

# Evaluation of Monocular Depth Cues on a High-dynamic-range Display for Visualisation

HAIDER K. EASA, RAFAŁ K. MANTIUK and IK SOO LIM, School of Computer Science, Bangor University, UK

The aim of this work is to identify the depth cues that provide intuitive depth-ordering when used to visualize abstract data. In particular we focus on the depth cues that are effective on a high-dynamic-range (HDR) display: contrast and brightness. In an experiment participants were shown a visualization of the volume layers at different depths with a single isolated monocular cue as the only indication of depth. The observers were asked to identify which slice of the volume appears to be closer. The results show that brightness, contrast and relative size are the most effective monocular depth cues for providing an intuitive depth ordering.

Categories and Subject Descriptors: 1.3.3 [Computer Graphics] Three-Dimensional Graphics and Realism-Display Algorithms

Additional Key Words and Phrases: HDR, monocular depth cues, depth ordering, depth perception, brightness, contrast, transparency, visualisation

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## 1. INTRODUCTION

Multiple layered abstract data is difficult to visualize on 2D displays, especially when the spatial arrangement of depth needs to be shown. One of the methods used is to remove less important layers to reveal underlying layers [Viola et al. 2005]. Although the layers are revealed, they often appear as painted on a skin outer surface (Figure 1(a)). Transparency is another method which is used for visualising volumes [Krüger et al. 2006]. In this case, the front layer is partially transparent, which provides the user with an intuitive depth cue. However, as shown in Figure 1(b), the depth order is not easy to see and it often needs to be deduced from the knowledge of the visualized phenomena, which is the human anatomy in this case.

In this work, we use a high-dynamic-range (HDR) display [Seetzen et al. 2004] to determine whether it can provide a better impression of depth order when visualising abstract data on 2D displays. While conventional displays are usually restricted by the peak luminance of 200-500 cd/m<sup>2</sup> and the contrast

Author's address: Haider K. Easa, Shaqlawa Technical Institute, Erbil Polytechnic University, Erbil, Kurdistan region/Iraq; email: [haidereesa@yahoo.com](mailto:haidereesa@yahoo.com); Rafał K. Mantiuk, School of Computer Science, Dean Street, Bangor LL571UT, UK; email: [mantiuk@bangor.ac.uk](mailto:mantiuk@bangor.ac.uk); Ik Soo Lim, School of Computer Science, Dean Street, Bangor LL571UT, UK; email: [i.s.lim@bangor.ac.uk](mailto:i.s.lim@bangor.ac.uk).

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Fig. 1. Examples of visualizing depth layers. (a) The revealed layers appear as painted on the skin outer surface [Viola et al. 2005] © 2005 IEEE. (b) It is difficult to determine the depth order [Krüger et al. 2006] © 2006 IEEE.

1000:1, HDR displays can produce as high luminance as  $4,000\text{-}8,000\text{ cd/m}^2$  and contrast exceeding 10,000:1. Such a luminance range is much closer to that found in physical scenes. The images shown on such displays are strongly preferred [Daly et al. 2013] but there are also indications that the expanded contrast range can enhance contrast perception [Rempel et al. 2011].

Depth perception enables our visual system to perceive objects in 3D rather than flat. The human visual system integrates information from multiple *depth cues* to reconstruct 3D information from 2D retinal images. Typically, depth cues can be classified into three main categories: oculomotor, binocular and monocular depth cues. These cues help to estimate size and distance of objects in the 3D world by giving a more accurate interpretation regarding the perceived images [Held and Cooper 2010]. Depth cues may also be classified as physiological and psychological cues [Cutting and Vishotom 1995]. When judging distance using monocular cues, we depend more on cognitive psychological responses. However, with the binocular cues accommodation and convergence, we use physiological mechanisms, such as pupil dilation and eye convergence to judge distance. All monocular cues are psychological cues.

The monocular cues that are investigated in this paper are: blur, contrast, shadow, relative size, brightness, overlap and transparency. Although the transparency, in fact, is not one of the monocular depth cues, it is commonly used in visualisation of a multiple layer phenomena. We chose these cues because all of them contribute, in some extent, to depth ordering.

## 2. RELATED WORK

Depth cues have been extensively studied. Surdick et al. [1994] conducted an experiment comparing depth cues to check which cue provides the most effective depth information. They tested seven cues (relative brightness, relative size, relative height, linear perspective, foreshortening, texture gradient and stereopsis) using a modified Wheatstone stereoscopic display. They found that the effectiveness of the perspective cue (linear perspective, foreshortening, and texture gradient) was superior to other cues, including relative brightness. Their study, however, was restricted to standard low-dynamic-range displays.

