Measuring the Allocation of Control in a 6 Degree-of-Freedom Docking Experiment

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ABSTRACT
Coordination definitions and metrics are reviewed from the motor control, biomedical, and human factors literature. This paper presents an alternative measurement called the $\mathcal{M}$-metric, the product of the simultaneity and efficiency of a trajectory, as a means of quantifying allocation of control within a docking task. A 6 degree-of-freedom (DOF) longitudinal virtual docking task experiment was conducted to address how control is allocated across six DOFs, how allocation of control changes with extended practice, and if differences in the allocation of control are input device dependent. The results show that operators, rather than controlling all 6 DOFs equally, allocate their control to the rotational and translational DOFs separately, and switch control between the two groups. With practice, allocation of control *within* the translational and rotational subsets increases at a faster rate than across all 6 DOFs together.

Keywords
Coordination, interaction techniques, allocation of control, virtual docking task, the $\mathcal{M}$-metric, evaluation methods, motor control, input devices, 6 degree-of-freedom control

INTRODUCTION
As technologies for interacting with systems such as CAD workstations, process control plants and remotely controlled robots become more sophisticated, humans are frequently faced with the necessity of controlling multiple variables simultaneously. The question of how operators actually allocate their control across many degrees-of-freedom (DOFs) is important for the design of effective input devices and appropriate displays. Before this question can be addressed, however, it is essential first to develop a *metric* for evaluating allocation of control. Traditional performance measures such as task completion time and root-mean-square error do not tell us very much about how operators actually allocate their control. An allocation of control measurement tool is expeced to be useful not only for the design of systems such as those mentioned above, but also for applications involving neurological assessment and modeling of human motor control.

Applications which Motivate the Metric's Development
Teleoperation & input device design
For high DOF systems, deciding whether the "optimal" distribution of DOFs should be across only one or two hands is less than clear. For example, Zhai [21] has pointed out that while the Space Shuttle Remote Manipulator, one of the most prominent instances of 6 DOF control, requires two-handed operation (due to zero gravity considerations), the literature supporting such design decisions is not unanimous.

During the past decade, many new input devices offering a large number (>2) of control DOFs have been introduced. Some of these devices, such as the IBM ScrollPoint® mouse and the PadMouse [3], are multi-channel or "mixed resistance mode" devices, for which different types of interaction devices, (such as isotonic mouse, touchpad, and isometric joystick) are merged together to form a single device. It has yet to be determined whether operators of mixed resistance devices are capable of using all available DOFs in a coordinated fashion, which will presumably be required as high-end computer applications such as computer-aided design, scientific data visualization, computer graphics animation, and 3D video games become increasingly common.

Process control
Measuring performance in a complex environment can help researchers understand the type of strategies operators may be using [19]. In process control environments, for example, operators are required to manipulate a multitude of different variables such as temperature, volume, pressure, and flow rates towards a goal state in real time. This type of manipulation is a coordination problem.

Human motor control
Understanding human coordination is one the fundamental issues in the motor control literature [16, 5]. A well known

coordination problem, known as "Bernstein's Problem", or the "degrees of freedom problem", is how a high number of DOFs in the body (individual muscles and joints) behave as if they were actually a much smaller number of DOFs. Studying and quantifying how a large number of DOFs work together in a coordinated fashion is one approach to understanding human motor control.

Neurologic assessment

Clinical evaluation of neurologic motor function often is "dependent on the skilled but subjective judgement of a physician"[11]. Such evaluations usually consist of having patients move their arms in certain prescribed motions while the physician assesses performance on an ordinal scale. Tests such as these are used, for example, to track the progression of Parkinson's disease, which is characterized by increased movement latency, slowing of movement execution, and difficulties in execution of multicomponent movements [8]. With the advent of relatively inexpensive computers, some researchers have focused on using computerized tracking tasks as a quantitative and objective means of assessing neurologic damage [18, 8, 1, 11]

Measures/Definitions of Coordination

Coordination is an all encompassing term meant to convey information about a trajectory that is usually lost in simple performance measures, such as task completion time or root-mean-square error. It is not obvious how to capture this trajectory information. Therefore, the literature contains many measures of coordination, each reflecting individual researchers' personal biases about what a definition of coordination should comprise. We believe that coordinated behavior, should result in *simultaneous and efficient* control of multiple variables. However, none of the existing measures address this allocation of control question. A selection of some of those measures/ definitions, with commentary, is presented here:

Time-on-target

Historically in the human factors literature, interest in human coordination [6] arose chiefly from military interests (and funding). Research in the late 1940's and early 1950's centered on anti-aircraft gunners' ability to hit targets, and time-on-target for each DOF was used mainly because it was feasible to compute. Poulton [15] has criticized time-on-target as a "not a very suitable measure", because errors which are slightly off-target are penalized just as much as errors which are far off.

Accuracy × speed

The "coordination index", proposed by Behbehani et al. [4] is a measure of accuracy multiplied by a measure of velocity, which is based on Fitts' speed/accuracy tradeoff law. This coordination index has been used in biomedical research as a means of quantifying upper extremity performance in Parkinson patients.

Spatial or temporal invariance

A common theme in the motor control literature is to use the amount of invariance in a repeated movement as a measure of coordination. Morrison & Newell wrote: "...coordination refers to the degree of spatial or temporal invariance, or both, in the motion of the respective limb effective units." [13] Measurement in the time domain is done by computing cross-correlations, while measurement in the frequency domain is through coherency and phase analysis. [13] This means of analysis is generally useful only for repeated rhythmic motions, such as walking, running and jumping.

Cross-correlations

Computing the cross-correlations [23] among error terms or joint angles [17] is another method for quantifying coordination. Unfortunately, this method usually restricts analysis to only two variables at a time.

Zhai [23] conducted a 6 DOF tracking study and analyzed the results by cross-correlating all pairs of DOF error terms. Interestingly, the correlation distributions showed that subjects were able to control all the DOFs equally well. However, simply correlating the error terms does not take into account task related performance, in that two errors which are decreasing, or even *increasing*, simultaneously will both result in high correlation coefficients.

Inefficiency

Addressing this problem, Zhai [21] has recently proposed a definition of coordination based on inefficiency. Applicable to docking tasks only, coordination is computed as the ratio of the length of the actual path followed divided by the length of the shortest path. With his unified metric, all the DOFs are combined to produce a single length, so it is not possible to make any conclusions as to relative allocation of subjects' control across different DOFs.

Integrality

Integrality [7] is not strictly a coordination measure, though it has been used in that way. (Balakrishman et al., for example, used integrality to demonstrate that subjects could control three degrees of freedom simultaneously with a two translational + one rotational DOF device, the Rockin'Mouse [2]). Two stimulus dimensions are considered integral if they are perceived as a single dimension, or separable if the dimensions seem unrelated [7]. Jacob, et al. [10] have proposed a means of quantifying integrality in the action domain, based upon whether or not movement exists simultaneously in all DOFs. Integrality, as defined by Jacob et al. is a task *independent* measure; that is, movement of any kind is considered integral regardless of whether or not the movement is contributing towards reaching the goal.

Allocation of control

The ability to measure the allocation of control is a new and powerful tool for the analysis of trajectory information in complex multi-DOF tasks. We propose the $\mathcal{M}$-metric, introduced in the following section, as a means for quantifying allocation of control in a docking task. The *m*-metric is a task dependent measure which may be used to analyze any number (≥2) of DOFs.

THE *m*-METRIC

The *m*-metric is based on the supposition that assessment of allocation of control across an n (where n ⩾ 2) DOF docking task must take into account both the simultaneity and the efficiency of control across the DOFs. A docking task is defined here as a task for which an object, such as a cursor or a graphic object, must be moved from an initial position to a goal position, with no constraints on either the trajectories that may chosen or the time allowed to complete the movement from initial state to goal. Such tasks can thus be considered self-paced, or time-minimizing [12]. As justified in the following, it is the *product* of simultaneity and efficiency which defines the *m*-metric.

Simultaneity of Control

Simultaneity of control is calculated by first computing the *normalized error reduction function* for each DOF separately. Error for each DOF is defined here as the difference between the goal position and the current position. Error reduction is the instantaneous amount by which the difference between the goal position and the current position is *reduced* (i.e. the error term moves closer to zero). Error reduction is a function of time and is set equal to zero during time periods in which the error may have actually increased (i.e. movement away from the goal). In other words, *error reduction represents the instantaneous value of the derivative of the error term*, but only for positive values.

