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Individual differences in tracking

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The present experiment compared differences in response strategy of participants performing a two-dimensional tracking task at three different levels of task difficulty. Twelve participants tracked an iconic aeroplane target as accurately as possible for nine repeated trials each of 5 min duration. The random input and individual response output were calculated in terms of direction and velocity. Specifically, for each 200-ms sample period, a calculated combination of eight trajectories and three velocities provided a 24 combinatorial description of both random input and participant response. Distributions across these combinations represent descriptive results and reflect individual characteristics. The distributions were compared using the technique of correspondence factor analysis. The outcome of this multidimensional method was that first, between-participants discrimination was best served by the up-vertical and low-velocity combination and, second, that the former pattern typified poor performers, while more skilled individuals used all directional options at the highest velocity level. Implications for individualized controls are examined.

1. Introduction

In many fields of human-machine interaction, such as the medical sciences, tele-operation and vehicle control, skilled manual control remains a major component of performance. Indeed, the earliest focus of human-machine investigation dealt primarily with the problems of manual control of complex systems (Birmingham and Taylor 1954, Craik 1947a,b). While interest in the motor component of human-interaction has fluctuated, innovations in technology such as virtual reality have again begun to highlight how important an understanding of manual control is to human performance in general and to ergonomics in particular. With respect to tracking capability, there are numerous authoritative texts that have considered multiple facets of the overall problem (Poulton 1974). While general models of the human controller have provided

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considerable insight into performance (McRuer and Jex 1967, Levison *et al.* 1969, Abdel-Malek and Marmarelis 1990) one question that has yet to be fully resolved is that of individual differences in performance capability. Indeed, it is a supportable assertion that many of the common methods of analysis in this realm seek principally to distinguish normalized trends across individuals, so that idiosyncratic or individual variations are given diminished attention or frequently they are not considered at all.

When examining tracking performance there are many ways in which to distinguish the relationship between input and output (Viviani and Campadelli, 1987). Of critical concern are the causal relations between task variables and the resultant response characteristics. In a human-machine system, inputs and outputs have to be considered, according to the nature of their scales (qualitative or quantitative), and their origins (deterministic or stochastic, Sandquist 1985). The combination of these two points of view yield several modelling techniques. These techniques depend upon how the experimental data are integrated. The data may be summarized over space, over time, across individuals, or controlled factors, or through separated or combinatorial methods. For example, in the time or frequency domain, transfer functions or stochastic models have been proposed (Phatak and Bekey 1969, Smith 1967). If the data are integrated over both time and space, global indices such as normalized or non-normalized root mean square error, time delay, and gain can be computed (Ikeura and Inuoka 1990, and see Mates and Radil 1992). For a given experimental design, the approach that is most often used to assess the influence of the input factors on these indices is analysis of variance (Mead 1988).

Thus, in the data procedures used in the previous experimentation two problems emerge. First, as analytic methods have mainly dealt with time, frequency, or more global approaches, the multidimensional aspect of response has rarely been taken into consideration. When it is considered, the different dimensions are generally analysed through separated ways and through indices computed for each dimension (Massimino *et al.* 1989). Second, these procedures mainly focus on the 'global quality' of task performance through summed indices such as root mean square of the error signal, time spent on target, or time lag and not on the actual behaviours emitted during task performance. Individual differences can arise from intrinsic variation in physical characteristics such as skill level, musculature, or the susceptibility to fatigue, or from cognitive differences in, for example, response selection strategy, or indeed from combinations of these factors. Therefore, the primary aim of the present paper is to promulgate a descriptive and multidimensional approach to examine individual responses in a two-dimensional tracking control task.

2. Experimental method

2.1. *Experimental participants*

Twelve, right-handed male individuals volunteered to participate in the present experiment. They formed a convenience sample drawn from the faculty, staff and students of the University of Minnesota. Their mean age was 31.1 years, with a range from 22 to 38 years. Each was in professed good health at the time of testing. None had any visual or motor impairment that would restrict capability in respect of the required tracking task.

2.2. *Experimental design*

The present experiment employed a within-subject design in which each participant took part in all three experimental conditions. Each of the three conditions were administered as separate sessions and each consisted of three sequential 5-min trials. For each session, the first and last trials were fixed at a medium level of difficulty. By varying the difficulty of the middle trial between high (H), medium (M), and low (L) levels, the three experimental conditions were created: MLM (low difficulty condition), MMM (medium difficulty condition), and MHM (high difficulty condition). All participants first completed a training phase consisting of one session at the medium difficulty level (MMM). For the subsequent testing phase, each participant completed three additional sessions, one for each level of difficulty. Thus, including the training trials, each participant completed four sessions of three 5-min trials, amounting to a total of 60 min of tracking performance under the various conditions. The order of administration of the sessions in the testing phase was randomized across participants. There were at least two days between each session to avoid acute effects associated with any localized muscle fatigue (see Hancock *et al.*, 1989).

