Full title

Seeing our 3D world while only viewing contour-drawings

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All relevant files are available from the Open Science Framework repository (<https://osf.io/t5jgb/>).

Abstract

Artists can represent a 3D object by using only contours in a 2D drawing. Prior studies have shown that people can use such drawings to perceive 3D shapes reliably, but it is not clear how useful this kind of contour information actually is in a real dynamical scene in which people interact with objects. To address this issue, we developed an Augmented Reality (AR) device that can show a participant a contour-drawing of a real dynamical scene in an immersive manner. We found that contour information, alone, is sufficient to perform a variety of run-of-the-mill tasks under natural viewing conditions. This contour information may be sufficient to provide the basis for our visual system to obtain *all* of the 3D information needed for successful visuomotor interactions in our everyday life.

19 Introduction

20 Artists can represent a 3D object by using only contours in a 2D contour-drawing [1-5]. These
 21 contours often represent an abrupt change of the luminance, color, or texture in the image of the object.
 22 Such a change can happen at a mark on the surface of the object, at self-occluding boundaries on the
 23 surface [6-8], on ridges on the surface [9, 10] (see [11, 12] for reviews). Neither the luminance-polarity nor
 24 luminance-gradients are present in a contour-drawing.

25 Human beings can see the shape of a 3D object veridically when given only 2D drawings of it, and
 26 they can also recognize such objects reliably [1, 3, 4, 13, 14, 15, 16, 17, 18, 19]. These well-known facts
 27 present a problem because according to Inverse-Problem Theory, the recovery of the shape of a 3D object
 28 from a 2D drawing is an ill-posed inverse problem. There are infinitely many 3D interpretations of a 2D
 29 contour-drawing. This inverse problem can be resolved by imposing *a priori* constraints on the family of
 30 possible 3D interpretations [3, 4, 20, 21, 22]. Now, consider ordinary objects we see and use in our everyday
 31 life. Such objects are not composed of a random scattering of points. They can be characterized by
 32 regularities of their shape, for example, their symmetry, volume, the planarity of their contours, and the
 33 presence of rectangular corners. These regularities, which introduce specific features into the drawing, also
 34 could be used to detect the presence and shape of an object [22-25]. Our visual system could make use
 35 these regularities as the *a priori* constraints needed to recover the shape of a 3D object from a 2D contour-
 36 drawing of the object [26-30]. These studies have shown that people can obtain 3D information from a
 37 contour drawing, but it is not clear just how useful such contour information actually is in real dynamical 3D
 38 scenes in which ordinary objects are recognized and utilized under natural viewing conditions.

39 To address this issue, we developed an Augmented Reality (AR) device that can show a participant
 40 both a contour-drawing and a grayscale-image of a real dynamical 3D scene in an immersive manner (see
 41 [31-33] for earlier studies using AR devices to test the human visual system). The gray-scale images were
 42 used as a control. They provided a baseline for the performance of a participant conducting our kind of

tasks while wearing this device in our experiments. Our AR device allowed us to determine how well the participant can interact dynamically with objects in a scene, by using only contours in the contour-drawing or by using luminance-polarity and luminance-gradients in the gray-scale image.

General Methods

AR device

The AR device used in this study showed, in an immersive manner, a contour-drawing *and a grayscale image* that represented a scene "out there" (Figure 1). The device was composed primarily of a smart phone (Lenovo Phab 2 Pro) and a wearable stereoscope (VR head-set). The phone ran on the Google Android OS which was equipped with an LCD screen and a camera located on the back of the screen. The two halves of the screen were seen individually by the two eyes of a participant who looked through the lenses of the stereoscope. The distance between the eyes and the screen, when the stereoscope was worn, was 8.5 cm. The screen's resolution was 1248 x 2560 pixels, and its size was 6.9 × 14.2 cm.

Figure 1. Contour-drawings of real scenes generated by the AR device used in this study.