The error reduction function for each DOF is normalized by dividing it by the total distance moved towards the goal over the entire docking task for that DOF. Thus, when all the normalized error reduction functions are graphed against time, the areas under each curve are all equal to each other. More formally, the Normalized Error Reduction Function, $NERF_i(t)$ (where i = 1,2, ... n are the degrees of freedom being analyzed, and t is time), is defined as:

$$NERF_i(t) = \frac{-dE_i(t)}{dt} * \frac{1}{ACT_i} \qquad \text{, for } \dot{E}_i < 0$$

$$= 0 \qquad \text{, for } \dot{E}_i \geq 0$$

where E_i = error, (goal position - cursor position)

ACT_i = total actual error reduced for the *ith* DOF; in other words, ACT_i is equal to the area under the non-normalized error reduction function and can only be computed when the task is over. [1]

[1] Note that the *m*-metric, as presently defined, can not be computed for docking tasks which are not successfully completed.

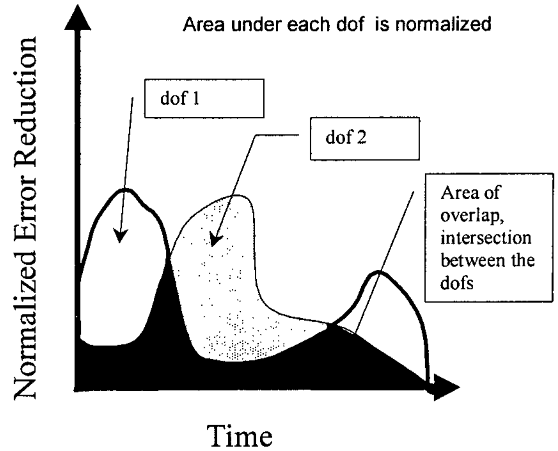


Figure 1. A normalized error reduction graph.

Figure 1 shows the normalized error reduction curves for two DOFs. The area of overlap between the curves depicts the simultaneity of control. Any number (n ≥ 2) or subset of DOFs may be analyzed by computing the overlaps between the normalized error reduction curves. Simultaneity of control (SOC) is therefore defined as:

$$SOC = \int_0^T Min\left(NERF_1(t), NERF_2(t), \ldots NERF_n(t)\right)dt$$

where *Min* where returns minimum value over all *$NERF_i(t)$'s* as a function of *t*, and T=total task completion time. The minimum function (*Min*) defines the contour of the curve to be integrated, for computation of the area of overlap, as illustrated in Figure 1.

Efficiency of Control

The *efficiency* component of the *m*-metric is a weighted average of the ratios of the length of the optimal trajectory for each DOF (OPT = length of the optimal error reduction function trajectory) divided by ACT for that DOF. Efficiency (EFF) is thus defined here as:

$$EFF = \sum_{i=1}^{n} \left(\frac{OPT_i}{ACT_i} * W_i \right)$$

where the weights, W_i, are equal to: $W_i = \frac{k}{n} * \frac{OPT_i}{\sum_{j=1}^{k} OPT_j}$

and k = number of members in the same subset as the *i*th DOF. A *subset* of the total DOFs is a grouping of (k) DOFs that are similar in nature and measured in the same units. The purpose of the weights, W_i, is two-fold: 1) to weigh DOFs of the same units by their optimal trajectory magnitude, and 2) to deal with DOFs which might be measured in different units. Note that the sum of the n weights must be unity. Thus, for example, the W_i values for X-Y-RZ (where X, Y are translational DOFs, and RZ is a rotational DOF about the Z axis)[2], for a case in which the $OPT_{X, Y, RZ}$ values are 4 cm, 5 cm, 60° respectively, are:

$$W_X = \frac{2}{3} * \frac{4}{4+5} = 0.296$$

$$W_Y = \frac{2}{3} * \frac{5}{4+5} = 0.370$$

$$W_{RZ} = \frac{1}{3} * \frac{60}{60} = 0.333$$

To summarize, the object of the $\mathcal{M}$-metric is to measure how control has been allocated among different DOFs during a task and to express this via a value between 0 and 1. A value closer to 1 indicates efficient and essentially synchronous control across DOFs, while a value closer to 0 indicates a switching of control between the DOFs in a relatively inefficient manner. The two components of the $\mathcal{M}$-metric have been defined with this in mind, such that we can now define it as being equal to:

$$\mathcal{M}\text{-}metric = SOC \times EFF$$

A Note on the Time Dimension

The final $\mathcal{M}$-metric score is not a function of the total length of time taken to complete a docking task, even though the metric explicitly takes into account the time dimension. What the "time dimension" refers to here rather is the *timing of events*. In other words, what the $\mathcal{M}$-metric measures is the *degree of simultaneous error reduction occurring in multiple DOFs*, as opposed to measuring whether the error reduction took a particular amount of time to complete.

HYPOTHESIS

Similar to what has been observed in the motor control literature [17], we predict that novice operators attempting to control a large number of DOFs will not allocate their control equally across all the DOFs. Instead, subjects will control certain subsets of the total number of DOFs at a time and switch control between those subsets. Furthermore, the subsets controlled will not be arbitrary; rather, it is expected that rotation and translation DOFs will be treated separately. Imai and Garner [9] have identified a perceptual preference in discriminability between translation and rotation dimensions. We believe this perceptual preference extends into an action preference. Specifically, for a 6 DOF virtual docking task, operators will tend to allocate their control globally between the three translational and three rotational DOFs, and switch back and forth between them.

We further predict that input devices which support more "natural" modes of interactions (i.e. closer to real-world interactions) should show a more uniform allocation of control across all 6 DOFs.

Finally, we predict that, as expertise develops, and concurrently task completion time performance improves, one of two behavioral tendencies is likely to emerge:

1. Operators will continue to allocate their control between the translation and rotation DOFs, and only their control will improve, or
2. Uniform allocation of control across all 6 DOFs will continue to develop over time.

EXPERIMENT

Goals

Corresponding to the above hypotheses, the experiment presented here was designed to address three explicit questions:

1. How do people allocate their control across six DOFs in a virtual docking task?
2. Are differences in the allocation of control device dependent? Specifically are there differences between isometric (pressure or force sensing without movement) and isotonic (displacement sensing or free moving without resistance) devices? Isometric and isotonic represent the two extremes of possible controller resistance.
3. How does the allocation of control change over an extended period of practice?

Method

Subjects

12 right handed volunteers from the University of Toronto community were recruited as subjects. Three subjects were rejected for failing to discern a binocular disparity of at least 50 seconds of arc at 40 cm, as tested using the Randot® Stereotest (Stereo Optical Co., Inc., Chicago, IL). A fourth subject was rejected for being unable to complete the docking tasks. The remaining 4 male and 4 female subjects ranged in age from 25 to 32, and were paid $55 CND upon completion of the experiment. None of the subjects had previous experience with any 6 DOF computer input device, or any stereoscopic virtual displays.

Experimental Platform

The experiment was conducted on a Silicon Graphics Indigo™ workstation with a 20 inch color monitor, running MITS (Manipulation in Three Space) software, developed by Zhai [20], to create a through-the-window virtual environment. IMAX® liquid crystal glasses (IMAX Ltd, Toronto, Canada) operating at 120 Hz were used to allow stereoscopic viewing. For the isometric condition, subjects used a Spaceball® (Model #2003) manufactured by Labtec Inc. (Vancouver, WA), operating in rate control mode. For the isotonic condition, subjects used the Fingerball [22, 20] powered by a Flock of Birds™ (Ascension Technology Corp., Burlington, VT), operating in position control mode. The MITS software sampled subjects' data at 15 Hz.

[2] The symbols RX, RY, and RZ are used to represent the Euler angles ϕ, θ, and ψ respectively.

Task

A three-dimensional virtual docking task was used in this experiment (see [21, 20] for a more detailed description of the task). Subjects were told to align a tetrahedrally shaped cursor onto an identically shaped target tetrahedron as quickly as possible. Whenever a corner of the cursor was successfully matched to its corresponding target, the corner changed colour, indicating a correct docking. All four corners had to stay docked for 0.7 seconds to complete the trial. The sides of the tetrahedrons were colour coded and drawn in wire frame mode. For all trials, the initial position of the cursor was the center of the screen, while the target appeared in one of eight off-center locations. Target locations were selected so that a similar difference existed in all translational and rotational DOFs between the target and the cursor.