2.3. *Experimental procedure*

The participant was seated in front of a computer display in a darkened room and was asked to track an aeroplane icon target that moved randomly across the screen. The forcing functions of the X and Y direction were generated by summing a large number (40, 45, 50, respectively, for each condition of increasing difficulty) of sinusoids of different frequencies, uniformly separated in log scale and arbitrary phases. The spectra of the forcing functions were rectangular with cut-off frequencies of 0.2, 0.4 and 0.6 Hz for the L, M and H levels of difficulty respectively (i.e. the forcing functions were equivalent to band limited white noise). The relative amplitude ratio of these forcing functions was 1.0 : 1.5 : 2.0. Therefore, the target moved more quickly and with larger excursions in the H level task and moved slower and less widely in the L level condition. The object of the task was to keep this target inside a central circular gun sight area using a joystick (FlightStick, CH Products, Vista, CA). Therefore, the task was a two-dimensional compensatory tracking task with first-order control. The control gains of the joystick in the X and Y directions were identical. The duration of each individual trial was 300 s. Preceding and following each trial, the participant was asked to provide a response on a critical flicker fusion test and to evaluate subjective workload using the computerized version of the NASA-TLX task (Hart and Staveland 1988). Results from these latter measures are described elsewhere (Hancock *et al.* 1995).

3. Data analytic procedures

The data analysis procedures required sampling of target and control motions at 5 Hz, which resulted in a 1500 samples for each 5-min tracking trial. There were 108 experimental trials (12 Participants $\times$ 3 Sessions $\times$ 3 Trials) yielding a total of 162 000 data samples. The primary goals for the analysis of these data were to characterize and compare the tracking behaviour of individuals. To achieve these goals, tracking behaviour was considered in terms of discrete intervals based on successive 200-ms trajectories of tracking. As illustrated in figure 1 (a), this tracking data was decomposed into two modalities, direction and velocity, both of which were consequences of movement given to the joystick. Combined data from these two modalities were then used to classify the tracking behaviours of each participant into 24 categories. Thus, this procedure yielded a data set containing information about the frequencies of specific behavioural outputs in response to input from the tracking task.

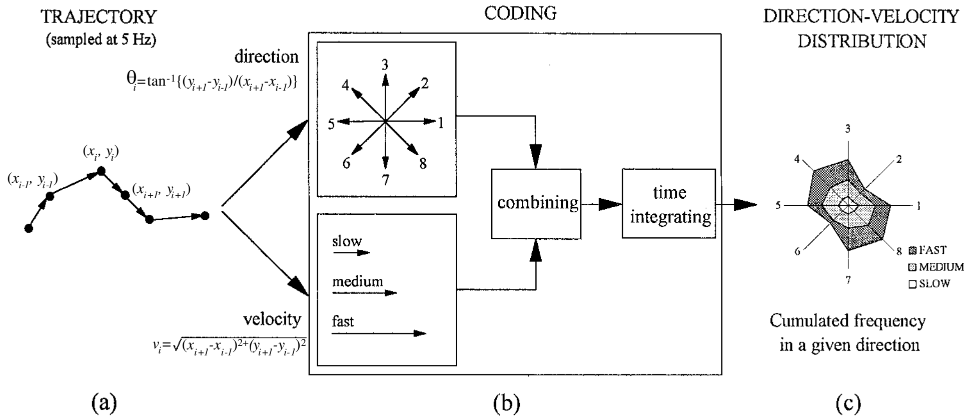

Figure 1. Control motion encoding to obtain the direction-velocity distributions expressed as histograms.

In the present experiment, the principle of the Freeman chain code was used to describe the trajectory direction (Pavlidis 1980). This technique consists of defining eight basic directions, as shown in figure 1 (b), and to associate the speed vector orientation to one of them. To describe the magnitude of the speed, three categories were considered, namely 'slow', 'medium' and 'fast', figure 1 (b). The 'slow' speed ranges were smaller than 135/40 arbitrary units (17 pixels/s) and the 'fast' speed was greater than 135/16 arbitrary units (42 pixels/s). These values are nearly equivalent to the maximum speed of the low-level input signal and the maximum speed of the fast-level input signal, respectively. The range of the 'medium speed' was between 135/16 and 135/40 arbitrary units (17 – 42 pixels/s). Then, the eight directions and three speed levels are combined in 24 categories. Each point of the ongoing response is approximated by one of these 24 combinations. In this way a qualitative variable V with 24 categories was created (and see Fingleton, 1984; Linhart and Zuchini, 1986). As shown in figure 1 (c), frequency distributions of V can be illustrated via direction-velocity histograms that were created by applying this coding technique for a sample and integrating over the point set corresponding to 5-min trial period. This procedure was also applied to the trajectories of the target. Thus, to assess the accuracy of tracking performance and to compare the tracking responses of each individual, the behaviour of the target and each participant was characterized by the distribution computed over all respective periods of tracking. The next stage of analysis was to study the influence of the input difficulty level on the observed direction-velocity behaviour patterns. The statistical method used to analyse the outcome histograms is the correspondence factor analysis (Benzecri 1992) and the principles of this method are summarized in the following section.

3.1. *Correspondence Factor Analysis principle*

Correspondence Factor Analysis (CFA) was introduced to analyse contingency tables defined on two $\boldsymbol{I}$ and $\boldsymbol{J}$ finite data sets with, respectively, m and n elements. The generic term of the table is rated r_{ij}, i.e. the number of occurrences the category i of $\boldsymbol{I}$ and the category j of $\boldsymbol{J}$ are simultaneously present in the data set. This is represented in figure 2.

