

# Characterizing Perceptual Differences Due to Haptic Exploratory Procedures: An MDS Approach

Theresa Cooke\*

Christian Wallraven†

Heinrich H. Bühlhoff‡

Max Planck Institute for Biological Cybernetics  
Tübingen, Germany

## ABSTRACT

Previous work in real and virtual settings have shown that the way in which we interact with objects critically influences their perceptual representation. This paper provides new, quantitative evidence that the exploratory procedure used in haptic interaction with a set of objects changes the way they are represented in the brain. Subjects rated similarity on a set of nine novel, 3D objects after either following their contours, laterally rubbing their centres, gripping them, or sequentially touching their tips. A multidimensional scaling (MDS) technique was used to analyze the similarity data. The analysis showed that subjects were able to recover the topology of the input parameter space and perceived its dimensions as shape and texture. A large amount of variability in the way subjects weighted dimensions was found for all procedures except lateral motion, in which the texture dimension strongly dominated shape. The results provide clear evidence that using different procedures changes the relative perceptual weighting of object properties, but that even when exploratory procedures are strictly controlled, there can be large individual differences in the weightings of object properties. Our MDS-based analysis framework can be used to visualize and quantify perception under various real-world scenarios. In addition, this paper discusses its use as a benchmarking and validation paradigm for haptic rendering and virtual environments in general.

**Keywords:** haptic perception, exploratory procedures, shape, texture, multidimensional scaling

## 1 INTRODUCTION

There is a growing number of validation studies being carried out in the haptic virtual reality community, but many studies have focused on optimizing device-related parameters. Given the tight coupling between perception and action in haptic interfaces, it is also important to address how the action of a system's user affects the perceptual outcome. This study investigates how *modes of interaction* and, more specifically, how *exploratory procedures* (EPs) affect perception. There is a large body of work by Klatzky & Lederman about the role of EPs in real-world human perception (see [21] for a review). In virtual environments, Klatzky & Lederman have also studied the effects of exploratory factors and tool parameters [15]. Recently, Dostmohammed & Hayward investigated the role of active vs. passive exploration on curvature perception using a fingertip stimulation device [9]. The present paper represents an extension of Klatzky & Lederman's work on exploratory procedures in which the perceptual effects of changing EPs are visualized and quantified using a multidimensional scaling (MDS) framework

\*e-mail: [theresa.cooke@tuebingen.mpg.de](mailto:theresa.cooke@tuebingen.mpg.de)

†e-mail: [christian.wallraven@tuebingen.mpg.de](mailto:christian.wallraven@tuebingen.mpg.de)

‡e-mail: [heinrich.buelthoff@tuebingen.mpg.de](mailto:heinrich.buelthoff@tuebingen.mpg.de)

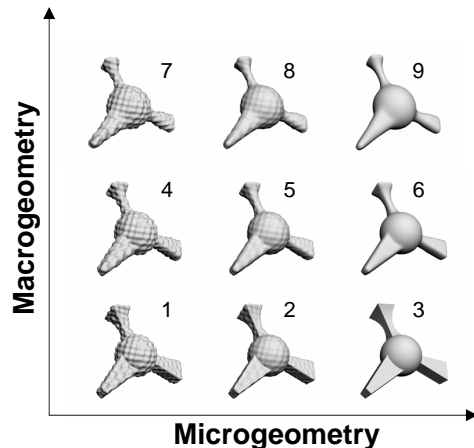


Figure 1: Stimuli: The stimuli consisted of 9 novel, 3D objects varying in terms of microgeometry ("texture") and macrogeometry ("shape"). Objects were created with 3D modelling software and manufactured in plastic using a 3D printer. Along the microgeometry axis, the objects' bumpy texture gradually becomes smoother. Along the macrogeometry axis, sharp angles in objects' meshes are relaxed.

recently developed for studies of crossmodal human perception and validation of computer vision algorithms [7, 6]. In this paper, we also discuss how the MDS framework can be used as a tool for comparing and benchmarking perception in real and virtual environments.

In a psychophysical experiment, participants haptically explored pairs of novel, 3D objects which varied in shape and texture (Figure 1) and rated the similarity between pairs of objects. Each participant explored the objects using four different EPs. Three of the EPs provided access to both shape and texture information (contour-following (CF), sequential exploration of object tips (TP) and enclosure or gripping (GR)), while the fourth EP, lateral rubbing motion along the surface (LM), provided access to texture information but little or no shape information. Similarity data were analyzed using MDS, a technique which returns a map of stimuli in a perceptual space. The spaces resulting from the use of different EPs were compared to test whether a change in haptic exploratory procedure affects participants' psychological representation of the objects.

The results of this study provide clear evidence that using different EPs to explore a set of objects changes the relative perceptual weighting of object properties. Furthermore, these changes can be quantified in terms of a relative property tradeoff value. Finally, we observed that even when EPs were strictly controlled, there were large individual differences in the weightings of object properties.

## 2 RELATED WORK

Here, we review studies of haptic exploratory procedures and motivate the choice of EPs evaluated in the current study.

Extensive studies of haptic explanatory procedures (EPs) have been carried out by Lederman and Klatzky [20, 21]. They classified exploratory hand movements into six main types (lateral motion, pressure, static contact, holding, enclosure, and contour following) and characterized each EP based on factors such as compatibility amongst different EPs and the speed with which different EPs can be executed. Of particular interest for this study is their demonstration that each EP has specific consequences for the kind of object information which is extracted during exploration. They expressed these biases in terms of *EP-to-property weightings*, which represent the extent to which a property can be extracted using a given EP. Lateral motion, a back-and-forth rubbing motion of the fingers over a surface, is best for extracting texture, but provides little or no shape information; enclosing objects in the hand provides information about global shape and texture, but little exact shape information; contour-following provides access to texture and global shape, and provides the most information about an object's exact shape.

Lakatos and Marks [18] further investigated how the use of different EPs affected subjects' weighting of local vs. global shape features for haptic similarity judgments. Subjects explored a set of 16 geometric objects using either a contour-following or an enclosure procedure and then rated the similarity between pairs of objects. Ratings were comparable in both conditions and the authors concluded that neither EP (contour-following or enclosure) is exclusively associated with a differential emphasis on local versus global shape. Interestingly, they found an effect of exploration *time* on the weighting of local vs. global shape: subjects had been biased towards local shape for exploration times of 1s and 4s, but this effect decreased significantly for exploration times of 8s and 16s, i.e., global shape became more important for judging similarity when more time was provided for exploration.

