# Visual Performance in Multidimensional Data Characterisation with Scatterplots and Parallel Coordinates

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## Abstract

*We present a study on the visual assessment of relative data point distances in Parallel coordinate systems and scatterplots in Cartesian coordinate systems. Specifically, we assess the impact of coordinate system type, dimension, and relative point distance deviation. We performed an online pilot experiment with 100 participants using Amazon's MechanicalTurk. The experiment design and methodology are presented in detail and results indicate that there may indeed be a difference in human performance when visually assessing distances in the considered coordinate systems. We argue that further investigations are needed to draw stronger conclusions. These should consider inclusion of other factors into the experiment design, such as the relative angle between data points that is expected to have a significant impact on the outcomes.*

## Introduction

Visual assessment of graphical perception has been of research interest for several decades with pioneering work by Cleveland et al. [5] on fundamentals of using graphical elements to quantify visual information. Since then, there has been a large body of work covering many aspects of visual perception in visualisation and graphics [21]. Generally, we distinguish between works that focus on the assessment of low level perceptual attributes in the spirit of Cleveland's work [15] and comparison of high level complex visualisations [1, 19].

Scatterplots in Cartesian coordinate systems have been around for a long time and are widely adopted to visually represent data points. Their limitations of representing multivariate data have sparked the development of new techniques, such as Parallel coordinates [13]. Parallel coordinates have since become a standard tool for the visualisation of multivariate data by representing N-dimensional points as polygonal lines crossing N parallel axes. Similar to Cartesian coordinates, this layout allows one to read off data values at different levels of dimensionality: individual axes represent one-dimensional information, pairs of axes represent two-dimensional projections, and retrieving values from multiple axes provide enough information to reconstruct multidimensional data. While some studies suggest that Cartesian coordinates outperform parallel coordinates in conveying two-dimensional linear correlations, others have shown that parallel coordinates may provide a very effective interface for tracing the values of a single data point across multiple dimensions.

In this study, we extend this line of research by assessing the visual performance of novice users in value retrieval and comparison/characterisation tasks for Cartesian Coordinates (CC) and Parallel Coordinates (PC). Specifically, we investigate human performance in estimating relative distances between data points in CC and PC in various dimensions. We hypothesise that the performance of PC relative to CC increases with the dimension of the coordinate system. Towards this end, we conducted an on-line psychophysical experiment using Amazon's MechanicalTurk. We found that there may indeed be a difference in human performance when visually assessing distances in the considered coordinate systems. We argue that further investigations are needed though to draw stronger conclusions with regard to our hypothesis. We consider this experiment to be a pilot to a larger body of work that investigates low level perceptual attributes in data visualisation to effectively represent data properties.

The remainder of the paper is organised as follows. In the following section we briefly review some more related work. We then go on introducing in detail the experiment design and methodology, followed by an analysis and discussion of the experiment results. We finish with concluding remarks.

## Related Work

A single scatterplot in a CC system is typically used to visualize points in two dimensions. For $N$-dimensional data, multiple two-dimensional scatterplots can be used to convey the full dataset in $N - 1$ (typically axis-aligned) two-dimensional subspaces. These can be arranged in various ways [4, 18, 20], with the scatterplot matrix [8] (SPLOM) being the most common approach.

Parallel Coordinates [13] have become a standard technique for the visualization of multidimensional data. Since the first publication [12], many techniques have been proposed to address the most common challenges in traditional PC (see [10] for a recent overview), typically by modifying either the layout of axes or the appearance of lines. While most of these were evaluated in comparison to the traditional, line-based PC plot [14], only little is known about the effectiveness of traditional PC in conveying simple properties of the underlying, *multidimensional* data.

Two independent studies [6, 17] found that scatterplots outperform PC in conveying linear correlation. However, both studies investigated two-dimensional data. Holten & van Wijk [11] further found that participants in their study identified the number of clusters faster and more accurately with a set of scatterplots. While clusters are a multidimensional property, its number does not change once identified in any of the subdimensions. In contrast, the relative distance of points as investigated in this work can only be judged accurately after looking at all dimensions.