In the present work, j is a category of the variable V, while i is an experimental trial, i.e. a given individual's response for a single trial of a session. In our case, these

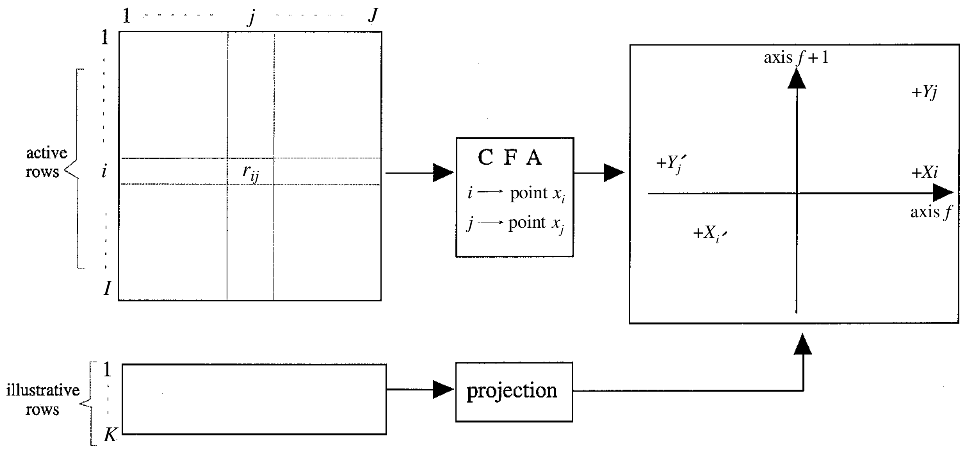

Figure 2. Schematic representation of correspondence factor analysis (CFA).

correspond to the frequencies for the direction-velocity in the category j ($j = I, \ldots, n = 24$) for an observation i ($i = I, \ldots, m$), where an 'observation' is one of the 108 total trials, being a combination of a trial subset, session subset and individual subset. The following values are considered:

$$r_i = \sum_{j=1}^{n} r_{ij},\ r_j = \sum_{i=1}^{m} r_{ij},\ r_j^i = r_{ij}/r_i,\ r_i^j = r_{ij}/r_j.$$

Two clouds of points can be associated to the frequency table: $^*N(\boldsymbol{I})$ is composed of m points X_i situated in $\boldsymbol{R}^n$ space. Each point is characterized by a weight r_i and a co-ordinate set $\{r_j^i\}$ $j = 1 \ldots n$. The distance measured in $\boldsymbol{R}^n$ is the chi-squared:

$$d^2(X_i, X_{i\prime}) = \sum_{j=1}^{n} \frac{1}{r_j}(r_j^i - r_j^{i\prime})^2.$$

The centre of gravity of $N(\boldsymbol{I})$ is GI:

$$\mathrm{GI} = \sum_{i=1}^{m} r_i X_i.$$

The inertia of $N(\boldsymbol{I})$ is In($\boldsymbol{I}$) and explains the variation within $N(\boldsymbol{I})$:

$$\mathrm{In}(\boldsymbol{I}) = \sum_{i=1}^{m} r_i[X_i - \mathrm{GI}]^2 = \sum_{ij} \frac{(r_{ij} - r_i r_j)^2}{r_{ij}}.$$

$^*N(\boldsymbol{J})$ is composed of n points Y_j situated in $\boldsymbol{R}^m$ space. Each point is characterized by a weight r_j and a co-ordinate set $\{r_i^j\}$ $i = 1 \ldots m$. The distance used in $\boldsymbol{R}^m$ is again computed using the chi-squared metric:

$$d^2(Y_j, Y_{j\prime}) = \sum_{i=1}^{m} \frac{1}{r_i}(r_i^j - r_i^{j\prime})^2.$$

The centre of gravity of $N(\boldsymbol{J})$ is GJ:

$$\mathrm{GJ} = \sum_{j=1}^{n} r_j Y_j,$$

and the variation within $N(\boldsymbol{J})$ is explained by its inertia, $\mathrm{In}(\boldsymbol{J}) = \mathrm{In}(\boldsymbol{I})$.

Given that the present study seeks to identify patterns of individual differences, CFA is more appropriate than traditional confirmatory methods of analysis (e.g. ANOVA, multiple regression) since, among other reasons, it is free of the constraints imposed by an *a priori* hypothesis. CFA is an inductive method generally used as an explanatory tool to uncover fundamental empirical regularities within a large categorical data set, such as that employed in the present study. Specifically, CFA brings to the fore the informative elements inside the rows and columns and points out relationships among this more meaningful data. To accomplish this, CFA seeks to compute orthogonal axes that minimize the inertia between the factors and their initial values. The CFA method is fully discussed in Benzecri (1992) and is nearly analogous to principle components analysis (PCA). A critical distinction between these two statistical methods is that PCA is most suitable for analysing continuous variables whereas CFA is designed for analysing categorical contingency tables. Like other factor analytic methods, the output of CFA can be considered as a qualitative and multidimensional pattern of the data. Moreover, it is possible to consider extra observations that do not participate to the building of factor axes, but are directly projected on them (Benzecri 1992). An eminently useful result of CFA is the correspondence map that provides a visual representation of the relationships between the row and column categories as well as an indication of an individual's temporal progression across trials.