Procedure

Subjects were first tested for binocular disparity using the Randot® Stereotest. A short questionnaire was administered to collect subject information and experience with stereoscopic viewing and 6 DOF control devices. The questionnaire also included questions from the Edinburgh inventory [14] to assess handedness. Subjects were then introduced to their control device and asked to manipulate the cursor up/down, left/right, in/out, and then to rotate about those corresponding axes in a targetless environment. This introduction to the control device took less than two minutes. Subjects were then given a single docking trial as a training/explanation of the task. For all trials, subjects used only their dominant hand.

Design

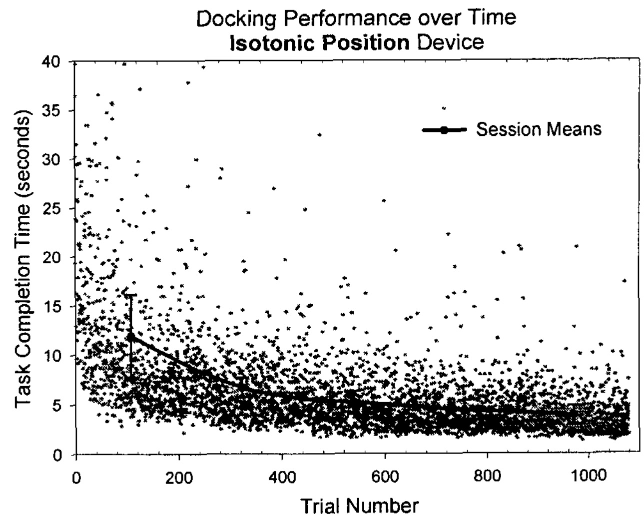
The experiment was a 2 × 5 × 216 between subjects design. The independent variables were as follows:

Input Device	isometric rate, isotonic position
Session	1, 2, ... 5
Trial	1,2, ... 216

The above conditions with 8 subjects represent a total of 8640 trials, collected over 40 hours of experimentation. A stratified random method was used to assign subjects to either the isometric rate or isotonic position conditions, such that each group was composed of 2 males and 2 females. The number of trials, 216 per session, was chosen so that each session would last about an hour. Subjects completed one session per day on five consecutive days. A mandatory rest period of 90 seconds after every 24 trials was enforced by the software. Each block of 24 trials consisted of 8 randomly shuffled target locations selected three times.

RESULTS

The number of trials, 216, was chosen so that each session would take about an hour. In reality, the subjects' first session took between 90 and 100 minutes to complete, while the fifth (final) session took only 40-50 minutes to complete.



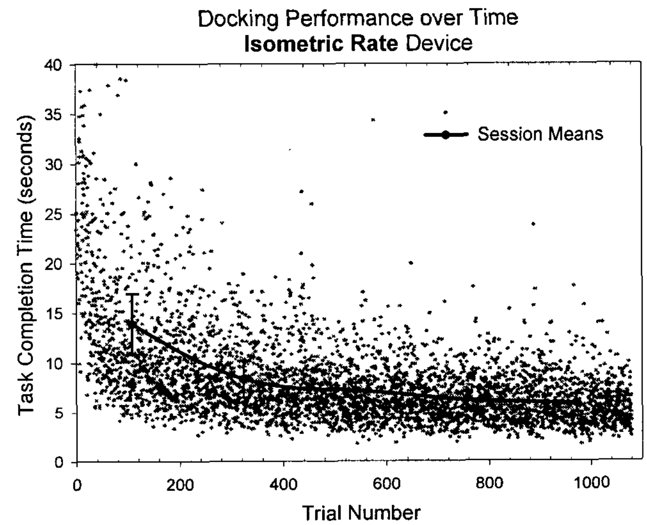


Figure 2. Task completion times by input device: Isotonic above and Isometric below. Session means, standard deviations (216 trials per session), and raw data times (4320 trials across 4 subjects per device) are shown.