Dostmohammed and Hayward compared curvature discrimination using four different modes in which users could interact with a virtual fingerpad display [9]. They found that curvature discrimination varied as a function of interaction mode: active, two-finger exploration offered higher sensitivity than active one-finger exploration and one/two-finger semi-active exploration.

In previous work [6], we compared visual, haptic, and visuo-haptic similarity ratings and category judgments of novel, 3D objects. In this study, haptic exploration was always performed using a *contour-following* procedure. Because the object set varied parametrically in shape and texture, it was possible to calculate a perceptual shape/texture tradeoff value. When subjects touched the objects, they weighted shape and texture information roughly evenly in similarity judgments. However, when they saw the objects, similarity judgments were clearly dominated by shape changes in the stimulus set. Although the greater importance of texture for haptic similarity judgments could be a general effect of using the haptic modality, it could also have been due to the specific contour-following EP used (e.g., [17] reported high correlation between the frequency of EPs best-suited for extracting a given property and its cognitive saliency). When subjects performed contour-following on our object set (Figure 3.1), they spent relatively little exploration time in contact with regions of high curvature. We reasoned that if the exploratory procedure had indeed affected the shape/texture tradeoff, having subjects spend proportionally more time exploring the tips of the objects should lead to a greater influence of shape in haptic similarity judgments. For this reason, we included a "tip-touching" procedure in the present experiment. We also reasoned that the tip-touching task would be less demanding than the contour-following task because spatial integration of object information could occur in three, smaller local patches instead of over

the entire object contour; we hypothesized that decreasing the spatial integration demands of the task would also help to bias subjects towards shape in the tip-touching procedure.

In the current study, we were therefore primarily interested in comparing the property weights obtained when subjects used contour-following and tip-touching. In addition, we chose to include two other EPs: gripping (also referred to as enclosure) and lateral motion. Gripping was included because of its frequency in real-world haptic interactions, which is likely due to its relative breadth of sufficiency (i.e., it provides information about a wide range of object properties), the fact that it can be performed quickly, and the fact that it is compatible with almost all other EPs (e.g., you can apply pressure to test an object's hardness while enclosing) [21]. Lateral motion was included as a control condition since it is known to provide a large amount of information about an object's texture, but little or no information about its shape.

The main difference between our study and previous work on haptic object perception and EPs is our use of multidimensional scaling (MDS) techniques and parametrically-varying stimuli, which allow perceptual dimensions to be identified and their relative weights to be quantified. MDS refers to a family of algorithms which operate on proximity data taken between pairs of objects. The output is a configuration of objects embedded in a multidimensional space. Psychologists have used MDS to explore perceptual representations of visually and haptically explored object sets (e.g., [25, 11, 13, 1, 6]). The technique has also found a large following in domains such as knowledge mapping [5] and marketing [4] because it allows for the identification of important psychological dimensions of stimulus variation (e.g., dimensions along which buyers differentiate amongst competing products) and quantification of perceptual distances between stimuli (e.g., how "closely"-related one field of research is to another). In cognitive psychology, the inputs are generally human similarity ratings taken over a set of objects; the output configuration is then be interpreted as a *map of the objects in a psychological space* which explains the similarity data [2].

MDS analysis provides the following types of information about the psychological representation of stimuli:

1. how many dimensions of variation in the stimuli are apparent to the participants;
2. whether these dimensions correspond to properties which were deliberately being manipulated;
3. whether one or more unexpected perceptual dimensions were also apparent to the participants;
4. interstimulus distances in the psychological space;
5. the relative weights of the psychological dimensions.

By applying this technique to the study of exploratory procedures, we hope to obtain new, quantitative insight into how modes of interaction shape the representation of objects in the brain.

## 3 METHODS

This section describes the stimuli used in the experiment, the experimental procedure, and data analysis using MDS.

### 3.1 Stimuli: Novel 3D objects

A family of nine novel, 3D objects (Figure 1) varying in shape and texture were used in the experiments. The objects were designed in 3D graphics software (3D Studio Max) and manufactured using a 3D printer (Dimension 3D Printer, Stratagics, Minneapolis, USA). The complete design and manufacturing process is described in [6].

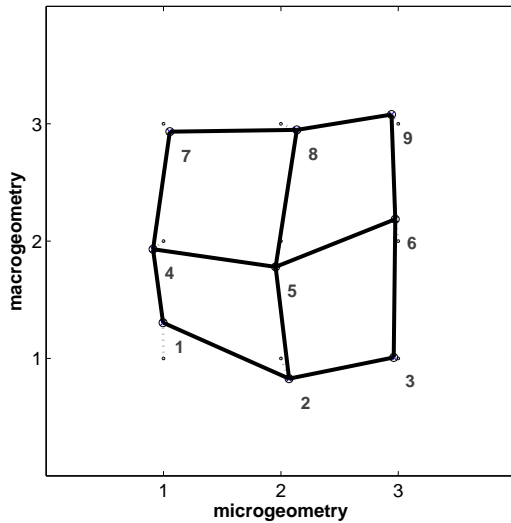


Figure 2: Two-dimensional psychological stimulus space resulting from MDS analysis of subjects' similarity ratings. The map is scaled such that the relative importance of each dimension is uniform.

Each object consists of 1) three parts connected to a center sphere, defining the object's macrogeometry ("shape") and 2) a displacement map applied to the 3D mesh, specifying the object's microgeometry ("texture"). The displacement map applied to the objects consisted of repeated conical elements (base width of 3mm, a peak width of 2mm, and a maximum height of 2mm from the surface of the object; texture elements were spaced 3-5mm apart). Variations amongst the objects were generated by two manipulations: microgeometrical smoothing and macrogeometrical smoothing. Microgeometrical smoothing was performed by decreasing the amount of mesh displacement caused by the displacement map. Macrogeometrical smoothing was performed by the 3DS "relax" operator, which moves mesh vertices towards a local average, removing sharp angles in the global shape. Note that manipulations created *input* dimensions corresponding to parameters in the 3D software package, but which does not imply that these dimensions will necessarily be recovered in the perceptual *output* space. Revealing the dimensions which are important for human perception is precisely one of the reasons for performing MDS analysis of human similarity ratings.