4. Experimental results

Since the main objective of the present work is to compare the individual behaviours, analysed observations were the distribution of the 12 subjects. The distributions corresponding to the 108 periods of 5 min (12 Participants $\times$ 3 Sessions $\times$ 3 Trials) and to the input (low, medium, high, and overall input) are considered as illustrative rows. Thus the active table has $J = 24$ columns and $I = 12$ rows, while the illustrative table has $J = 24$ columns and $K = 18$ rows.

4.1. *Inter-individual differences*

In lieu of the 12×24 active table that is too large to be directly illustrated here, figure 3 presents the results in the more comprehensible form of a correspondence map. the map indicates a factor plane with two axes accounting for 80% and 10%, respectively, of the total inertia. The relative position of the 12 tracking profiles corresponding to each participant's average performance are indicated with black circles. Average profiles of the target's behaviour under low, medium, and high conditions are labelled Input L, Input M, and Input H, respectively, and the point corresponding to the mean overall input profile is labelled Input X. The first factor was principally influenced by slow velocity upward direction-speed combination, gives as 3 s in figure 1 (c) and was, by and large, determined by the performance of a single participant, BR. The relative position of BR along axis 1 indicates that this particular participant made excessive use of slow, vertical tracking behaviour. The

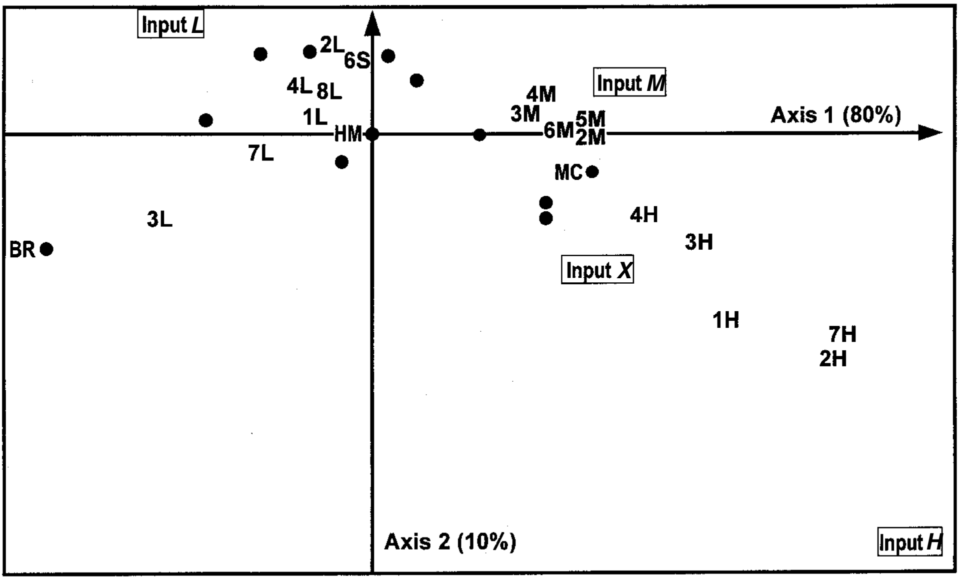

Figure 3. Factor plane of the 12 participants and representative direction-velocity combinations plotted together with the input level of tracking difficulty. Each individual participant's performance is represented as a black circle on the illustration.

finding that participants on the opposite side of the first axis had low relative values for 3 s further indicated that vertical tracking behaviour was a salient discriminator among these data. Similarly, points corresponding to combination 3 s and participant BR also had dominant influences in defining the second axis. Further inspection revealed that, along with BR, another participant made excessive use of combination 3 s. When controlling for the substantial anomalous influence from these two participants, the most discriminatory combination was 7 s, indicating that slow vertical behaviour was still the best between-participant discriminator.

Figure 4 presents the individual trial profiles for the most and least accurate participants, respectively, MC (points denoted in diamonds) and BR (points denoted in crosses). The nomenclature used for these points describe the three-trial sequence of a particular experimental session, where the specific trial being processed is in capital typeface. For example, the two profiles labelled Mhm refer to the performance of the first trial that was at a medium level of difficulty, where the difficulties of the second trial and third trials were high and medium, respectively. When considering the positions of the four input distributions (Input *L*, Input *M*, Input *H*, and the summed Input *X*), it is evident that the tracking response of BR does not vary with the different levels of input difficulty. Additionally, the large absolute distance of BR from the input distributions is indicative of poor tracking performance, while the close proximity of MC represents highly accurate tracking performance. The trajectories of the dashed lines connecting the various profiles of participant MC indicate that this participant was consistently able to closely match the input distribution across trials and levels of difficulty. Participant HM performed at the average level for the whole sample group, and thus, is situated at the intersection of the two axes. To underscore the individual differences brought to the