Figure 2 shows task completions times over the five sessions, broken down by input device. Task completion times for the isotonic condition were an average 1.8 seconds faster per session than then isometric condition, however, this difference in mean times was not statistically significant.

$\mathcal{M}$-metric scores were computed for all DOF groups (15 two-way comparisons, 20 three-way comparisons, 14 four-way comparisons, 6 five-way comparisons, and 1 six-way comparison) for a total of 56 different groupings. A *within* grouping subset is defined here as a set where all the DOFs in the set are either of the translation or rotation type. For example, for the 20 three-way comparisons, there are only 2 groups which are considered within groups, X-Y-Z and RX-RY-RZ. An *across* group subset is defined here as a set where at least one DOF is of the translation type and at least one is of the rotation type. So for the example of the 20

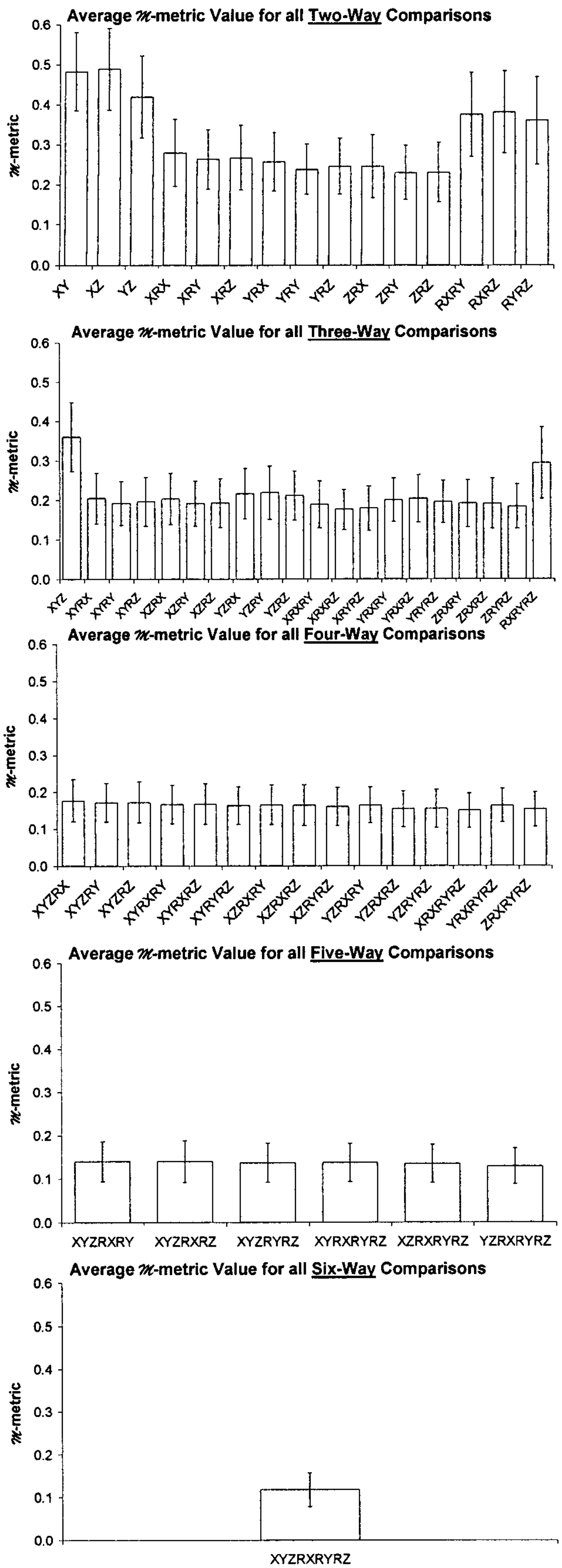


Figure 3. 𝓜-metric means and standard deviations across all trials.