The 3D models were printed out (Dimension 3D Printer, Stratasys, Minneapolis, USA) into hard, white, and opaque objects, measuring 9.0 +/- 0.1 cm wide, 8.3 +/- 0.2 cm high, and 3.7 +/- 0.1 cm deep and weighing about 40 g.

### 3.2 Experiment: Haptic similarity ratings

Ten naive, right-handed subjects (4 men, 6 women) were paid 8 Euros per hour to participate in the experiment. Their task was to rate the similarities between pairs of objects on a scale between 1 (low similarity) and 7 (high similarity) after exploring them haptically. The same experimental setup was used in all conditions (Figure 3). Subjects used a chin rest placed 40 cm away from the stand on which the objects were presented; the height of the chin rest was set such that the centre of the object was aligned with the line of sight. An opaque curtain hung between the subjects and the stand. A set of grooves and a section of rubber tubing on the mount piece ensured that the objects were securely held in place in exactly the same upright position on every trial.

On each trial, the experimenter placed the first object on the



Figure 3: Experimental setup for haptic similarity ratings. The experimenter places the objects on a mount placed behind an opaque curtain. The participant haptically explores the object using one of four exploratory procedures.

stand, verbally instructed the subject to start the exploration, counted to three using a stopwatch as a metronome, and removed the objects after 3s. The presentation time of 3s was chosen because it was the minimum amount of time that subjects needed to perform the longest of the procedures (contour-following) in a pilot experiment. The experimenter then replaced the first object by a second object, instructed the subject to begin exploration, and then removed the object after 3s. The experimenter then waited for the subject's response. Before the experiment, subjects were sequentially presented with the two pairs of objects in the outermost corners of the space, allowed to palpate each one in their hand for about 5s and told that these were the largest differences they would encounter in the experiment.

The experiment consisted of four blocks of 45 randomized trials (each object was compared once with itself and once with every other object resulting in  $9 + (9-8)/2 = 45$  trials) and the order of appearance of stimuli was randomized over blocks. Each trial took about 20-30 seconds and the total experiment ran for approximately two hours. At the end of the experiment, subjects were asked to write a short description of the objects and to comment on the difficulty of each EP.

In each of the four blocks, subjects explored the objects using a different procedure. The order of procedures was randomly selected for each subject. The following procedures were used: contour-following (CF), lateral motion (LM), contact of object tips (TP), and enclosure or gripping (GR).

### 3.3 MDS analysis of similarity data

We used the individual differences weighted Euclidean distance model implemented as part of the ALSCAL MDS package in SPSS [3, 32], with proximity data taken as ordinal measurements (i.e., non-metric) and untangling of tied proximities allowed. This particular MDS technique allows for comparison of individual subject data and also has the advantage of uniquely specifying the dimensions of the output space, allowing for clearer interpretation [8]. As input, the common choice is a set of mean similarity data taken over multiple ratings provided by a single user. However, since we wished to search for variations in psychological representations due to exploratory procedure, we considered each block of the experiment as a separate unit of analysis or "individual". For a specified dimensionality, MDS returns a single underlying stimulus configu-

ration and a set of weights specific to each set of similarity data included in the analysis. The weights specify how the underlying configuration should be scaled along each dimension to best fit each set of similarity data. Weights can be analyzed to look for differences across individuals and exploratory procedures. In addition, the SPSS implementation provides a goodness-of-fit measure, Young’s S1 Stress, which is the normalized difference between the fitted distances and the observed proximities. Although establishing a threshold for acceptable values of stress is controversial, Monte Carlo studies have indicated that values below 0.2 point to an output configuration which fit the similarity data well [8].

## 4 RESULTS AND DISCUSSION

We begin by discussing the dimensionality of the perceptual space recovered using MDS and how these dimensions can be interpreted. We then examine how the dimensions of this perceptual space were affected by the use of different EPs.

### 4.1 Dimensionality and recovery of ordinal relationships

Stress for a two-dimensional configuration was 0.15, indicating that an MDS model with two perceptual dimensions is a good model of our data (see section 3.3). A 2D model agrees with subjects’ descriptions of the objects: 10/10 mentioned shape properties and 9/10 mentioned texture, while only 1/10 mentioned another property (material).

The stimulus configuration in psychological similarity space is plotted in Figure 2. Note that the map shown here is scaled such that both dimensions have equal weight (see 3.3). This map shows that subjects were able to recover the ordinal relationships which had been established between the objects in the software parameter space using the mesh displacement (“texture”) and the mesh relaxation (“shape”) operations. These results agree with previous findings in which subjects were also able to recover these dimensions with an extended stimulus set of 25 objects, including the ones used in this study [6]. This is a non-trivial task given the high-dimensionality of the measurement space, as demonstrated by computational studies [7].

### 4.2 Dimension weights: Mean data

Shape/texture tradeoffs<sup>1</sup> for each exploratory procedure are shown in Figure 4 (CF:  $M=0.67$ ,  $SE=0.06$ ; TP:  $M=0.59$ ,  $SE=0.06$ ; GR:  $M=0.66$ ,  $SE=0.08$ ; LM:  $M=0.91$ ,  $SE=0.02$ ). All mean values were greater than 0.5, indicating that texture dominated shape in subjects’ similarity ratings. Given the wide variability in the data, we tested the hypothesis that the weights came from a distribution with a mean of 0.5, representing equal importance for shape and texture properties; rejection of this hypothesis would indicate a clear texture-dominance. A single-sample t-test at the 95% confidence level rejected the hypothesis for two EPs: lateral motion ( $t[9]=16$ ,  $p<0.001$ ) and contour-following ( $t[9]=3$ ,  $p=0.01$ ). No significant difference was found for the tip-touching procedure ( $t[9]=1.4$ ,  $p>0.1$ ) or the grip procedure ( $t[9]=2$ ,  $p=0.08$ ). Overall, we found a large variability in the way subjects weighted the dimensions, except in the lateral motion condition. We now discuss specific results for each EP in turn.