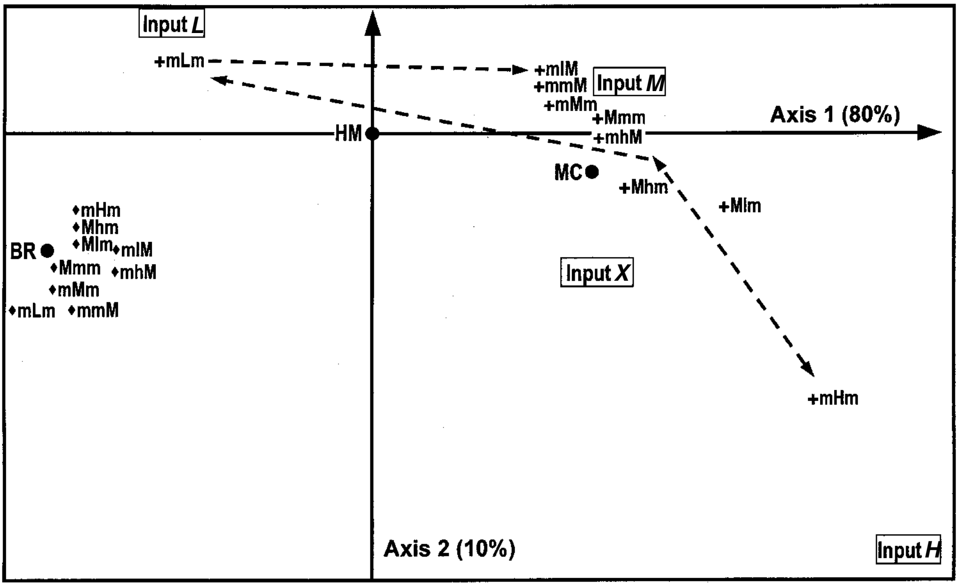

Figure 4. Factor plane showing the performance of three specific individuals, namely BR, HM, and MC. These points represent the data for the individual recording the best performance (MC), the worse performance (BR), and the performance of the individual closest to the group mean (HM). The profiles for each trial for each session for BR and MC are also illustrated. BR produced poor performance in failing to respond to different levels of input demand, MC showed superior performance and the adaptation of MC to different levels of demand is illustrated by the arrows connecting MC's response.

fore by the analysis, figure 5 presents direction-velocity histograms corresponding to the overall input distribution (Input) and these for the best (MC), the worst (BR), and the representative closest to the mean (HM) of the tracking performances. It is clear from the patterns illustrated by these histograms that BR and MC represent two extreme cases in our experimental sample and, moreover, that the primary distinction among these three distributions is the reliance on vertical-velocity combinations.

4.2. *Influence of input distributions*

The points corresponding to the 18 trials of the two most extreme participants (BR and MC) and the three input distributions (H, M, and L) have been projected as illustrative rows in figure 6. Overall, the performance of BR, represented by the direction-velocity histograms on the left, does not vary with the input in a significant manner, whereas, on the opposite side, MC has large correspondent changes with the input. Further, the histograms for the target input and these two participants show two distinct ways in which the tracking performance of a participant is influenced by the input difficulty level. The individual distribution patterns are very characteristic. For BR, the three distribution patterns present changes that are not consistent with the corresponding input distribution, i.e. whatever the input, BR mainly uses up-down movement with slow speeds. At the opposite, MC shows distribution patterns that are close to the input patterns in both speed and direction.

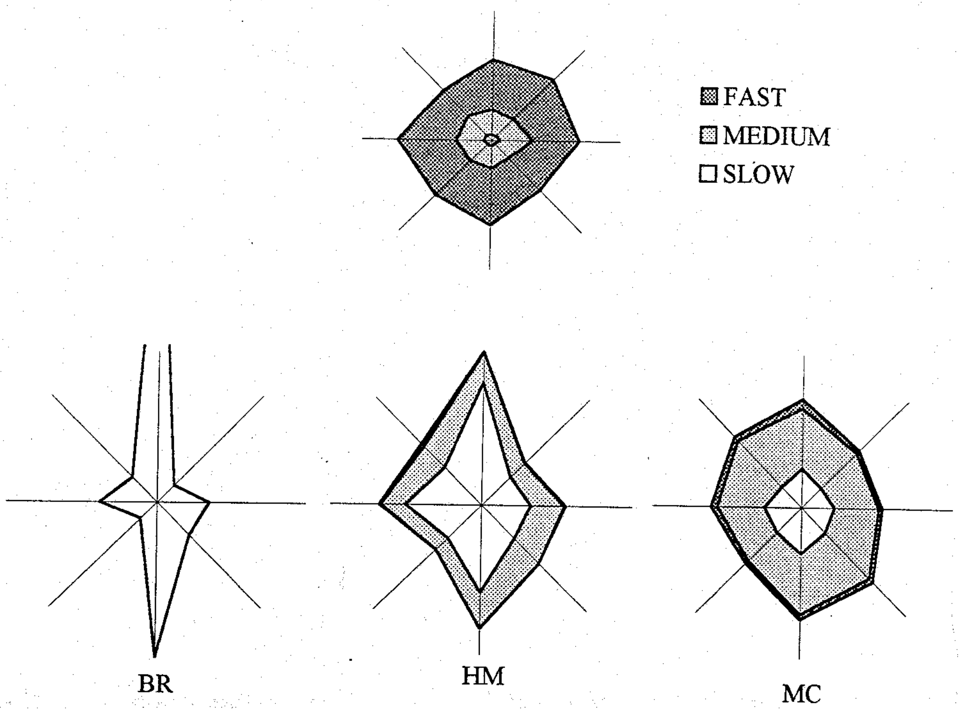

Figure 5. Overall direction-velocity histograms for three different individuals in comparison with the input, at top of figure.