Kuang et al. [16] compared the performance of a value retrieval task in PC with three variations of scatterplots. Value retrieval is a subtask for many other tasks [2], including the estimation of relative distances. The results of their study show that PC outperform scatterplots in CC for sparse data. This is expected, as PC support the task naturally by resolving the correspondence of point coordinates over multiple dimensions visually, i.e. by connecting them with a line. In order not to confound our results with the value retrieval task, we use color to resolve the correspondence of points between multiple dimensions.

# Psychophysical Experiment

## Experiment Design

We designed the experiment with the main goal to investigate the relative performance of PC and CC for multi-dimensional data characterisation. We considered 2-dimensional, 3-dimensional, and 4-dimensional coordinate systems. For the purpose of assessment, we simply presented 3 data points in each coordinate system labelled **A**, **B**, and **C**. Observers were instructed to identify the point B or C that is closer to point **A**. We did not control the overall distance and angles between the data points but the relative distance deviation of **A** to **B** and **A** to **C** to add variability to the experiment. Given the above, we had three independent variables: coordinate system type $T$, coordinate system dimension $D$, and point distance deviation $\delta$. The latter is defined as the absolute difference of the respective distances of **A** to **B** and **A** to **C**. The details of these independent vairables (IV) are summarised in Table 1. We did a full factorial design of these IVs resulting in $2 \times 3 \times 11 = 66$ stimuli.

**Table 1: Summary of independent variables.**

| Variable name | Variable values | # |
|---|---|---|
| Coordinate system type $T$ | Parallel / Cartesian | 2 |
| Coordinate system dimension $D$ | 2 / 3 / 4 | 3 |
| Point distance deviation $\delta$ | 0 / 0.05 / 0.1 / 0.15 / 0.2 / 0.25 / 0.3 / 0.35 / 0.4/ 0.45 / 0.5 | 11 |

## Stimuli Creation

We created the stimuli using R. For each plot, three data samples were presented in the respective coordinate system type and dimension. While the IVs summarised in Table 1 were fully controlled, the overall distances and angles between data samples were randomly computed. Example stimuli are presented for 2D, 3D, and 4D coordinate systems in Fig. 1, Fig. 2, and Fig. 3, respectively.

While the design of PC lends itself to visual representations in coordinate system of three or more dimensions, CC are most suitably presented in two dimensions. We therefore chose to present three and four dimensions in our experiment as a series of 2D CC systems. Specifically, two 2D CC systems are needed for 3D representation and three 2D CC systems are needed for 4D representation.

The axes for all coordinate systems are referred to as $Xi, i \in \{1,2,3,4\}$. For the PC we chose the most intuitive arrangement for these axes by simply sorting them in increasing order from left to right. The strategy for arranging the CC axes was not as intuitive. Several such strategies are discussed in Kuang et al. [16] and we decided for an arrangement that we consider to be fairest