*Lateral motion (LM):* As we had hypothesized, texture was indeed heavily weighted when subjects explored the objects with a

<sup>1</sup>INDSCAL returns one weight per dimension, however these weights are constrained to lie on a circle in the 2D case. Therefore, we report a single shape/texture tradeoff index which is calculated as the arc tangent of each point in the weight space, with 0 representing maximum shape dominance, 0.5 representing equal weight for shape and texture, and 1 representing maximum texture dominance.

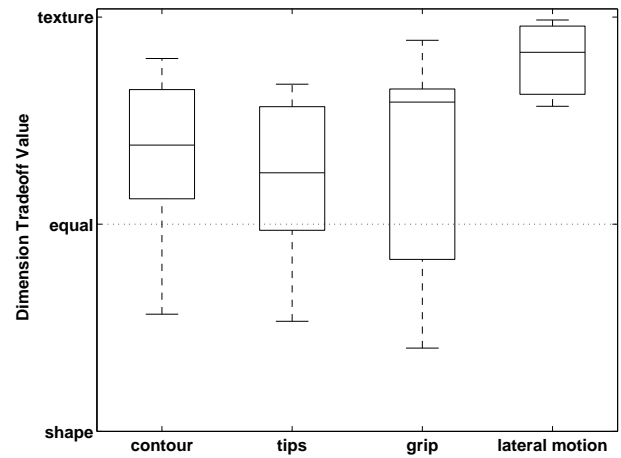


Figure 4: Dimension weights: All participants. The normalized shape/texture tradeoff value is plotted according to the exploratory procedure used. Lines within boxes are located at the lower quartile, median, and upper quartile values. Whiskers show the full extent of the data.

lateral rubbing motion. Subjects were instructed to rub the objects’ centres, which were extended areas of low curvature offering little object-specific shape information. The mean shape-texture tradeoff value ( $M = 0.91$ ,  $SE = 0.02$ ) was significantly different from tradeoff values obtained when other EPs were used (LM-GR:  $p=0.014$ ; LM-TP:  $p<0.001$ ; LM-CF:  $p<0.01$ ). (There were no other significant differences between CF, TP, and GR mean weights.) Moreover, the variability of weights was smaller for LM than in the other three conditions (LM:  $SE=0.02$ ; CF:  $SE=0.06$ ; TP:  $SE=0.06$ ; GR:  $SE=0.08$ ). This indicates that the observed variability in the other EP conditions has to do with their greater degree of shape sensitivity: the more access an EP provided to object shape, the more variable subjects were in their use of shape vs. texture for judging similarity.

*Contour-following (CF):* When subjects followed the objects’ contours, they weighted texture more heavily than shape on average (shape-texture tradeoff  $M=0.67$ ,  $SE=0.06$ ). As mentioned above, the mean tradeoff value was also significantly different from 0.5. [21] reported the following EP-to-property weightings for contour-following: 3 for “exact shape”, 1 for “global shape” and 1 for texture. Converting these values to shape-texture tradeoffs for comparison, the exact shape-texture tradeoff would be 0.25, corresponding to a stronger weighting of exact shape compared to texture. The global shape-texture tradeoff would be 0.5, corresponding to equal weight for global shape and texture in contour-following. What factors could account for the greater degree of texture bias found in the present study? It could be that the limited exploration time of 3s per trial and the relatively short time subjects spent performing this exploratory procedure overall (about 20 minutes) limited subjects’ ability to use shape information in the similarity judgment task. As mentioned in section 2, one study has shown that the importance of global shape information for haptic similarity ratings increases with the amount of exploration time provided. Another explanation for the texture bias is that the texture changes may have been slightly more discriminable than the shape changes [22]. However, any discriminability differences would have caused an overall shift of the weight distribution towards texture; other factors must also be at play to have caused the large variability observed (see discussion on the grip EP below).

*Touching object tips (TP):* The shape-texture tradeoff value (TP:

$M=0.59$ ,  $SE=0.06$ ) was not found to be significantly different from 0.5 on average, indicating equal weighting of shape and texture in similarity judgments. In addition, we found no significant difference between mean tradeoff values in the TP and CF conditions ( $t(17.7)=0.9$ ,  $p=0.4$ ). This was contrary to our hypothesis (see section 2) that shape would become more important when exploration was focused on object tips as opposed to the whole contour. Although subjects were indeed significantly more shape-biased when performing either CF or TP than they were when performing LM, they were not significantly more shape-biased when performing TP than when performing CF. We attribute this to inherent limitations in haptic macrogeometric processing capacity [16, 18]. We had hoped to ease the processing demands of the CF task by creating three, smaller spatiotemporal windows of integration, however subjects' reports indicate that the TP task was as or more difficult than the CF task. 4/10 subjects spontaneously reported that they found TP to be the most difficult EP, whereas only 1/10 reported that CF was the most difficult. In addition, 2/10 subjects spontaneously reported that CF was the easiest procedure, but none said the same for TP. It appears that the introduction of "haptic saccades" between the three tips may have had the opposite effect of what we had intended. Even though there is relatively more high-curvature stimulus information available to the haptic system per unit time in the TP procedure, its discontinuous nature may have prevented subjects from using the additional information to judge similarity.

*Enclosure/grip (GR)*: We had hypothesized that enclosing the objects in the hand would give rise to shape-dominated tradeoff value, but instead, we found a texture-dominated value ( $M = 0.66$ ,  $SE = 0.08$ ). Klatzky and Lederman [15] reported relative EP-to-property weights of 2 for global shape, 0 for exact shape, and 1 for texture. Converting these to shape-texture tradeoff values for comparison yields a shape-texture tradeoff of 0.33 for global shape/texture (i.e., somewhat shape-biased) and 1 for exact shape-texture (i.e., completely texture-biased). Our findings can be reconciled with this data by considering the perceptual shape dimension in our experiments as a combination of exact and global shape. In support of this, subjects in an extended study involving these objects mentioned both global and part shape when explaining how they performed haptic similarity judgments [6].