5. Discussion

The findings from the present study warrant discussion from both the behavioural and the statistical points of view. The most striking result from the behavioural perspective is the high variability among the response patterns of individual participants, despite having received comparative training and identical inputs on all trials. Since the input trajectories were the same for each participant, we have considered that an ensemble distribution computed over the nine trial periods (when integrating over the dependent variable) of a given operator *is* an individual characteristic. The clearest difference in the response distributions was in the degree that participants tracked along the vertical axis and, specifically, was manifested as different relative time spent executing up-slow movements and down-slow movements, respectively, shown as combinations 3 s and 7 s, on figure 1 (c). Therefore, two salient individual behaviour characteristics are implicated by these results. The first corresponds to participants who mainly use up-down movement with low velocity while the second corresponds to participants who employed a more comprehensive set of direction-velocity combinations. This represents an initial differentiation between individuals' continued tracking performance.

The first category of behavioural response can mainly be accounted for primarily by the physiology of the joint mechanism involved, specifically wrist dynamical limits and second, only by decision-making behaviour. To explicate this theory let us assume that a position mismatch signal is sensed by the visual system and fed back to

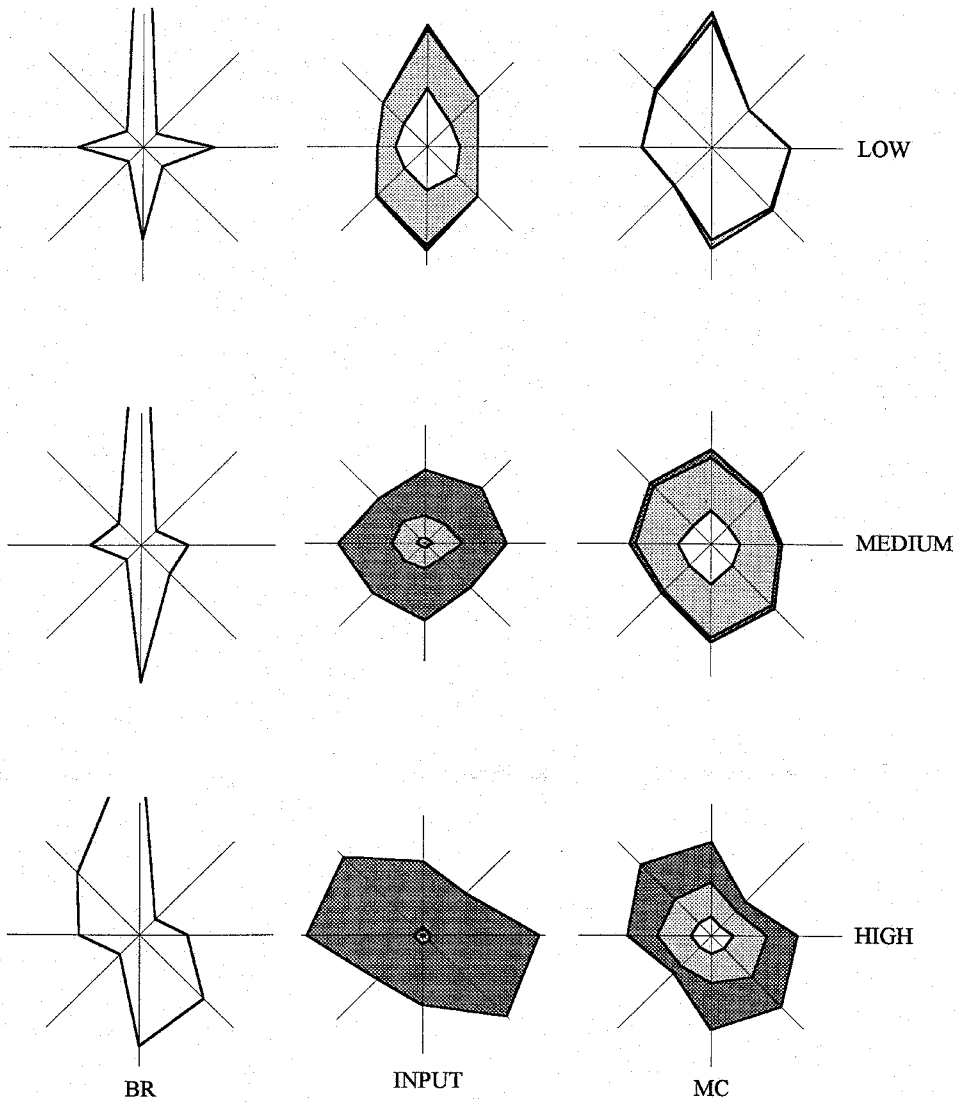

Figure 6. Direction-velocity histograms obtained for the three input levels for the two most extreme individuals, BR and MC.