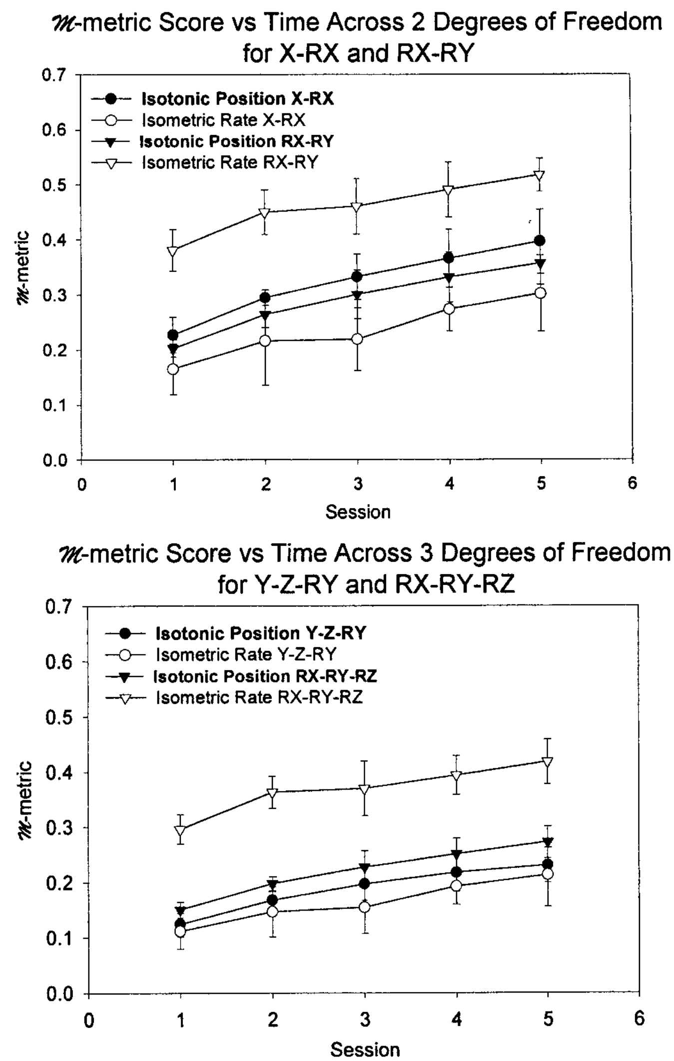


Figure 4. Changes in 𝓜-metric scores over sessions (216 trials) broken down by input device and number of compared DOFs. Only a representative sample of comparisons are shown.

three-way comparisons, the eighteen remaining groups are considered as *across* groups.

Mean 𝓜-metric scores broken down by number of DOFs compared are presented in Figure 3. For the two-way comparisons (X-Y, X-Z, ...RY-RZ), *within* rotation and *within* translation pairings had significantly higher (paired t test, $p < 0.0001$, using the Bonferroni method for multiple comparisons) 𝓜-metric scores than pair-wise comparisons *across* a rotation and translation DOF. The three-way comparisons showed similar results, with the within translation condition (X-Y-Z) and the within rotation condition (RX-RY-RZ) showing significantly higher (paired t test, $p < 0.0001$, Bonferroni) 𝓜-metric scores than their *across* rotation and translation counterparts (X-Y-RX, X-Y-RY,..., Z-RY-RZ). However, for the four-way and five-way comparisons, no significant differences in 𝓜-metric scores existed for any subset.

Figure 4 shows changes in $\mathcal{M}$-metric scores over time/session, broken down by input device and number of comparisons. Only a subset of $\mathcal{M}$-metric scores are shown, to save space. All $\mathcal{M}$-metric scores increase over session. For the two-way comparison case, X-RX and RX-RY have been selected as representative of an across translation-rotation pairing and a within rotation pairing respectively. Across all the two-way comparisons, the highest $\mathcal{M}$-metric scores always belonged to the within rotation isometric rate conditions. The isotonic scores for both the within and across conditions were always lower. The lowest $\mathcal{M}$-metric scores, for the two-way comparisons, always belonged to isometric rate across translation and rotation pairings.

The three-way pairings, depicted in Figure 4 by Y-Z-RY and RX-RY-RZ show this same pattern. Isometric within scores were the highest, followed by isotonic $\mathcal{M}$-metric scores, with the lowest scores belonging to the isometric across groups. For the four, five, and six-way comparisons, isotonic position $\mathcal{M}$-metric scores were in fact larger than their isometric rate counterparts, though in all cases the values were small.