We also observed large variability in the way subjects weighted shape vs. texture when using the grip EP ( $SE = 0.08$ ), especially compared to the LM condition ( $SE=0.02$ ). Variability in property weights was also quite high in the TP ( $SE=0.06$ ) and CF conditions ( $SE=0.06$ ). When we analyzed weighting patterns for individual subjects, we observed that subjects could be classified into two groups - a rather shape-biased group and a rather texture-biased group. The difference between the two groups was most striking in the GR condition: four subjects relied more on shape in this condition as well as in the TP and CF conditions (Figure 5, while six subjects were clearly texture-biased in the GR condition and showed relatively more influence of texture in the TP and CF conditions (Figure 6). These data are discussed in more detail in the following section.

### 4.3 Dimension weights: Individual data

Individual subject dimension weights are plotted in Figures 5 and 6. Subjects were binned into two groups according to whether they were strongly texture-dominated when gripping the objects or not.<sup>2</sup> Subjects who were texture-biased while gripping the objects (CF:  $M = 0.76$ ,  $SE = 0.05$ ; TP:  $M = 0.72$ ,  $SE = 0.04$ ; GR:  $M = 0.84$ ,  $SE =$

<sup>2</sup>Note that the subjects were grouped post-hoc; to test whether two distinct groups of subjects actually do exist (one group which is shape-biased in gripping and one group which is texture-biased in gripping), a larger number of subjects would be required.

0.03) were consistently texture-biased in all EP conditions. In contrast, subjects who were more shape-biased when gripping the object were consistently more shape-biased when performing contour-following or touching object tips (CF:  $M = 0.54$ ,  $SE = 0.09$ ; TP:  $M = 0.40$ ,  $SE = 0.09$ ; GR:  $M = 0.38$ ,  $SE = 0.06$ ). Another difference between the two groups is that absolute variation across subjects in the texture-biased group was lower for the three shape-sensitive EPs (CF: 0.34; TP: 0.25; GR: 0.17) than for the shape-biased group (CF: 0.39; TP: 0.32; GR: 0.29). This is another indication that the use of shape as a perceptual dimension increases variability in dimension weights across subjects. Finally, subjects' individual "trajectories" in "EP-tradeoff space" exhibit a degree of systematicity: for shape-biased subjects, there is a downward trend from CF to TP to GR; for texture-biased subjects, there is a slight upward trend from CF to TP to GR. It may even be possible to model intersubject variation by a constant offset parameter. A larger number of subjects is needed to further investigate this possibility.

What factors could have given rise to the consistent shape/texture bias we observed for specific individuals? First, we checked for a correlation with gender; this possibility was ruled out. Second, we checked for an order effect, in case initial experience with certain EPs provided a bias for the remainder of the experiment; however, we did not find any patterns in the data which could be attributable to order effects. Instead, we propose that the biases result from intrinsic subject-specific biases towards shape or texture. For example, a highly "visual" person, who makes spontaneous use of visual imagery and is at ease with spatial judgments may be intrinsically biased towards shape, while a more "touch-oriented" or "kinaesthetic" person may have higher sensitivity to vibration or roughness, and thus bring an intrinsic bias towards texture to bear on the similarity judgment task. In future studies, we plan to retest the participants in this study to determine whether the bias is a lasting one and if so, whether it can be correlated with other measures of bias towards shape/texture.

### 4.4 Relevant results for the design of haptic devices

Two results of this study are particularly relevant to the designers of virtual haptic environments. First, we found a clear effect of exploratory procedure on the perceptual weights of object properties (the tradeoff for LM being significantly more texture dominated than for all other EPs), which clearly shows that the mode of interaction has an effect on perceptual object representations. Second, we found high variability in property weights when subjects used more shape-sensitive exploratory procedures. Thus, even though subjects were presented with exactly the same objects and their mode of interaction with them was strictly controlled, the perceptual outcomes differed. This finding is of particular importance for two-fingered haptic interfaces such as the PHANTOM, in which EPs such as tip-touching, lateral motion, and contour-following may be frequently used.

### 4.5 An MDS framework for comparative and validation studies

In the current study, a stimulus space with known perceptual dimensions was provided as input to MDS; MDS was used to quantify the tradeoffs amongst these pre-specified dimensions. Using MDS in this "known parameter mode" provided the opportunity to study the effects of changing EPs on dimensions which were known to be of perceptual importance. However, MDS can also be used in a number of other ways which can be helpful for virtual reality design. In "parameter discovery mode", the important dimensions of variation are unknown at the outset - in this case, MDS returns a map of stimuli in a perceptually meaningful space whose dimensions, however, need to be labelled or interpreted, e.g., by using subjects' verbal reports. MDS can also be used in "parameter evaluation mode" to

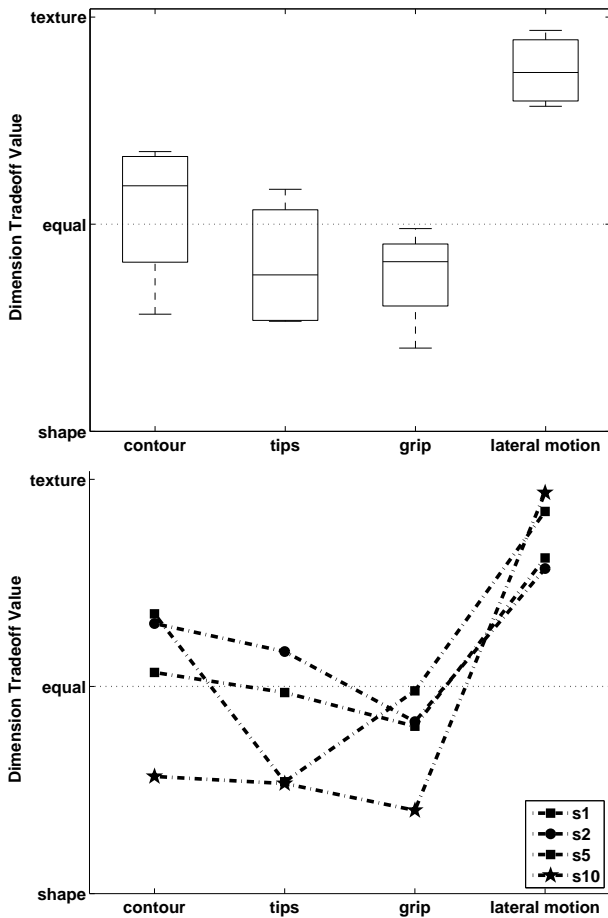


Figure 5: Dimension weights: Shape-biased group. Top: Group data. Lines within boxes are located at the lower quartile, median, and upper quartile values. Whiskers show the full extent of the data. Bottom: Weights belonging to a single subjects are connected by dashed lines.