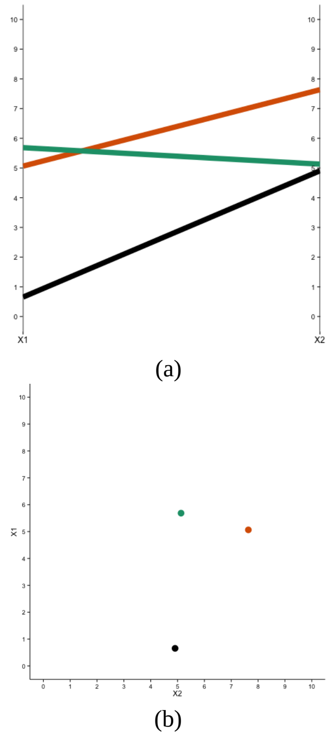



***Figure 1.*** *Example 2D stimuli for (a) PC and (b) CC systems.*

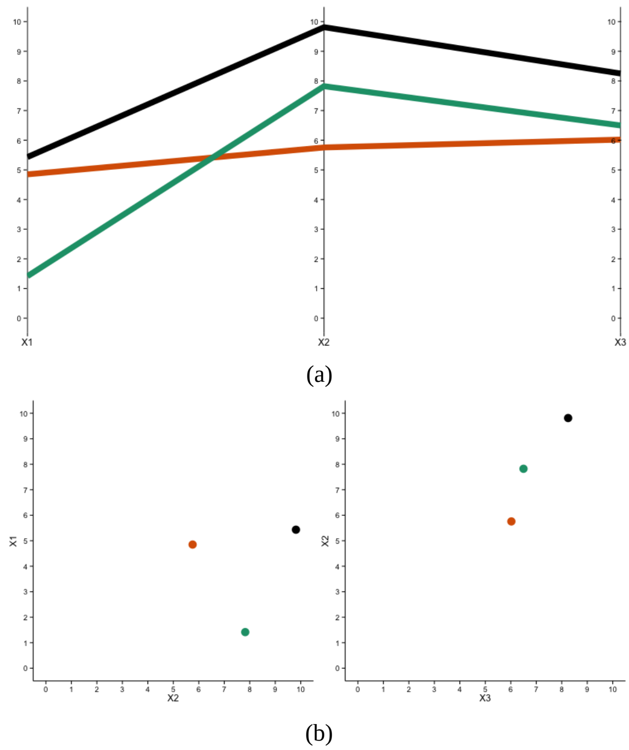
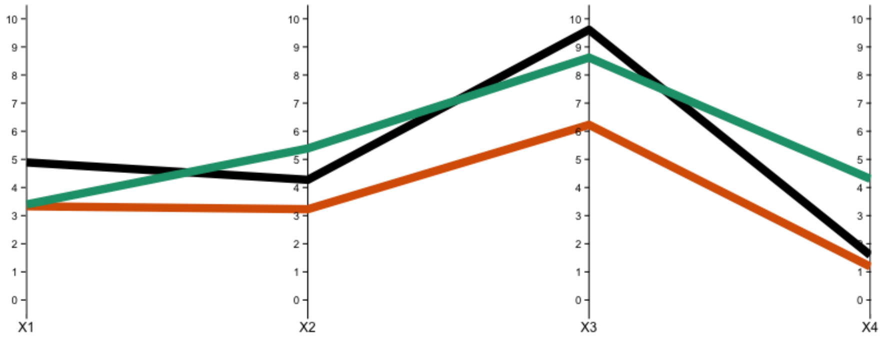
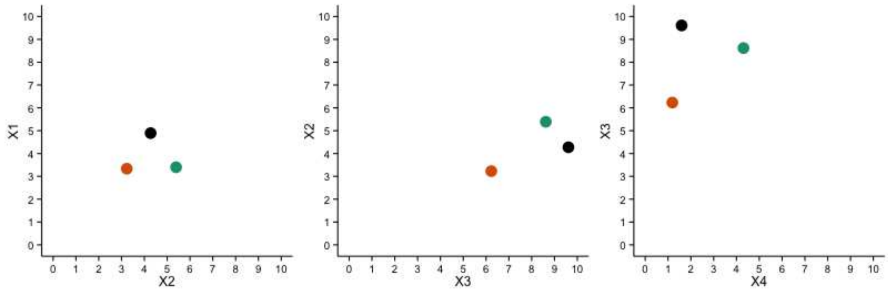



***Figure 2.*** *Example 3D stimuli for (a) PC and (b) CC systems.*

for comparison with PC: mapping consecutive dimensions onto




(a)




(b)

***Figure 3.*** *Example 4D stimuli for (a) PC and (b) CC systems.*

consecutive axes (referred to as ’Remember Value’ by Kuang). Specifically, the first CC system is mapping $X1$ onto $X2$ and, if applicable, the second and third CC systems are mapping $X2$ onto $X3$ and $X3$ onto $X4$, respectively.

The colours of the lines and points are the same between the PC and CC and were chosen from ColorBrewer [7] for them to be distinguishable also by participants with colour vision deficiencies. Legends were provided that mapped the colours onto the labels: black for **A**, red for**B**, and green for **C**.

### Experiment Methodology

The experiment was performed online using Amazon MechanicalTurk [3], which has been shown to be a viable technique for graphical perception assessment [9]. Our experiment consisted of three stages as follows.

