupling by exploring the motor irradiation phenomenon, that neural inputs sent to one limb as part of unilateral limb activity, are involuntarily transmitted, in a smaller proportion, to the homologous limb. The coupling was searched for in two forms - static and dynamic.

Since this study was an examination of the motor irradiation phenomenon, by definition the task needed to be designed as an active/dormant task in order to separate it from an active bimanual study. A force task was chosen with prior knowledge that it would suppress reflexive behaviour [34, 11]. Motor irradiation is expected to occur due to excitability of one limb [7]. It was considered that a force task, inviting different levels of activation and stiffness from the subject, would be a good way to examine corresponding changes in the homologous limb. A previous study [35] at TU Delft, with an active/dormant hand combination, had used a position task for the active hand, finding mildly significant changes across all intrinsic parameters (inertia, viscosity and stiffness) for the dormant hand and no significant differences for reflexive parameters. This present study sought to improve upon the results of the previous study by invoking more concentration and effort from the user, and employing comprehensive data processing and analysis using a MIMO approach (the previous study used SISO approach).

A majority of the datasets could be described well by the subspace estimated models (Figure 5). However, some poorly identified datasets remained, with very low VAFs. These poor VAFs are attributed to non-linear behaviour from the subject and/or the subject’s inability to perform that particular trial as per instruction. Low VAFs were seen for random trials only and did not have a subject-wide spread, suggesting that subjects were usually able to perform the task as per instruction, with some bad trials in between.

Figure 6 shows the multiple coherence across subjects, against the averaged frequency spectrum. A sharp decrease in coherence is seen in the right hand between 4 and 5 Hz, which is expected since 4 Hz is the cut-off frequency of the 2nd order filter used during perturbation signal design. This drop can also be attributed to non-linearities, due to the active task being performed by the right hand. Changes in contraction level (due to the varying force levels across the task) also lead to changes in the eigen frequency and stiffness of the wrist, which explains the spread of the poor coherence around 4 - 5 Hz. There is a milder drop in coherence at the same frequencies for the left hand, but this is followed by a decrease in coherence again at the higher frequencies. We expect coherence to stay high at the higher frequencies, and this is seen in right hand coherence. Possible reasons for high frequency non-linearities in left hand coherence are that the left hand, being dormant throughout the task, had a low signal-to-noise ratio and/or was not sufficiently well clamped into position. Improper clamping is possible due to the poor wrist clamping setup of the Wristalyzer seen in Figure 1. The left hand Wristalyzer did not have a support to keep the palm tightly pressed against the handle, and one had to be fashioned by the author for this experiment to be carried out. The reliability of
this clamping is questionable and is a likely reason for the lower coherence (0.8 for median data) at high frequencies.

Partial coherence plots (Figure 7) were expected to be one of the two important indicators of dynamic coupling between the hands. It was expected that, in the event of dynamic coupling, the off-diagonal, ‘between-hand’ plots would show high coherence. However, as the spread of the confidence regions (interquartile range) indicates, negligible cross-coherence is seen across subjects. This suggests that there was no cross-linking at the signal level between the two hands. The negligible reflex activity is another reason for the low between-hand coherence.

The diagonal plots, indicating within-hand coherence, are similar to the multiple coherence plots and indicate good overall coherence with a sharp drop around the perturbation signal cut-off frequency for the right hand. The spread of the confidence region shows that non-linear behaviour was seen quite often during the task, and several datasets had poor coherence even for the dormant hand. The probable cause for this could be the force task itself. It was seen that subjects sometimes had trouble maintaining a constant force, and would oscillate about the red, target bar which they had to reach on the screen (Figure 2). Although subjects were explained that the task goal was to keep force steady, this continued to occur in some cases and was more or less unpreventable. Another possible cause for this could be the fact that the thumb would come out of the palm-clamping apparatus during the experiment. The left hand Wristalyzer’s palm-clamping apparatus had no proper accommodation for the thumb, which influenced the application of forces on the handle and thus the coherence of measured torque with angular displacement.

The other important indicators for dynamic coupling between the hands were the FRFs coming from the 2 off-diagonal subsystems, $H_{12}$ and $H_{21}$, out of the 4 subsystems modelled during subspace identification. It was seen that these systems which would indicate signal-level cross-lateral effects, i.e. torque from right hand against angular displacement of left hand and vice versa, had close to zero gains. This meant that there was no active, temporal correlation of signals across the limbs, suggesting no dynamic coupling. This is expected, after seeing the poor between-hand coherence plots (Figure 7). The VAFs for the 6th order subspace model were comparable against the 8th order model in Figure 3 as well, suggesting reflexes were not a major influence. These results, considered together, ruled out dynamic coupling as a possible coupling between the limbs.

As a result, the data analysis was continued with the diagonal subsystems, i.e. input from right (left) hand against output of right (left) hand ($H_{11}$ and $H_{22}$), to look for evidence of static coupling in the gains of these 2 subsystems.