Mather and Smith [2004] tried to find the effect of the available number of depth cues on the speed and accuracy of depth ordering judgment. They used three depth cues (blur, contrast and interposition) and found that the observers responded faster when three cues were present than when only one cue was present. Our aim is to check which monocular depth cues provide an intuitive depth ordering when no other cues are available.

Marshall et al. [1996] discuss how blur can be used to establish depth-order. They argued that the edge between the blurred and unblurred part plays an important role in depth order judgment. Mather [1996] claimed that sharp edges make the unblurred part look closer.

In images that contain a different amount of contrast, the furthest objects will have less contrast than the nearest objects [Ichihara et al. 2007]. Rempel et al. [2011] found that observers perceived increases in contrast to correspond with increases in perceived depth. Blackburn et al. [1994] claimed that contrast is an effective depth cue in the absence of other depth cues.

Depth can also be estimated between objects according to their cast shadow [Mamassian et al. 1998]. Elder et al. [2004] argued that our visual system is capable of rapid judgment of depth depending on shadow properties.

The relative size of a familiar object or two similar objects can provide a strong depth cue. But also other cues can affect the perception of size. For example, in the “corridor illusion” phenomenon [Fineman 1981] two objects of identical size are located in the near and far end of a corridor (without accounting for the perspective projection). The linear perspective and texture gradient cues [Aks 1996] of the corridor make the object in the near end of the corridor appear larger even though the geometric size of both objects is exactly the same.

Overlapping is one of the cues that occurs in most images. Objects in an image might be fully or partially overlapped with each other. Edges, generated by partial overlapping, play an important role in depth ordering. Bertamini and Lawson [2008] showed that the response in the figure-ground segmentation task is faster when the surface in front is bounded by a convex contour instead of a straight contour. We named this particular overlap cue “convex”.

Since closer objects tend to reflect more light than distant objects, brightness is an effective cue for depth ordering. Increasing the luminance of an object of interest will make the object appear closer [Swain 2000].

Transparency in an image gives a perception of a multiple layers. Zheng et al. [2012] claimed that transparency is the important visual cue in the perception of depth ordering for semi-transparent structures. When two or more semi-transparent layers are overlapped, they may or may not give rise to X-junctions (crossing of two semi-transparent edges), which affect the perception of transparency (refer to Figure 2). Adelson et al. [1990] claim that X-junctions can determine the nature of transparent intersections and depth ordering of the layers. Depending on the luminance in the region surrounding the X-junction, as shown in the small squares in Figure 2, they classify X-junctions into three types: non-reversing, single-reversing and double-reversing junctions. Transparency can be seen only in non-reversing and single-reversing X-junctions (Figures 2(a) and 2(b)). Non-reversing X-junctions cause bistable percepts which give an ambiguous perception of depth ordering, since either layer can be seen as a transparent filter. The correct depth order can be figured out only for the single-reversing type [Delogu et al. 2010; Singh and Anderson 2002; Anderson 1997].

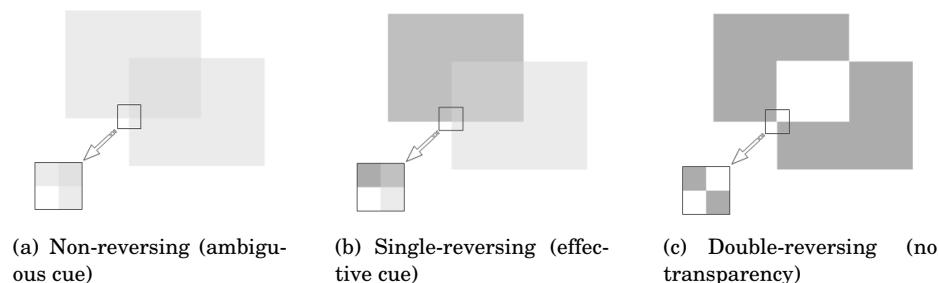


Fig. 2. X-junction occur when two semi-transparent layers are overlapped. The small rectangles show enlarged sections including the X-junction. (a) non-reversing junction results in an ambiguous depth-order, (b) single-reversing junction provides the correct depth order, and (c) double-reversing junction does not evoke the impression of transparency.