The phone's camera captured a photographic image of the scene in front of the participant. A contour-drawing and grayscale-image representing the scene were generated from this photographic

59 image. This image was first converted to a grayscale-image I_G . Then, I_G was passed through a set of image
 60 filters to generate the contour-drawing I_C :

$$61 \quad I_C = 0.5|(I_G * B) * S_V| + 0.5|(I_G * B) * S_H|$$

62 where B was a Gaussian filter and S_V and S_H were Sobel filters [34] that detected vertical and horizontal
 63 edges:

$$64 \quad B = \frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

$$65 \quad S_V = \begin{bmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{bmatrix}$$

$$66 \quad S_H = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix}$$

67 This image process was implemented as an Android app using OpenCV library [35]. The resolution of the
 68 original photographic image and of the processed images was the same as the resolution of the screen
 69 (1248 x 2560 pixels).

70 Two image segments (1248 x 1280 pixels) taken from regions in the grayscale-image I_G or in the
 71 contour-drawing I_C were shown on the left and right halves of the screen (Figure 2). These regions were
 72 horizontal translations of one another in I_G and I_C . The size of the translation Δ_s could be adjusted to allow
 73 the participant to fuse the retinal mages of the halves of the screen when the screen was viewed with the
 74 stereoscope. Note that the two halves of the screen were seen binocularly but binocular depth cues
 75 (binocular disparity and vergence) could not be used to perceive the 3D scene. These cues just represented
 76 a frontoparallel plane [36].

Figure 2. (A) Regions of two image segments (blue and red) taken from the contour-drawing I_C , or from the grayscale-image I_G , and (B) an image composed of these segments on the LCD screen. These regions are horizontal translations of one another for Δ_S in I_G and I_C .

A small wide-angle lens was attached to the camera to widen the camera's field of view. The visual angle of each image segment that was displayed on half of the screen was $53 \times 54^\circ$ from the camera when this lens was attached. The visual angle of each screen half was $58 \times 59^\circ$ from the eye of the participant. The refresh-rate of the screen was 10 Hz because of the time required to generate the grayscale-image and draw the contours. These processes also introduced a delay of 200-300 msec into the time required to refresh the screen.

A shutter panel was also attached to the camera. This panel fully occluded the camera's view when it was closed. A clicking signal produced by pressing the middle button of a mouse was triggered when the shutter panel opened. This signal was used to signal the onset of a trial in the experiments.

Procedure

The experiments were conducted in a well-lit room (Figure 3A). The participant's tasks were different from one another, but all of the tasks required interacting with objects on a desk in front of the participant. During these tasks, the participant sat on a chair in front of this desk and viewed the objects on it through our AR device. Note that the participant could only see objects that were relevant to the task at hand during each trial. All other objects were hidden from view.

Figure 3. (A) A representative view of an experimental session. (B) The AR device used in this study with its shutter panel closed (left) and opened (right).

The two conditions with different image filters were blocked within each experiment and the participant put on the AR device with one of the image filters before each block. The block started with a training phase during which the participant was asked to look at their hands and to examine the scene through the device for 1 minute. The participant got used to viewing through the filter in this adaptation phase. All of the objects relevant to the tasks used in the experiments were hidden from the participants during the adaptation phase.

Before each trial, the shutter panel of the AR device was closed to occlude the participant's view (Figure 3B). The trial began by opening the panel. The participant was asked to finish a given task as soon as possible and to press a large green button on a wall in front of the participant when s/he was finished. The response time between opening the shutter panel and pressing the green button was recorded. Thirty-six volunteers participated. All had normal or corrected-to-normal vision. There were 12 participants in Experiment 1, 12 participants in Experiment 2, and 12 participants in Experiment 3 (see <https://osf.io/t5jgb/> for details). All were naïve with respect to the purpose of the study. Informed consents were obtained from all of them, and they were compensated with 100 Rubles for their participation.

The experiments reported in this study were conducted in accordance with the Code of Ethics of the World Medical Association (Declaration of Helsinki).

Experiment 1: Shape Matching

In Experiment 1, we measured performance of a shape matching task with the image filters.