The parameterization process, done over two runs as explained, yielded values with reasonable SEMs (Standard Error of Mean). Most SEMs are very low, indicating that the parameter values are reliable. The FRFs of the two hands of a typical sample, plotted in Figure 8, show that the parameterized model of a typical sample fits the measured data and the subspace model FRFs reasonably well. VAFs of the parameterized model versus the measured data also show satisfactory values.
The presence of low right hand VAFs is indicative of non-linear control behaviour such as oscillating about the required torque level (as explained above) as well as experimental setup issues, more of which will be discussed below. Left hand VAFs show predominantly higher numbers, which is probably because the left hand was dormant throughout the task and easy to estimate.

The values obtained for the different parameters offer a good picture of both the limitations of the experimental setup and the achievements.

We see statistically significant change in the value of right hand inertia for the ‘Do Nothing’ condition against the other torque levels. This is explained when we look at the Wristalyzer’s forearm clasp to keep the arm securely in position. Subjects were instructed to use only their wrists to apply forces to the handle, and the shape of the handle prevents finger flexion as well. However, the forearm clasp (seen in Figure 1) is a single-sized frame which can be too small for some subjects and too large for others. In the first case, the simple velcro of the clasp is not sufficient to ensure that the forearm does not influence the force measured at the handle. In the latter case, it allows subjects more room inside the clasp to unintentionally move their forearms while applying force against the handle. This leads to an obvious miscalculation of inertial values, explaining how the values change significantly across conditions. No significant change in inertial value was found for the left hand, further proving that improper clasping of the hand actively involved in the task was the reason for improper estimation of right hand inertia.

The statistically significant differences in activation frequency and reflexive time delays across conditions do not offer much insight into the neuromuscular system, because no significant changes are seen in the reflexive velocity gain, which would be the strongest indicator of reflexive action. In addition, values of time delay reach the upper boundary of the parameterization quite often, with large spreads within the permitted range of 0.02—0.06. Seeing that the values of reflexive gain are very near zero (Figure 11), and that the values for activation frequency do not deviate much from the initial value (of 8 Hz) except for the ‘Do Nothing’ condition, these statistical differences are discarded as meaningless to overall reflexive action in the limbs, which is itself close to zero. The negligible reflexive velocity gain, a sign of near zero muscle spindle feedback, is in accordance with previous research conclusions [11, 24].

Static coupling is clearly evident in the change of stiffness values across left and right hand. Stiffness of the right hand across the conditions is seen to vary significantly with every other condition, which is expected since the right hand was involved actively in the force task. Of great significance to this bimanual study is the stiffness of the left hand. Although the left hand was dormant throughout the task, its stiffness varied significantly for every torque condition against the ‘Do Nothing’ condition. This fact indicates that there is static coupling between the right and left hand even when only the right hand is involved in a task.

The results of this study show quantified proof of motor irradiation (in the form of static coupling of parameters) between the limbs. This suggests bilateral coupling occurring at the cortical or spinal level due to the motor irradiation phenomenon,
in accordance with neuroscientific reviews on the subject \cite{7,30}. The existence of motor irradiation is of great relevance to further bimanual coordination studies with a similar approach, those with the intention of further understanding this phenomenon as well as those applying it to stroke rehabilitation therapy.

It should be noted that, in the context of an active/dormant task such as this one, a high degree of interlimb interaction was not expected to occur. These findings raise hopes of scientifically insightful and significant results when active bimanual experiments are conducted.
6 Conclusions

Carson [7] states in his review of neural pathways mediating upper limb bilateral interaction that it is essential to determine those features of observed behaviour that can be accounted for on the basis of bilateral interactions arising from unimanual movements (i.e. motor irradiation) before invoking mechanisms that are specific to bimanual coordination. The findings of this study are the first, in the author’s knowledge, to offer proof of the motor irradiation phenomenon with physiologically-interpretatable parameters. With cortical/spinal-level control in the static coupling of parameters between limbs for healthy subjects, the experiment can be reproduced for examination of stroke patients, to evaluate differences in parametric values. This research also paves the way for studying bimanual coordination tasks. This would be of immense benefit to stroke rehabilitation research, providing a means to not only assess stroke-related disability but also a quantified measure of improvement over time.
7 Recommendations for future studies

This study serves as a starting point for active bimanual research focusing on quantifiable, physiological parameterization. Recommendations for such research would include the following points:

- Use of a single, dual wrist/limb manipulator is highly advised. This would allow for more precise control of the experiment through a central computer. Limitations of the commercially developed Wristalyzer in properly clamping the forearm and minimizing grip dynamics with the handle, have affected this study.

- Reflexive behaviour would tell us a lot more about neural interactions controlling active bimanual coordination. Closed loop tasks and identification techniques are advised to successfully include these factors in research.

- The effects of external loads (inertial, viscous and spring) have not been well-explored with respect to bimanual coordination. This was pointed out by the author in the previously submitted literature report as well. Future research can focus on finding the benefits or difficulties to bimanual coordination posed by such environmental factors. This may help in the design of rehabilitation equipment as well as in expanding what is known via the Dynamic Pattern Theory.
References


REFERENCES