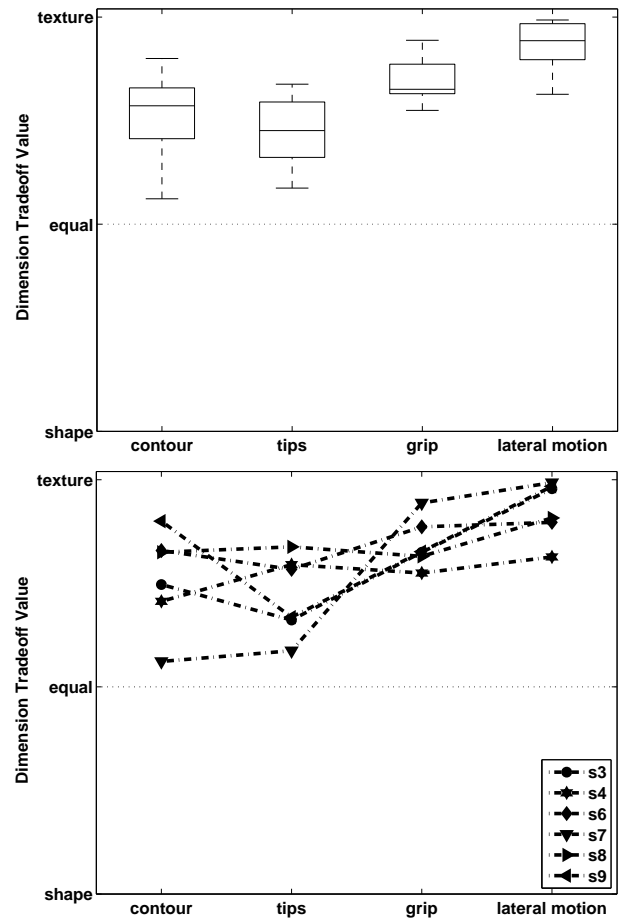


Figure 6: Dimension weights: Texture-biased group. Top: Group data. Lines within boxes are located at the lower quartile, median, and upper quartile values. Whiskers show the full extent of the data. Bottom: Weights belonging to a single subjects are connected by dashed lines.

test the relative perceptual importance of a given parameter. This should be particularly helpful in haptic interface design: while the number of parameters involved in creating a virtual reality environment is reasonably tractable in the visual domain, it is less so in the haptic domain due to the complexity of sensors, actuators, and object models, the lack of standard displays, the expense of computations required for real-time control, the high number of degrees of freedom of the human body, and a relatively undeveloped understanding of the haptic sensory system. Using MDS in "parameter evaluation mode", the stimulus set would contain objects which vary along the parameter to be evaluated, e.g., a parameter which one suspects to be unimportant for perception and could be allowed to vary freely. By examining stress values, MDS can be used to judge subjects' sensitivity to change along this dimension.

These ideas can be incorporated into an analytical framework for comparative studies of human perception in real or virtual environments, as shown in Figure 7. In the first step, features are extracted from a real or virtual environments. Proximity data are then derived from these features. Note that in this paper, we have focused on human similarity ratings on objects as our dataset. However, proximities can be derived from any relevant interaction parameter, such as hand or tool dynamics. MDS is then used to 1) construct maps of the objects in perceptual spaces and 2) to compute relative

dimension weights. Comparing these data provides an opportunity to visualize and quantify differences in:

1. perception under different real-world conditions (e.g., using different EPs, as done in this study);
2. perception under different virtual reality conditions (e.g., using two different rendering algorithms);
3. perception in a real-world vs. a virtual environment (e.g., to assess haptic fidelity).

The results of all three types of studies can be used to optimize the parameters of virtual environments, as indicated by the dotted lines in Figure 7. Since the study presented in this paper compares different real-world perception scenarios, it relates to study type 1 (Figure 7, upper portion). Extensions to studies of different virtual reality scenarios (study type 2) and comparisons between results obtained in real and virtual scenarios (study type 3) are planned as future work (see section 5).

This framework is not only applicable to haptic interfaces, but also to interfaces for other modalities, as well as multimodal interfaces. It addresses a growing need for tools which allow for 1)