### 3. EXPERIMENT

We conducted an experiment to determine which monocular cues provide intuitive depth ordering when all other cues are reduced or eliminated. We visualized a volume by slicing it diagonally, starting either from the left or the right side (Figures 4(a) and 4(b)). This simulates a practical scenario in which it is necessary to reveal the internal layers of a volume. Also, since the visualized volumetric data is mostly abstract, it is almost impossible to guess the correct depth ordering from the content of the volumetric data and without any depth cues. Four computerized tomography (CT) volumes<sup>1</sup> were used in this experiment. Each volume consists of four slices of  $512 \times 512$  pixels (see Figure 3). To reveal more detail and also to reduce the need for large luminance contrast, we used a false-color map instead of gray-scale images.

The fifth volume was generated from the superposition of 3D Gaussian functions with randomized parameters. Then, we took four slices of the resulting 3D function. Gaussian noise was added to the volume in order to better see the effect of blur and transparency cues. Such an abstract volume was introduced to see the effect of each cue without any contextual information (see Figure 11).

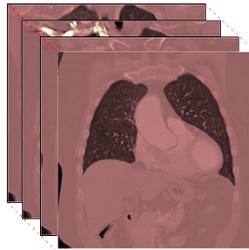


Fig. 3. Four slices of the CT volume of the lung.

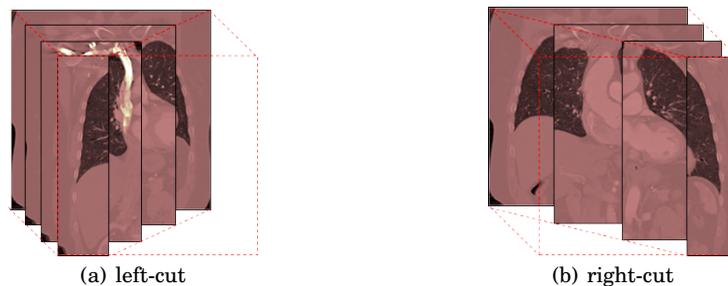


Fig. 4. Examples of slicing a volume. A cut has been made either (a) from the left, or (b) from the right side of the volume.

To prevent any possibility of guessing the depth order from the volume content, a set of “flipped” volumes was created, in which each slice was flipped horizontally and in depth (along z-axis). Figure 5 shows two pairs of original and flipped volumes. Note that the choice of the stimuli was dictated by the necessity to eliminate bias in the experiment rather than a common practice in volume visualization.

<sup>1</sup>CT volumes are the courtesy of OsiriX Imaging Software: <http://www.osirix-viewer.com/datasets/>

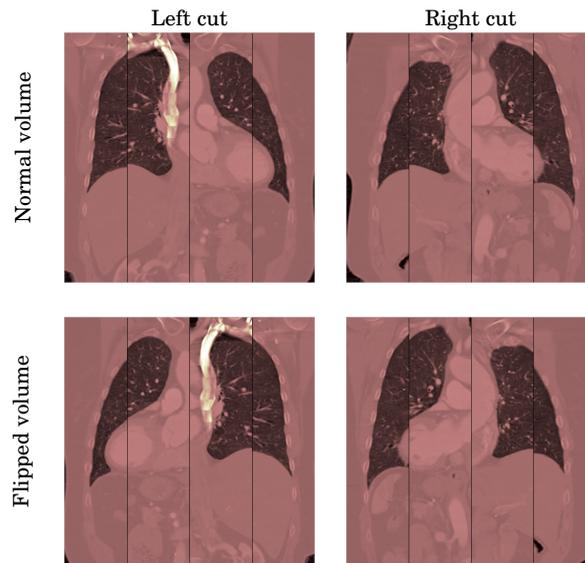


Fig. 5. An orthogonal projection of the volume after cutting. These images contain no cues therefore it is impossible to determine whether the cut was made from the left or the right.

### 3.1 Observers

Twenty one volunteers participated in this experiment, seven female and fourteen male, between 23 and 40 years old. All observers had normal or corrected to normal vision. All observer were naive to the objective of the experiment.

### 3.2 Stimuli

Seven cues were used in the experiment: blur, convex, contrast, shadow, relative size, brightness and transparency. In the following paragraphs we explain how these cues were generated.

**Blur cue** Marshall et al. [1996] argued that the appearance of an edge, that separates blurred and sharp region, is important for determining the depth order. They demonstrate that if the separating edge is sharp, the sharp region (in focus) is perceived as closer. Figure 6(a) shows an example of the blur cue stimulus.