the movement-production system (Johnson and Phatak 1990). The strategy used to null the error consists of first applying slow velocity vertical movements. However, when the adjustment speed does not compensate to match the target's trajectory, the operator does not have enough time to match both X and Y signals. The preference to perform first the Y movement rather than the X movement can be explained by the asymmetry between push-pull and left-right rotational movements. Moreover, the much higher frequency of upward vertical combinations suggests that the push exertion is preferred to a pull motion. Thus, the dynamical limits of the wrist and/or the forearm constrain movement velocity regardless of target velocity; this behaviour is summarized on figure 7 (a). The second individual behavioural characteristic

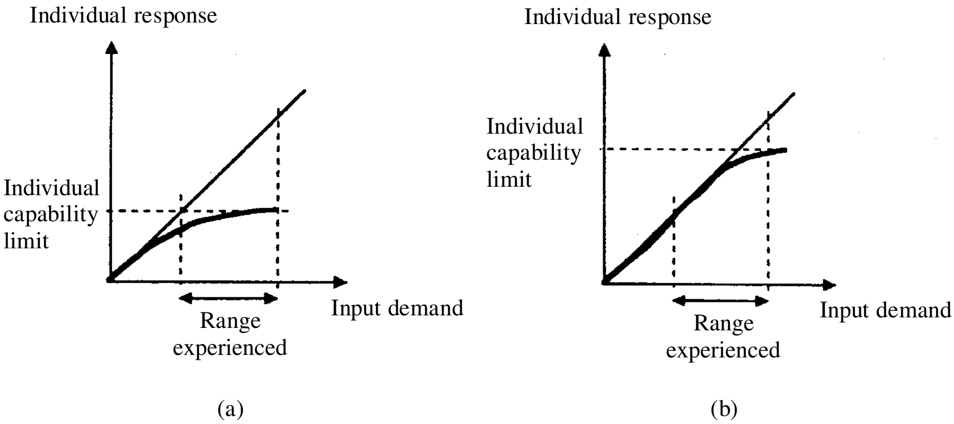

Figure 7. Theoretical structure for the basis of encapsulating observed individual differences.

indicated by these data, in contrast to the first, corresponds to individuals who were free of directional and speed limitation while tracking. As illustrated in figure 7 (b), by utilizing a wider range of direction-velocity possibilities, these individuals achieved better accuracy due to a higher limit in tracking capability. Velocity-based accounts of individual differences have also been related previously, but no preferential direction has been demonstrated in such studies. Given the novelty of our findings, independent replication is needed to ensure that certain local conditions, e.g. the sample of participants recruited, the specific input device employed, do not exert distortional effects on the respective tracking response.

From the statistical perspective, the present study demonstrated a procedure that, first, describes individual motor control behaviour and, second, facilitates the comparison of the obtained idiographic behavioural characteristics. Statistical differences between individual performances are better served by a confirmatory method such as ANOVA and are commonly assessed using data from the transfer functions for the X and Y components of the inputs and responses. Descriptive output from a CFA is generally in the form of a correspondence map. In regard to the present study, this map relates for each individual both the accuracy of performance and the ensemble of motor behaviours that comprise the underlying strategies used to track the target. Therefore, CFA is a means for uncovering different tracking strategies utilized across individuals. This information may be derived from the correspondence map by studying the relative position of profiles corresponding to an individual's output behaviour (both the mean or on a per trial basis), the input behaviour, and the eight direction-velocity combinations. Large distances between these points are then indicative of substantial differences in tracking behaviour.

More particularly, this procedure offers a unique contribution to the assessment of individual differences over and beyond that of more traditional methods such as analysis of the root mean square (RMS), transfer functions, or other input-output parameter of the behaviour output. Comparatively, the disadvantage of using these other methods is that the intrinsic behavioural properties of the operators cannot be distinguished. The RMS and RMSE (root mean square error) are time-averaged values and are primarily suited to describe the accuracy of the operator's responses.

While there may be significant differences in RMSE between participants, such a measure does not include speed and directional information. Therefore RMSE is not well suited to distinguishing behavioural properties, especially for distributions of tracking behaviour with more than one dimension. RMSE does not account for the motions comprising participant BR's tracking behaviour and, therefore, does not relate this participant's reliance on vertical control movements with low velocity that occurred regardless of the input behaviour. While the transfer function or some other parameter that relates input and output (i.e. time constants and gains, or traditional parameters) may provide information about directional dominance, analysis performed separately on the X and Y axes does not facilitate the identification and characterization of specific tracking strategies or response patterns at the level attained via CFA. For example, the information contained by the left-reclined pattern depicted by the direction-velocity histogram of figure 5 (MC, High), describes the frequencies which each direction and velocity possibility were utilized and is far more meaningful than an overall rating of accuracy or directional dominance.