DISCUSSION

Regardless of which input device was used, subjects tended to allocate control within rotation and translation groups separately. Previous research from the motor control literature has observed that novices control subsets of their total available degrees of freedom [17]. In addition, research from the psychology literature [9], has identified a perceptual discriminability preference to categorize stimuli into rotational and translational groups. However, this is the first time, to the authors' knowledge, that quantitative evidence has demonstrated an action preference to alternate between rotational and translational manipulations. This is exactly the type of analysis that is extremely difficult to do without the $\mathcal{M}$-metric.

An isotonic position control imposes fewer restrictions on an operator's allowed movement; muscle groups are allowed to move in a manner similar to perhaps how they are used in real word manipulation. This may mean that an isotonic position controller is a more "natural" means of interacting with a virtual environment. We expect that a more natural means of input should thus result in a more even distribution of control across available DOFs. Therefore, the higher $\mathcal{M}$-metric scores in the isotonic position condition for the across rotation and translation conditions, as compared to the isometric rate across conditions, are reasonable.

If an isometric rate controller is a less natural interaction method, and this could mean that the isometric rate device is comparably more difficult. A more complicated interaction method therefore should thus result in an uneven distribution of control. In Figure 4, in the 2-way comparison graph, the difference between the X-RX condition (an *across* translation and rotation group) and the RX-RY condition (a *within* rotation group) for the isometric rate is very large. Thus, for more complicated interaction devices, it is arguably more important for subjects to reduce the complexity of the task by controlling only a subset of the total 6 DOFs at a time. Switching control between subsets of the total available DOFs appears to be the method subjects used even after 1000 trials.

Task completions times across all subjects from session 4 to session 5 dropped an average of only 0.40 seconds (from 5.27 to 4.87 seconds), compared to a mean 5.38 second drop from the 1st to the 2nd session. Therefore, the task completion times in Figure 2 show evidence of subjects approaching a minimum time floor. With additional sessions, any further time reductions would probably be very small in magnitude.

Conversely, however, the $\mathcal{M}$-metric scores depicted in Figure 4 show much less evidence of approaching a limit. If $\mathcal{M}$-metric scores continue to change at a faster rate than task completion times, it may be possible to use $\mathcal{M}$-metric scores as a more sensitive measure of manual control expertise.

One of the goals of this experiment was to try to understand what happens to the allocation of control with extended practice. The hypothesized model was that one of two possibilities may occur: subjects will either continue to allocate control within subsets or allocate control across all DOFs. Rather than an either/or hypothesis, it now appears that both cases occur. That is, subjects continue to allocate control between rotation and translation subsets but at the same time show some improvement in their ability to simultaneously control all the DOFs.

While there is a temptation to claim that equal allocation of control across all DOFs is "better" than unequal control, this may or may not be the case, depending on the task, the environment, or the users. For example, if one imagines a task where the trajectory taken is irrelevant to performance, and the cognitive load of simultaneously manipulating multiple variables is high, then unequal allocation of control would probably be the best strategy. Either way, in order to make such judgments, a framework for measuring the allocation of control, such as the $\mathcal{M}$-metric, is a necessary tool.

CONCLUSIONS

In a 6 DOF virtual docking task, operators do not allocate their control equally across all available DOFs. Instead, operators allocate control among subsets, by controlling rotational and translational DOFs separately and switching control between those subsets. In addition, the type of input device used has an effect on the strategy used by operators to allocate control. A more "natural" type of input device should allow operators to exercise a more even distribution of control across the available DOFs. On the other hand, an "unnatural" input device might force operators to control only subsets of the total number of DOFs at a time. Some simultaneous allocation of control does exist across all 6

DOFs, and the amount of this allocation appears to be a function of the type of device used.

It is important to note that, in a docking task the operator does not have to follow a required trajectory; any trajectory which accomplishes the docking goal is acceptable. It remains to be seen whether, in a dynamic tracking task, where simultaneous control of all 6 DOFs may be required, operators continue to choose to allocate control to subsets of DOFs or instead change strategies to control all DOFs together.

ACKNOWLEDGEMENTS

This research is funded by the IRIS NCE project "Effective display and tele-control technology integration for real and virtual environments", with further contributions from DCIEM.

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