- **Introduction:** The potential participants were provided with relevant information about the experiment, such as, the purpose, remuneration, and intent for use of the collected data. Participants were also informed that the experiment had been approved by the CSIRO Social Sciences Human Research Ethics Committee and have been provided with appropriate contact details should they have any questions or issues concerning the experiment. After carefully reviewing this information, participants were asked to give their consent for taking part in the experiment.
- **Training:** A detailed explanation of the experiment procedures as well as a brief tutorial on PC and CC was presented. A short training session was performed in which six stimuli were presented that were not part of the actual test stimuli. These stimuli were carefully chosen to represent all coordinate system types and dimensions and a range of point distance deviations. Only if the participants answered all six training questions correctly were they allowed to continue with the actual experiment.
- **Experiment:** The 66 test stimuli were all presented on a scroll-down screen, with the instructions provided above each stimulus and the radio buttons for choosing the answer being provided below the stimulus. The stimuli were presented in randomised order.

The ’Introduction’ and ’Training’ were both presented on the same screen and were part of a ’Qualification’ session. If passed, the participants could move on to the next screen to perform the actual ’Experiment’.

The experiment task presented to the participants for each of the stimuli was as follows: *Please consider the following coordinate system presenting three data points A, B, and C. Please choose the point B or C that is closer in distance to point A.*. The participant could choose one of three answers using radio buttons: ’B is closer’, ’C is closer’, ’Both are equally far away’. The overall time to perform the experiment was estimated to be 25-30 min, including the qualification session but excluding breaks.

### Participants

A total of 100 people took part in the experiment. The participants were paid 4 USD for their effort in line with the minimum US wage of 8 USD per hour. No demographic information has been collected from the participants.

## Results

Our target variable of interest is the correctness of answers that the participants provided to each of the stimuli. In the following we analyse the target variable with regard to the participants and all independent variables. We also provide an overview of the total response times of all participants.

### Correct responses per participant

Each participant responded to 66 stimuli. We designed the experiment in a way to challenge the participants and did not expect from them to be able to answer all questions correctly. Figure 4 provides an overview of the number of correct responses by each participant. The participants are sorted here in descending order of the number of correct responses.

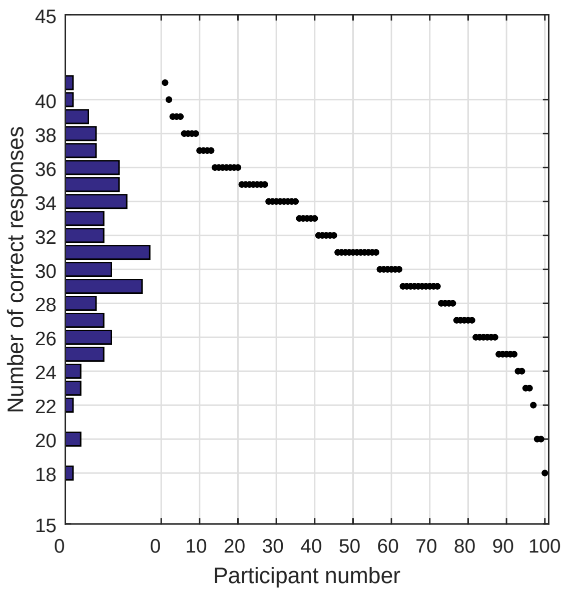



***Figure 4.*** *Number of correct responses for all participants. The participants are sorted here in descending order of the number of correct responses.*

We found indeed that participants were able to answer only about $1/3$ to $2/3$ of all questions correctly. Specifically, the best performing participant answered 41 questions correctly and the worst performing participant provided only 18 correct answers. The mean and median over all participants are 31, or just less than half of all stimuli. Given three possible answers, one could have expected 22 correct answers through random choice. There are 4 participants with 22 or less correct answers. As such one can argue that most of the participants made informed choices during the experiment. However, the performance by many individuals and as an average over all participants was lower than we initially expected. We believe that this is partly due to the point distance deviation being chosen rather low and therefore potentially challenging the participants too much.

### Correct responses: Parallel vs Cartesian coordinates

With this study we aimed to identify the relative performance in estimating visual distances in PC and CC. In Fig. 5 we therefore present the difference between the number of correct responses for PC and CC, referred to as $\Delta_C$. Positive and negative $\Delta_C$ indicate more correct responses for PC and CC, respectively. The difference $\Delta_C$ is provided for all coordinate system dimensions $D$ and point distance deviations $\delta$.