To generate an image with the blur cue, the left-most column was kept sharp while the other three columns were partially blurred, starting from their left side towards the middle of the column. Sinusoidal lines were used to separate the columns and provide a stronger cue. This procedure was performed to produce the blur cue possibly similar to that employed by Marshall et al. [1996]. The blur was using a Gaussian kernel with the standard deviation ranging from  $\sigma = 20$  on the side corresponding to the depth discontinuity, to  $\sigma = 0.1$  in the middle of the column. According to [Marshall et al. 1996], we expected the observers to choose the leftmost side as the closest.

**Overlap cue** (also known as interposition cue) Bertamini and Lawson [2008] showed that because of convexity, observers responded faster when asked to report on depth order, when two surfaces were overlapped by a curved line. Therefore, to generate an overlapped cue stimulus that corresponds to a left cut, Figure 6(b), we used curved lines to separate the columns. This way the curve direction opposed the cut direction (for example; for a left cut, the direction of the curves will be towards the

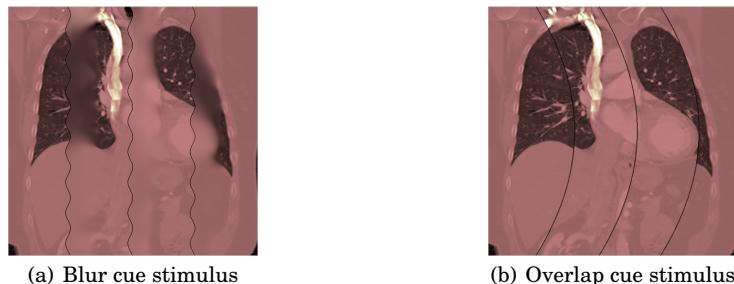


Fig. 6. Blur and overlap cues stimuli for the left cut of the volume. (a) The slices are blurred at the edge to visualise the discontinuity in depth. (b) Curved lines suggested the depth ordering for overlapping slices.

right). According to Bertamini and Lawson [2008] we expected the observers to choose the leftmost side as the closest.

**Contrast cue** To generate a contrast cue stimulus, each of the slices had its contrast modified so that the closest slice had the highest contrast. Before modifying slices, we converted them from the gamma corrected sRGB into a linear RGB color space and computed the relative luminance value for each pixel. Then, we adjusted the luminance contrast using the equation:

$$L_{out} = \left( \frac{L_{in}}{P} \right)^c \cdot P, \quad (1)$$

where  $L_{in}$  and  $L_{out}$  are input/output luminance,  $P$  is a luminance that should remain unchanged (usually background luminance) and  $c$  is the contrast modification factor. Since contrast change affects the perceived saturation of colours, it is necessary to correct for that. This can be achieved using the color transfer equation [Mantiuk et al. 2009]:

$$C_{out} = \left( \frac{C_{in}}{L_{in}} \right)^s \cdot L_{out}, \quad (2)$$

where  $C$  denotes one of the colour channels (red, green, or blue), and  $s$  controls colour saturation. Mantiuk et al. [2009] provide an empirical equation for finding the proper saturation correction factor:

$$s(c) = \frac{(1 + k_1)c^{k_2}}{1 + k_1c^{k_2}}, \quad (3)$$

where  $k_1$  and  $k_2$  are constants with the values 1.6674 and 0.9925 respectively.

Each slice in a volume was assigned a different  $c$  value depending on the direction of the cut. The  $c$  values (1, 1.7, 2.93 and 4.98) were selected to differ by a constant ratio, which resulted in approximately equal increase in perceived contrast. Figure 7 shows an example of the contrast stimulus at three virtual exposures.

**Shadow cue** Shadows help to determine a distance between objects. Shadows and in particular self-shadows can be efficiently approximated using the ambient occlusion method [Landis 2002]. Figure 8(a) shows a stimulus for a left-cut volume with a shadow cue. We generated a contact shadow for the right side of the first column of the first slice and merged it with the second column of the second slice. A sample space ambient occlusion (SSAO) algorithm [Mendez 2010] was used to generate shadows. We speculate that the observer will select the leftmost column as the closest side. To reproduce an equal distance between each slice, the size of the shadow spread was the same.