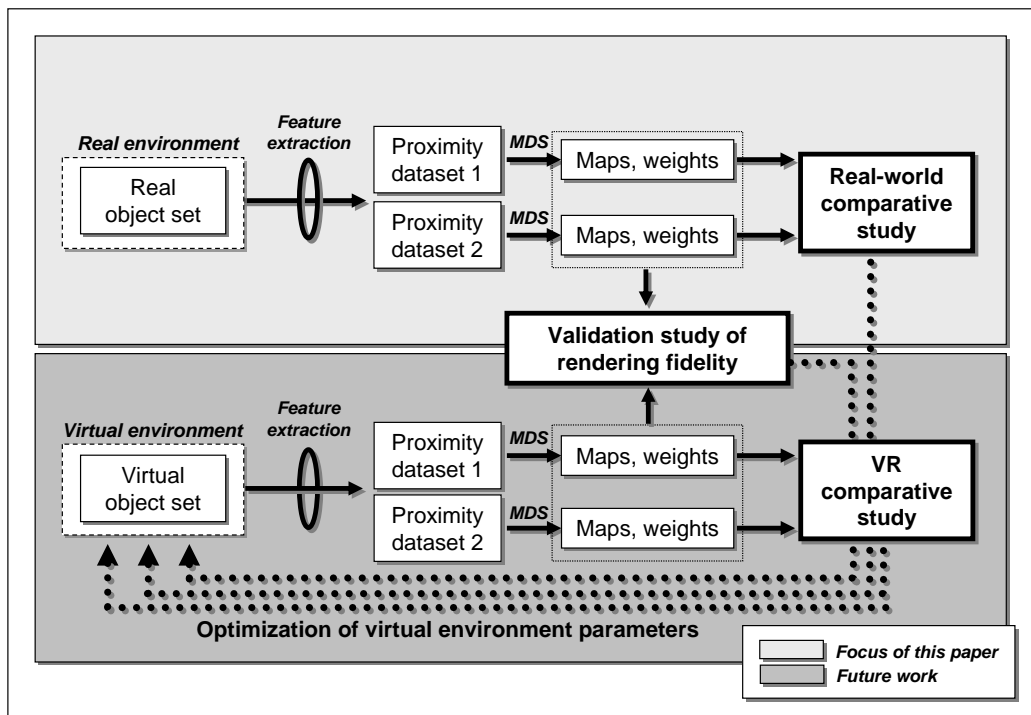


Figure 7: A framework for validation and comparative studies using MDS. Features are extracted from interactions in real or virtual environments and proximity data are derived from operations on these features. MDS is used to construct perceptual maps and compute relative dimension weights. Results are compared to evaluate perception 1) under different real-world scenarios (e.g., to characterize human perception), 2) under different virtual reality scenarios (e.g., to benchmark different technical systems), and 3) in real-world vs. virtual scenarios (e.g., to validate a particular technical system).

validation of haptic/multimodal displays relative to real-world perception and 2) comparison and benchmarking of different displays, algorithms, and usage patterns. A number of studies have already applied paradigms developed in the field of experimental psychology to the problem of interface validation. Several studies have measured the speed, accuracy, or forces exerted by a human user during a task and test how similar these are under real-world and virtual conditions, e.g., [29, 12, 30]. Magnitude estimation tasks have also been used to characterize the perception of virtual object properties, such as roughness, as a function of environment parameters, such as the type of probe used to explore the objects, e.g., [15, 14]. Other groups have measured the discriminability object properties, such as curvature, and used this as a metric, e.g., [19, 23, 26, 31]. Finally, some studies have begun to use metrics based on performance of more cognitive tasks such as object recognition, categorization, and similarity judgments [28, 12, 24]. Nevertheless, validation methods for haptic technologies are in the early stages of development and there is still a need for robust measures which provide insight into complex, cognitive human experience of virtual environments, while at the same time being easy and quick to use. We suggest that an ideal validation paradigm includes the following attributes:

1. The paradigm provides *robust statistics*, i.e., a set of statistics and corresponding measures of confidence, which allow differences between real-world and virtual experiences to be quantified and allow for benchmarking of different virtual experiences/systems.
2. The paradigm offers insight into *cognitive* aspects of virtual experiences, i.e., metrics and/or visualizations that reveal how

cognitive-level processes such as learning and coping strategies, meanings, and representations are affected by changes in the haptic environment. This may involve a shift towards "higher-level" similarity, recognition, categorization, semantic, and memory tasks [27].<sup>3</sup> Cognitive metrics also need to be flexible enough to extend to multimodal interactions.

3. The paradigm is *easy to use* in a general sense, i.e., the method used to gather data is easy to understand, straightforward to implement on a wide range of systems, and can be carried out quickly. The analysis procedure required to transform raw measures into the desired metrics should also be easy to implement or acquire and quick to carry out.

MDS approaches provide a partial answer: they offer quantitative measures (interstimulus distances, stress as a measure of dimensionality, and dimension weights) and they offer insight into higher-level stimulus representations. One drawback, however, is that pairwise similarity data are time-consuming to gather; different proximity measures such as same/different judgements or confusion errors may offer a solution to this. Secondly, data analysis requires several fitting and optimization steps, however standard implementations are available in packages such as MATLAB and SPSS. Despite these drawbacks, the flexibility and generalizability of MDS approaches makes them a powerful tool for investigating human perception in both real and virtual environments.

<sup>3</sup>As noted by [10], attributes that enable objects to be discriminated may not be those which play the most important role in their perceptual representation, although poorly discriminable properties likely do not play an important perceptual role.

## 5 SUMMARY AND OUTLOOK

This paper provides a quantitative characterization of how haptic modes of interaction alter object perception. Using MDS analysis of similarity data, we showed that subjects are able to recover the topology of the input parameter space and perceived its dimensions as shape and texture. However, the way in which subjects weighted these two dimensions was affected by the way in which they interacted with them: when subjects explored the objects using lateral motion, perceptual similarities were strongly dominated by texture variations, while shape differences were also taken into account when subjects performed contour-following, tip-touching, or enclosure. However, the relative weight given to shape vs. texture varied greatly when subjects used one of the three EPs which provided access to shape information. Two groups of subjects, one exhibiting more shape bias and one exhibiting more texture bias across these EPs, were tentatively identified, however a larger number of subjects is needed to properly characterize the distribution of weights.

These findings provide important insights for designers of haptic environments. Lateral motion yields a robust representation in which texture strongly dominates over shape; thus, it is the "safest" of the EPs to allow in a haptic environment if one wishes to guarantee a single perceptual outcome. Of course, it is highly limited in that it does not allow for shape information to be extracted. When incorporating new modes of interaction, designers need to be aware of the ambiguities which will be simultaneously introduced into the perceptual experience of the environment. Methods such as the one presented in this paper can be used to assess the magnitude of such variations and identify "lower-risk" modes of interaction.

In a follow-up study, we plan to compare the dimension weights which we measured in this real-world setting against dimension weights measured in a virtual haptic setting, e.g., by presenting the stimuli (or simplified variants) using a PHANToM device. In our framework (Figure 7), this would correspond to a virtual reality comparative study (bottom half of the diagram). The main goal of this study will be to compare dimension weights and variability under a specific set of virtual conditions against their real-world counterparts in order to identify modes of interaction which provide high-fidelity representations (i.e., distributions of dimension weights which match those measured in real-world interactions). We hope that this line of research will provide helpful groundwork in establishing MDS techniques as a paradigm for evaluating perception in virtual environments.

## ACKNOWLEDGEMENTS

The authors wish to thank Karin Bierig for technical assistance in carrying out the experiments, Steffen Baier and the staff of the workshop at the Max Planck Institute for Biological Cybernetics for helping to build the haptic setup, Martin Breidt and Mirko Thiesen for assistance in stimulus design and production, and Marc Ernst for helpful feedback.