Our original hypothesis was that CC may outperform PC for lower dimensions and PC outperform CC for higher dimensions. While we can see clear differences between the performance of PC and CC for the different dimensions, we cannot see a clear trend that provides evidence towards this hypothesis. There is also no clear trend of $\Delta_C$ changing with regard to the point distance deviation $\delta$.

### Correct responses for independent variables

Figure 6 presents correct responses aggregated for the individual independent variables. It can be seen that PC overall outperforms CC. Counter to our intuition, the number of correct responses is not inversely related to the dimensionality but exhibits a minimum for 3D coordinate systems. Similarly, we cannot observe an expected increase in correct responses with an increase in point distance deviation $\delta$.

We performed a 3-way Analysis of Variance (ANOVA) for main effects and two-factor interactions to further investigate the impact of all independent variables on the number of correct responses. The results are presented in Table 2.

None of the main effects and interactions is significant. Keeping in mind that the experimental evidence at this stage is limited, we are careful in rejecting our hypothesis that the dimensionality of the coordinate system has an effect on the success of PC versus CC.

**Table 2: Analysis of Variance (ANOVA) of the independent variables for main effects and two-factor interactions.**

| IVs | Sum of squares | df | Mean square | $F$ | $p$ |
|---|---|---|---|---|---|
| $T$ | 564.4 | 1 | 564.38 | 0.62 | 0.44 |
| $\delta$ | 7777 | 10 | 777.7 | 0.85 | 0.59 |
| $D$ | 1496.3 | 2 | 748.14 | 0.82 | 0.46 |
| $T \times \delta$ | 5188.8 | 10 | 518.88 | 0.57 | 0.82 |
| $T \times D$ | 1237.3 | 2 | 618.65 | 0.68 | 0.52 |
| $\delta \times D$ | 11228.1 | 20 | 561.4 | 0.61 | 0.86 |
| Error | 18267 | 20 | 913.35 | | |
| Total | 45758.9 | 65 | | | |

### Total response times

Figure 7 presents the total response times for all participants. A log scale is used on the ordinate as some of the response times were extremely large compared to the majority. The order of the participant numbers on the abscissa is the same as in Fig. 4.

One can see that completion time for the experiment varied widely. From visual comparison between Fig. 4 and Fig. 7 as well as correlation analysis, we observe that the completion time of

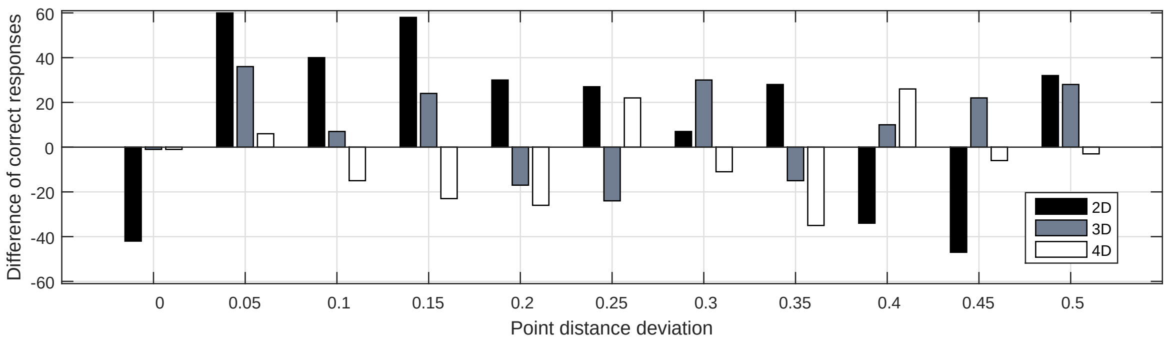



***Figure 5.*** *Difference between the number of correct responses for Parallel coordinates (PC) and Cartesian coordinates (CC). Positive and negative values indicate more correct responses for PC and CC, respectively. The difference is provided for all coordinate system dimensions $D$ and point distance deviations $\delta$.*