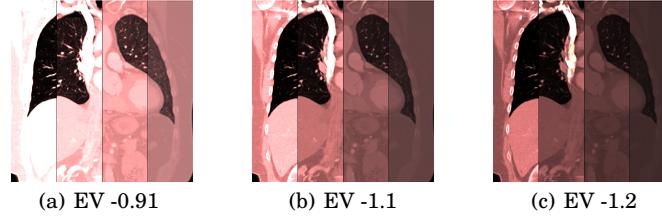


Fig. 7. Contrast stimulus. Because the stimulus is a high dynamic range image, it is shown at three different exposure values.

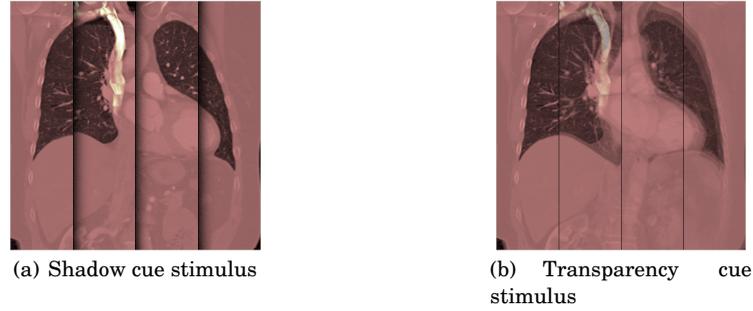


Fig. 8. Shadow and transparency cues for the left-cut of the volume. (a) An ambient occlusion was used to generate a shadow-like between columns. (b) The removed parts of the slices were made transparent.

**Transparency cue** Talbot's law states that the reflectance of a fusion colour is the weighted average of the reflectance of its component colour proportions mixed together [Beck et al. 1984]. Talbot's law can be expressed by the following equation:

$$c = \alpha a + (1 - \alpha)b, \quad (4)$$

where  $a$  and  $b$  are reflectance of the component colours which are going to be mixed together,  $c$  is the reflectance of the fusion colour and  $\alpha$  is the transparency factor (between 0 and 1). Equation 4 was the origin of *alpha blending* that is commonly known in computer graphics today [Kasrai 2004]. Alpha blending is a process used to produce transparency by combining two or more transparent foreground layers with a background layer using the equation [Bavoil and Myers 2008]:

$$C_n = \alpha_n C_n + (1 - \alpha_n)\alpha_{n-1}C_{n-1} + (1 - \alpha_n)(1 - \alpha_{n-1})\alpha_{n-2}C_{n-2} + \dots \\ (1 - \alpha_n)(1 - \alpha_{n-1})\dots(1 - \alpha_1)C_0, \quad (5)$$

where  $C_n$  is the output colour,  $\alpha_x$  is the alpha value of layer  $x$ , and  $C_x$  is the colour of layer  $x$  and  $C_0$  represents the background layer.

The stimuli were generated by making the parts of the slices transparent instead of removing them (as shown in Figure 4). The alpha values were:  $\alpha_4 = 1$ ,  $\alpha_3 = 0.5$ ,  $\alpha_2 = 0.333$  and  $\alpha_1 = 0.25$ , where  $\alpha_4$  corresponds to the nearest slice. The background color  $C_0$  was black (red, green and blue components equal to 0). Alpha values were chosen to result in identical contribution of each layer. An example of the transparency stimulus is shown in Figure 8(b).

**Relative size cue** Given a perspective projection and equal sized objects, the closest object will appear larger than the farthest object. The relative size cues were generated by reducing the size of each consecutive slice to 75% of the previous slice. An example of the relative size cue is shown in

Figure 9. This cue could be considered as one of the control conditions as we expect very few wrong answers for this very suggestive cue.

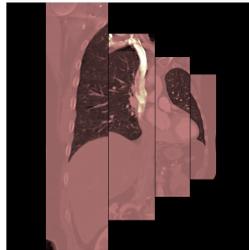


Fig. 9. A relative size cue for the left cut of the volume. The size of the further located slices is reduced.

**Brightness cue** Given two similar objects, the brighter one will appear to be closer to the observer [Gibson 1950]. The stimulus was created by increasing the luminance of each slice in a volume with higher luminance assigned to closer slices. We set the peak luminance of each slice to  $2000 \text{ cd/m}^2$ ,  $737 \text{ cd/m}^2$ ,  $271 \text{ cd/m}^2$  and  $100 \text{ cd/m}^2$ , from the closest to the farthest. The values correspond to equidistant points in the logarithmic space, which result in approximately the same steps in perceived brightness. Figure 10 shows an example of the brightness cue image as three different exposures of the corresponding HDR image.