## REFERENCES

- [1] T Bergmann, M Wouter, and AML Kappers. Analysis of haptic perception of materials by multidimensional scaling and physical measurements of roughness and compressibility. *Acta Psychol (Amst)*, 121(1):1–20, 2006.
- [2] I Borg and P Groenen. *Modern multidimensional scaling*. Springer, 2nd edition, 2005.
- [3] JD Carroll and JJ Chang. Analysis of individual differences in multidimensional scaling via an n-way generalization of "Eckart-Young" decomposition. *Psychometrika*, 35:283–319, 1970.
- [4] JD Carroll and PE Green. Psychometric methods in marketing research: Part ii, multidimensional scaling. *Journal of Marketing Research*, 34(2):193–204, 1997.
- [5] C Chen. *Mapping Scientific Frontiers: The Quest for Knowledge Visualization*. Springer Verlag, 2003.
- [6] T Cooke, F Jäkel, C Wallraven, and HH Büelthoff. Multimodal similarity and categorization of novel, three-dimensional objects. *Neuropsychologia*, in press:–, 2006.
- [7] T Cooke, F Steinke, C Wallraven, and HH Büelthoff. A similarity-based approach to perceptual feature validation. In *APGV 2005 - Symposium on Applied Perception in Graphics and Visualization*. ACM SIGGRAPH, August 2005.
- [8] TF Cox and MA Cox. *Multidimensional Scaling*. Chapman & Hall, 2nd edition, 2001.
- [9] H Dostmohamed and V Hayward. Trajectory of contact region on the fingerpad gives the illusion of haptic shape. *Exp Brain Res*, 164(3):387–394, 2005.
- [10] CP Garbin. Visual-touch perceptual equivalence for shape information in children and adults. *Percept Psychophys*, 48(3):271–279, 1990.
- [11] CP Garbin and IH Bernstein. Visual and haptic perception of three-dimensional solid forms. *Percept Psychophys*, 36(2):104–110, 1984.
- [12] S Greenish, V Hayward, VB Chial, AM Okamura, and T Steffen. Measurement, analysis and display of haptic signals during surgical cutting. *Presence*, 11(6):626–651, 2002.
- [13] M Hollins, R Faldowski, S Rao, and F Young. Perceptual dimensions of tactile surface texture: A multidimensional scaling analysis. *Percept Psychophys*, 54(6):687–705, 1993.
- [14] G. Jansson and C. Pieraccioli. Effects of surface properties on haptic perception of the form of virtual objects. In M Buss and M Fritschi, editors, *Proceedings of the 4th International Conference Eurohaptics 2004*, pages 211–216, München, Germany, 2004.
- [15] RL Klatzky, SJ Lederman, C Hamilton, M Grindley, and RH Swendsen. Feeling textures through a probe: effects of probe and surface geometry and exploratory factors. *Percept Psychophys*, 65(4):613–631, 2003.
- [16] RL Klatzky, SJ Lederman, and DE Matula. Haptic exploration in the presence of vision. *J Exp Psychol Hum Percept Perform*, 19(4):726–743, 1993.
- [17] RL Klatzky, SJ Lederman, and C Reed. There's more to touch than meets the eye: The salience of object attributes for haptics with and without vision. *Experimental Psychology: General*, 116(4):356–369, 1987.
- [18] S Lakatos and LE Marks. Haptic form perception: relative salience of local and global features. *Percept Psychophys*, 61(5):895–908, 1999.
- [19] DA Lawrence, L Pao, MA Salada, and AM Dougherty. Quantitative experimental analysis of transparency and stability in haptic interfaces. In *Proc. Fifth Annual Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*, Atlanta, GA, 1996.
- [20] SJ Lederman and RL Klatzky. Hand movements: a window into haptic object recognition. *Cognit Psychol*, 19(3):342–368, 1987.
- [21] SJ Lederman and RL Klatzky. Extracting object properties through haptic exploration. *Acta Psychol*, 84:29–40, 1993.
- [22] SJ Lederman, C Summers, and RL Klatzky. Cognitive salience of haptic object properties: role of modality-encoding bias. *Perception*, 25(8):983–998, 1996.
- [23] LY Pao and DA Lawrence. Synergistic visual/haptic computer interfaces. In *Proc. Japan/USA/Vietnam Workshop on Research and Education in Systems, Computation, and Control Engineering*, pages 155–162, Hanoi, Vietnam, 1998.
- [24] MA Salada, JE Colgate, MV Lee, and PM Vishton. Validating a novel approach to rendering fingertip contact sensations. In *Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*, pages 217–224, 2002.
- [25] RN Shepard and GW Cermak. Perceptual-cognitive explorations of a toroidal set of free-form stimuli. *Cognit Psychol*, 4:351–377, 1973.
- [26] MA Srinivasan, C Basdogan, and WC Wu. Visual, haptic, and bimodal perception of size and stiffness in virtual environments. In *Proceedings of the ASME Dynamic Systems and Control Division*, 1999.
- [27] C Swindells, JD Smith, and KE MacLean. An exploration of representations to aid design of haptic behaviours. In *Proceedings of*



*Conference on Human Factors in Computing Systems (CHI) Workshop – Hands-on Haptics: Exploring Non-Visual Visualization Using the Sense of Touch.*, pages 5–8. ACM Press, 2005.

- [28] H Tan, A Lim, and R Traylor. A psychophysical study of sensory saltation with an open response paradigm. In *Proceedings of the Ninth (9th) International Symposium on Haptic Interfaces for Virtual Environment and Teleoperator Systems*, pages 1109–1115, Orlando, FL, 2000. American Society of Mechanical Engineers Dynamic Systems and Control Divisio.
- [29] HZ Tan, MA Srinivasan, B Eberman, and B Cheng. Human factors for the design of force-reflecting haptic interfaces. In *Proceedings of the ASME Dynamic Systems and Control Division*, pages 353–359, 1994.
- [30] BJ Unger, RL Klatzky, and RL Hollis. A telemanipulation system for psychophysical investigation of haptic interaction. In *ICRA*, pages 1253–1258, 2003.
- [31] RJ Webster, TE Murphy, LN Verner, and AM Okamura. A novel two-dimensional tactile slip display: design, kinematics and perceptual experiments. *TAP*, 2(2):150–165, 2005.
- [32] FW Young and DF Harris. ALSCAL. In *SPSS 12.0 Command Syntax Reference*, pages 100–116. SPSS, Chicago, IL, 2003.