Procedures

A participant was given 12 prism-shaped objects on a tray and a box with 12 holes whose shapes corresponded to the 12 individual objects (Figures 3A, 4). The shapes of all of the holes were different from one another. They were the same as the shapes of the cross-sections of the individual objects, and the objects could go through only their corresponding holes. The participant had to insert all of the objects into the box by finding their unique holes. This task required matching the shapes of the objects with the shapes of the holes. Note that the participant could not see any of these objects before the first trial. The nature of this task was explained to the participant by using an analogous toy before the experiment. Put simply, this task required recognizing the objects' shapes and the shapes of their holes and then coordinating their relative positions and orientations.

The experiment had 2 blocks consisting of 3 trials. There were 2 groups of 6 participants. The first group ran the block with the contour-drawing filter first. This was followed by the block with the grayscale-image. The second group ran the blocks in the opposite order. The participants were asked to rest for 5 minutes between the blocks during which they did not wear the AR device.

Figure 4. Gray-scale images and contour-drawings of 12 prism-shaped objects on a tray (left) and the box with 12 holes (right) used in Experiment 1. The shapes of the holes corresponded to the 12 individual objects.

Results

Figure 5 shows the averaged results observed in Experiment 1. The ordinate shows the response time. The abscissa shows the trials. The colors of the plots (blue and orange) represent the image filters (contour-drawing and grayscale image) and the styles of the plots represent the two groups of participants. The results were analyzed by using a three-way mixed-design ANOVA with repeated measures on two factors [37]: groups of participants, image filters, and trial numbers in each block (1, 2, and 3). The effect of the trial numbers ($F_{2,50} = 9.0$, $p = 0.00046 * 7$, where 7 is multiplied for a Bonferroni correction, see [38]) and the interaction between the filters and groups ($F_{1,50} = 27$, $p = 3.5 * 10^{-6} * 7$) were significant. The results of the other effects were not significant: the filters ($F_{1,50} = 0.31$, $p = 0.58 * 7$), the groups ($F_{1,10} = 0.016$, $p = 0.97 * 7$), the trial numbers x filters ($F_{2,50} = 0.22$, $p = 0.80 * 7$), the trial numbers x groups ($F_{2,50} = 1.4$, $p = 0.26 * 7$), the trial numbers x filters x groups ($F_{2,50} = 5.4$, $p = 0.0075 * 7$). (Note that p-values are adjusted to 1 if the p-values become larger than 1 after multiplying the Bonferroni factor.)

Figure 5. The results obtained in Experiment 1. The ordinate shows the response time and the abscissa shows the trials. The colors of the plots represent the image filters and the styles of the plots represent the groups of participants.

A posteriori test (Tukey) was performed to test the interaction between the filters and groups. The response time was shorter in the first block than in the second block: $p = 0.00091$ for the group that ran the block with the contour-drawing filter first and $p = 0.0095$ for the group that ran the block with the grayscale-image. The effect of the filter was significant neither in the first block ($p = 1.0$) nor in the second block ($p = 1.0$).

These results show that a human participant could conduct the shape matching task reliably with both a contour-drawing and a grayscale image that represented a scene "out there". We did not observe any difference in performance with both types of representation.

Experiment 2: Object Recognition

In Experiment 2, we used our image filters to measure performance in an object recognition task.

180 Figure 6. (A) 4 collections of animal toys used in Experiment 2: pulp-paper (left-top), stuffed (right-top), plastic-
 181 cartoon-like (left bottom), and plastic-realistic (right-bottom) animals. (B) The collection of toy animals on the
 182 tray, and the open box as they were arranged on the desk before each trial.

183 Figure 7. Gray-scale images and contour-drawings of several samples taken from the 4 collections of animal
 184 toys used in Experiment 2.
 185

186 Results

187 All participants recognized all of the objects. They made no errors in both image filter conditions,
 188 *i.e.*, contour-drawing and grayscale-image.