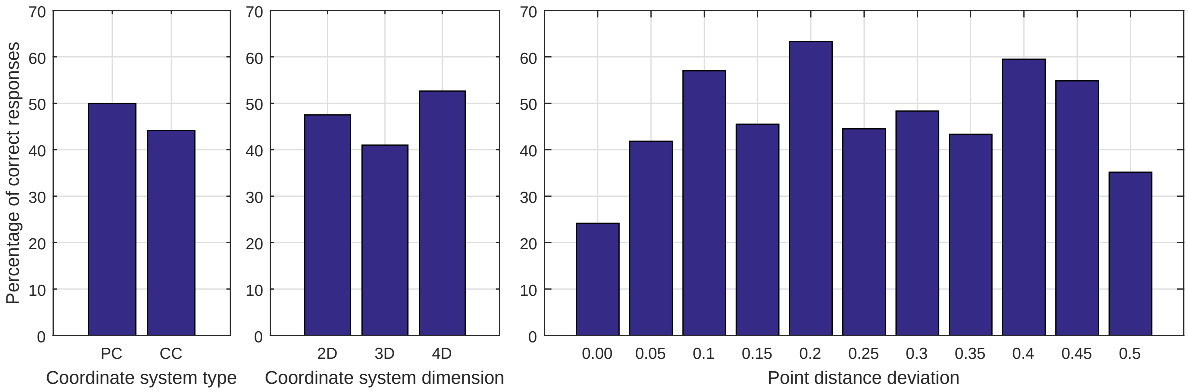



***Figure 6.*** *Number of correct responses for coordinate system type $T$ (left), coordinate system dimension $D$ (centre), and point distance deviation $\delta$ (right).*

the experiment is uncorrelated to the number of correct responses ($\rho = -0.1$). It therefore appears that participants who spent more time on the experiment did not necessarily perform better than participants who spent less time. Participants with completion times well above 100 min are expected to have not completed the experiment in one session but likely took extended breaks.

## Discussion and Conclusions

We performed an analysis of the target variable, the number of correct responses per stimulus, with regard to the IVs: coordinate system type $T$, coordinate system dimension $D$, and point distance deviation $\delta$. While visual analysis of the results shows clear differences within and between the IVs, we could not find any significant main and interaction effects. We can thus not draw strong conclusions with regard to our main hypothesis, that the performance of PC increases relative to CC with an incrase in dimention $D$. We believe that this may be partly due to the following experment design choices.

First, the point distance deviations $\delta$ were likely chosen too small, thus challenging the participants too much and not providing enough evidence towards 'obvious' cases. In future experiments, we will therefore more carefully design this factor by including more distinct point distance deviations.

Second, in our experiment, we did not control the relative angle between data points as well as overall distance. From looking at the results of this pilot study, we conjecture that especially the relative angle may have an impact on the results. This may be particularly true for the assessment in PC as the relative angle

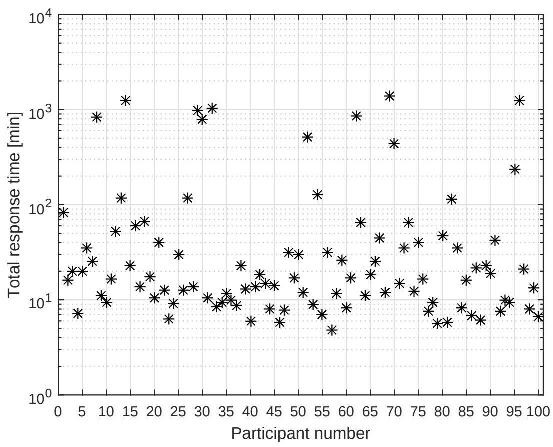



***Figure 7.*** *Total response times for all participants. The order of the participants is the same as in Fig. 4.*

results in entirely different patterns of the lines. In CC, the overall pattern would be subjected to rotation only, which is perceptually less demanding.

Finally, we used only one stimulus per condition. Given that the angle and overall distance were not controlled but are expected to have an impact, we believe that this would have an unwanted effect on the overall results. Controlling the angle and overall distance as outlined above should mitigate this problem.

In conclusion, we believe that this pilot experiment and the related analysis and discussion provide valuable insight into the visual assessment of relative distances in PC and CC. We will continue this effort taking into account the lessons learned in the experiment design. In laboratory based experiments, we also intend to include eye gaze tracking to obtain further insight into the visual assessment strategies of the participants.

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