In summary, to uncover and highlight inter- and intra-individual differences from this multivariate characterization, a powerful multidimensional, exploratory analysis was conducted. As required by the CFA method, the otherwise continuous tracking behaviour was discretized into categorical variables. The CFA applied to these data uses the chi-squared metric that is suitable for examining frequency data. The distinction between using a parametric or non-parametric approach was not the primary reason why CFA was used. Rather, with each trial being characterized by an empirical histogram with 24 categories, the problem devolves to having to indicate from which categories those differences originate and to identify the influence of individual factors and input factors on these more discriminating categorizations. Generally speaking, CFA, as opposed to more global techniques, is not based on the assumption that inter-individual differences do not exist and that only one variable is sufficient to describe individual behaviour. From this descriptive and multidimensional approach, classes of individual behaviour and response to increasing difficulty input were represented. The obtained influence models constitute a description that could be used for future simulation procedures. The distinction made by this research between the individuals who use primarily low velocity vertical movements and individuals who use a full range of directions and velocities when tracking has implications for those designing control and display devices for use in tasks requiring accurate hand driven control. Instances of tracking-related displays in systems where accurate control is critical are those found in many forms of surgery, targeting systems of combat aircraft, as well as the control of ground and water-based vehicles. Knowledge about the individual differences uncovered by the present study may benefit both the selection and training of users of these systems. A simple test based on the procedures in the present work can be used to discriminate between the two types of individuals. Those who are determined to possess the individual characteristic whereby a more compressive dynamic range of motor behaviour is employed would be the most accurate trackers and most capable to deal with a wide array of input behaviour. Individuals who demonstrate poor tracking ability and who correspond with the individual characteristics associated with dominant use of slow, vertical movements, may respond more effectively to a training regime that focuses on deficiencies in these specific aspects of tracking control.

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References

Abdel-Malek, A. and Marmarelis, V. 1990, A model of human operator behavior during pursuit manual tracking—what does it reveal? *IEEE International Conference on Systems, Man and Cybernetics,* **1,** 674–676.

Benzecri, J. P. 1992, *Correspondence Analysis Handbook* (New-York: Marcel Dekker).

Birmingham, H. P. and Taylor, F. V. (1954). A design philosophy for man-machine control systems. *Proceedings of the IRE*, **41,** 1748–1758.

Craik, K. J. W. 1947a, Theory of the human operator in control systems. I: The operator as an engineering system, *British Journal of Psychology*, **38,** 56–61.

Craik, K. J. W. 1947b, Theory of the human operator in control systems. II: Man as an element in a control system, *British Journal of Psychology* **38,** 142–148.

Fingleton, B. 1984, *Models of Category Counts* (Cambridge: Cambridge University Press).

Hancock, P. A., Williams, G., Miyake, S. and Manning. C. M. 1995, The influence of task demand characteristics on workload and performance, *International Journal of Aviation Psychology,* **5,** 63–85.

Hancock, P. A., Robinson, M. A., Chu, A. L., Hansen, D. R. and Vercruyssen, M. 1989, The effects on practice on tracking and subjective workload, *Proceedings of the Human Factors Society*, **33,** 1310–1314.

Hart, S. G. and Staveland, L. 1988, Subjective workload as measured by the NASA TLX, in P. A. Hancock and N. Meshkati (eds), *Human Mental Workload* (Amsterdam: North Holland), 139–183.

Ikeura, R. and Inuoka, H. 1990, Teaching of robot task by manual control—iterative modification by human operator, *IEEE International Conference on Systems, Man and Cybernetics,* **1**, 525–526.

Johnson, W. W. and Phatak, A. V. 1990, Modeling human visuo-motor strategy during vehicle control, *IEEE International Conference on Systems, Man and Cybernetics,* **1**, 530–532.

Levison, W. H., Baron, S. and Kleinman, D. L. 1969, A model for human controller remnant, *IEEE Transactions in Man-Machine Systems*, **10,** 101–108.

Linhart, H. and Zucchini, W. 1986, *Model Selection* (New York: Wiley).

Massimino, M. J., Sheridan, T. B. and Roseborough, J. B. 1989, One handed tracking in six degrees of freedom, *IEEE International Conference on Systems, Man and Cybernetics,* **2**, 498–503.

Mates, J. and Radil, T. 1992, Two-dimensional manual tracking of periodic movements: event and time interval analyses, *International Journal of Psychophysiology*, **11,** 123–132.

McRuer, D. T. and Jex, H. R. 1967, A review of quasi-linear pilot models, *IEEE Transactions on Human Factors in Electronics*, **8,** 231.

Mead, R. 1988, *The Design of Experiments. Statistical Principles and Practical Application* (Cambridge: Cambridge University Press).

Pavlidis, T. 1980, *Structural Pattern Recognition* (Berlin: Springer-Verlag).

Phatak, A. V. and Bekey, G. A. 1969, Model of the adaptive behavior of the human operator in response to a sudden change in the control situation, *IEEE Transactions on Man-Machine Systems*, **10,** 72–80.

Poulton, E. C. 1974, *Tracking Skills and Manual Control* (New York: Academic Press).

Sandquist, G. M. 1985, *Introduction to System Science* (New York: Prentice-Hall).

Smith, H. J. 1967, Human describing functions measured in flight and on simulators, *IEEE Transactions on Human Factors in Electronics*, **8,** 264–268.

Viviani, P. and Campadelli, P. 1987, Visuo-manual pursuit tracking of human two-dimensional movements, *Journal of Experimental Psychology: Human Perception and Performance*, **11,** 62–78.

Miyake, S., Loslever, P., & Hancock, P.A. (2001). Individual differences in tracking. Ergonomics, 44 (12), 1056-1068.