Figure 8 shows the averaged results observed in Experiment 2. The two panels of bar-graphs show the results obtained in both image filter conditions. The ordinate shows the response time. The abscissa shows the collections of animals. The brightness of the bars represents the two groups. The results were analyzed by using a three-way mixed-design ANOVA with repeated measures on two factors: groups of participants, image filters, and collections of toys. The two main factors were significant: the filters ($F_{1,70} = 75$, $p = 1.0 \times 10^{-12} \times 7$, where 7 is multiplied for a Bonferroni correction) and the toy collections ($F_{3,70} = 7.5$, $p = 0.00020 \times 7$). The results of the other effects were not significant: the groups ($F_{1,10} = 0.028$, $p = 0.87 \times 7$), the groups x toy collections ($F_{3,70} = 2.7$, $p = 0.051 \times 7$), the groups x filters ($F_{1,70} = 1.6$, $p = 0.21 \times 7$), the filters x toy collections ($F_{3,70} = 0.062$, $p = 0.98 \times 7$), and the groups x filters x toy collections ($F_{3,70} = 3.2$, $p = 0.030 \times 7$).

Figure 8. The two panels of bar-graphs show the results obtained with both kinds of filters, *i.e.*, contour-drawing and grayscale-image. The ordinate shows the response time. The abscissa shows the collections of toy animals. The brightness of the bars represents represent the two groups.

A posteriori test (Tukey) was performed to test the effect of the toy collections. The response time was shorter with the plastic-cartoon-like animals than with the stuffed animals ($p = 0.00075$) and with the pulp-paper animals ($p = 0.018$). The response time was shorter with the plastic-realistic animals than with the stuffed animals ($p = 0.0047$). The other pair-wise comparisons were not significant: plastic-cartoon-like vs. plastic-realistic ($p = 0.94$), plastic-realistic vs. pulp-paper ($p = 0.074$), paper-realistic vs. stuffed ($p = 0.74$).

208 Experiment 3: Visuomotor coordination

209 In Experiment 3, we measured performance of a visuomotor interaction with objects in two tasks.

210 Procedure

211 The participants performed two visuomotor interactions, one with tongs (Figure 9); the second with
 212 a brick (Figure 10). In the tongs task, the participant picked up and moved 7 objects from a tray to an open
 213 box. The tongs were used to minimize haptic information being used to perform the task. In the brick task,
 214 the participant was given an open box containing 12 rectangular bricks and used his/her hands to build a
 215 stack, with 4 layers of 3 bricks on the top of a stand.

216 The experiment had 4 blocks: 2 image filters (contour-drawing and grayscale image) x 2 tasks (tongs
 217 and brick). Each block consisted of 3 trials. Three collections consisting 7 objects were used in the tongs
 218 task. These trials were repetitions of the blocks used in the brick task. The order of blocks and the order of
 219 trials within each block of the tongs task were randomized by using the Latin-square method with the
 220 following restriction: blocks with the contour-drawing and with the grayscale-image filters were conducted
 221 alternatively (see <https://osf.io/t5jgb/>). The participants rested for 5 minutes between blocks. They did not
 222 wear our AR device during these rest periods.

224 Figure 9. (A) A collection of 7 objects on a tray, and the open box as it was arranged on the desk before each
 225 trial of the tongs task in Experiment 3. (B) The 3 collections of objects used for the tongs task: plastic
 226 animals (left), wooden geometrical objects (middle), and plastic fruits-and-vegetables (right). (C) A gray-
 227 scale image and contour-drawing of the objects on the tray.

228 Figure 10. (A) The bricks and the stand as they were arranged on the desk before each trial of the brick task
 229 in Experiment 3. (B) A gray-scale image and contour-drawing of the 4 layers of 3 bricks built from the 12
 230 bricks on the stand.
 231

232 Results

233 Figure 11 shows the averaged results for the tongs and brick tasks observed in Experiment 3. The
 234 ordinate shows the response time. The abscissa in Figure 11A shows the trials within each block. The
 235 abscissa in Figure 11B shows the collections of objects. The colors of the plots (blue and orange) represent
 236 the image filters (contour-drawing and grayscale image).

237 The results of the tongs task were analyzed by using a two-way between-subject-design ANOVA
 238 with repeated measures: image filters, and collections of objects. The main factor, object collections, was
 239 significant ($F_{2,55} = 49$, $p = 6.4 * 10^{-13} * 3$, where 3 is multiplied for a Bonferroni correction). The effect of the
 240 filters and the interaction between the filters and object collections were not significant: the filters ($F_{1,55} =$

0.52, $p = 0.48 * 3$), the filters x object collections ($F_{2,55} = 0.18$, $p = 0.83 * 3$). A posteriori test (Tukey) was performed to test the effect of the object collections. The response time was shorter with the plastic fruits-and-vegetables than it was with the plastic animals ($p = 1.2 * 10^{-7}$) and with the wooden geometrical objects ($p = 4.1 * 10^{-12}$). The response time was shorter with the plastic animals than with the wooden geometrical objects ($p = 0.0042$).

The results of the brick task were analyzed by using a two-way between-subject-design ANOVA with repeated measures: image filters, and trials. No effect was significant: the filters ($F_{1,55} = 0.0046$, $p = 0.95 * 3$), the trials ($F_{2,55} = 3.2$, $p = 0.048 * 3$), and their interaction ($F_{2,55} = 0.29$, $p = 0.75 * 3$).

Figure 11. (A) The results of the tongs task obtained in Experiment 1. The ordinate shows the response time and the abscissa shows the collections of objects. The colors of the plots represent the image filters. (B) The results of the brick task obtained in Experiment 3. The ordinate shows the response time and the abscissa shows the trials. The colors of the plots represent the image filters.

General discussion

This study showed that human participants can interact dynamically with objects in a real 3D scene solely on the basis of a contour-drawing, or a grayscale-image that represented the scene. The participant could also recognize objects reliably from both contour-drawings and grayscale images (Experiment 2). But note that in our object recognition task, the response was slower with contour-drawings than with the

grayscale images. This difference in response time with these two types of images was not observed in our shape matching task (Experiment 1) or in our visuomotor coordination tasks (Experiment 3).

The results of Experiment 2 showed that a participant can recognize an object quite well when given a contour-drawing but recognition was even better when given its grayscale-image. This difference in performance can be attributed to the luminance-polarity and the luminance-gradient that are present in the grayscale-image but not in the contour-drawing. These two types of luminance information helped the visual system organize the luminance distributions and edges in the grayscale-images [31, 39-44]. The organization of these edges is especially important when many of the contours drawn are redundant and when some of the critical contours are not contained in the contour-drawing. A contour-drawing of a scene was generated by applying an image filter to a photographic image of the scene. This filter used a very simple algorithm that only detected the luminance edges on the basis of local information in the photographic image. This filter could not detect other types of edges, for example, an edge between two regions with different textures [45]. It could detect edges that are usually not drawn as contours in a drawing made by an artist, for example, the edge of a shadow [43] and details of texture. These missed and redundant edges can degrade performance in an object recognition task [24, 46-49]. Also, the luminance-gradient called "shading" could help the visual system to perceive the shape of the object's surface [10, 18, 19, 50-57] and to decompose the object on the basis of the surface's shape [58]. Note that this kind of luminance information did not improve performance in Experiments 1 and 3, which suggests that luminance information, unlike contours, is not very useful.

It is well-known that people can obtain 3D information from a contour drawing, but, until now, it was not clear how useful contour information actually is in a real dynamic scene. Our study shows that contour information, alone, is sufficient for ordinary people to perform a variety of run-of-the-mill tasks under natural viewing conditions. We believe that our demonstration suggests that contour information,

282 alone, may be sufficient to provide the basis for our visual system to obtain all of the 3D information
 283 needed for successful visuomotor interactions in our everyday life.

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290 **Conflict of interests**

291 The authors declare that there is no conflict of interest regarding the publication of this article.

292 **Data availability**

293 All relevant files are available from the Open Science Framework repository (<https://osf.io/t5jgb/>).

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