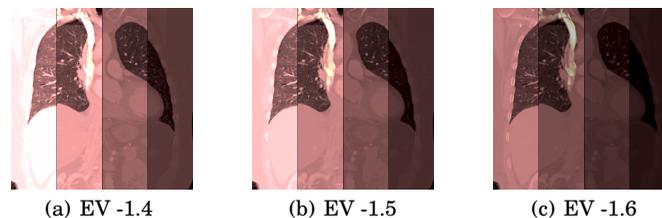


Fig. 10. Brightness stimulus. As the stimulus is a high dynamic range image, it is shown at three different exposure values.

**Control condition “no cue”** We also introduced images with no cues to the experiment, such as the one in Figure 5. They were used as a control condition for which the observers were expected to provide random answers. We use the label “No cue” for this condition.

### 3.3 Apparatus

The images were generated in the linearized RGB colour space (ITU-R BT.709 color primaries) and displayed using an experimental HDR display. The device was a modified version the SBT1.3 model ([Seetzen et al. 2004]), which consisted of a 4 000 lumen projector and a 15” LCD panel with a resolution of  $1024 \times 768$  pixels. The device’s peak luminance was  $2446 \text{ cd/m}^2$  and the black level was  $0.01 \text{ cd/m}^2$ . The details on the display can be found in [Wanat et al. 2012]. The viewing distance between each observer and the display screen was approximately 80 cm. The room lights were switched off to avoid screen reflections and maximize display contrast.

### 3.4 Procedure

Each observer was asked to read an instruction, which asked to select the slice (the leftmost or the rightmost) of the displayed image that appeared closer. The observer had to make the best guess if he or she was unsure which depth ordering was correct (two alternative forced choice). An observer could cancel and repeat the last measurement in a rare case of pressing a wrong key. The instruction explained how the images were created by slicing volumes and projecting them orthogonally. Each experimental session was preceded by a short training session to ensure good understanding of the task. In each session, the observer judged all 160 images (5 volumes  $\times$  2 cuts  $\times$  2 flips  $\times$  8 cues).

## 4. RESULTS

To test for the statistical significance, the data were analyzed using the Binomial test assuming the null hypothesis  $H_0$  that the cue has no effect on the perceived depth ordering and the observers make random choices. The binomial probability distribution is given by [Cunningham and Wallraven 2011]:

$$P(X = x) = \binom{n}{x} p^x (1 - p)^{n-x} \quad x = 0, 1, \dots, n, \quad (6)$$

where  $P(X)$  is the probability of  $X$  successes,  $p$  is the probability of success on any one trial (0.5 in our case) and  $n$  is the number of trials. We tested the hypothesis at the  $\alpha = 0.05$  significance level.

For each cue, we tested for  $H_0$  by computing the probability of observing a given number of correct answers assuming that the observers were guessing. Then,  $H_0$  was rejected when the probability was below the critical value. Figure 11 shows the result for all observers. The red-dashed lines mark the critical region for the Binomial test: all results within the range limited by the dashed lines are not statistically significant (shown in red).

The control condition cue (“No cue”) has no effect on depth ordering, which means that it was impossible to tell the depth order given no cue. This confirms that the stimuli were well balanced and the depth ordering could not be deduced from the content of volumes alone.

We found no statistically significant effect for the transparency cue in the case of two volumes: *Abstract* (50%) and *Knee-2* (57.1%). This could be explained by the lack of single-reversing X-junctions in the depicted volumes (refer to Figure 2). Such ambiguity of depth ordering can also be seen for *Knee-1* (60.7%) and *Knee-3* (60.7%) volumes since  $H_0$  was barely rejected. The highest correct rate for the transparency cue was achieved for the *Lung* volume (64%), which contains strong edges and thus makes the slices easier to recognize, as shown in Figure 8(b). Our findings showed that the transparency cue was strongly affected by the nature of the images. Moreover, the transparency cue has the lowest percentage of correct judgment among all other cues. This result is of particular interest, given that transparency is a common method of presenting multi-layered phenomena in visualization.

Another cue that is also affected by the content of the volume is blur. The  $H_0$  could not be rejected for the abstract volume (58%). The most likely reason for that is the lack of high frequencies and sharp edges in this volume, which are necessary to perceive blur. This cue could also be unsuitable for the visualization application in which blurring and therefore the loss of details is not permissible.

For all the remaining cues the results are statistically significant for all volumes, which means that there is an evidence that these cues help in the depth ordering task. However, the success rate varies between the cues.

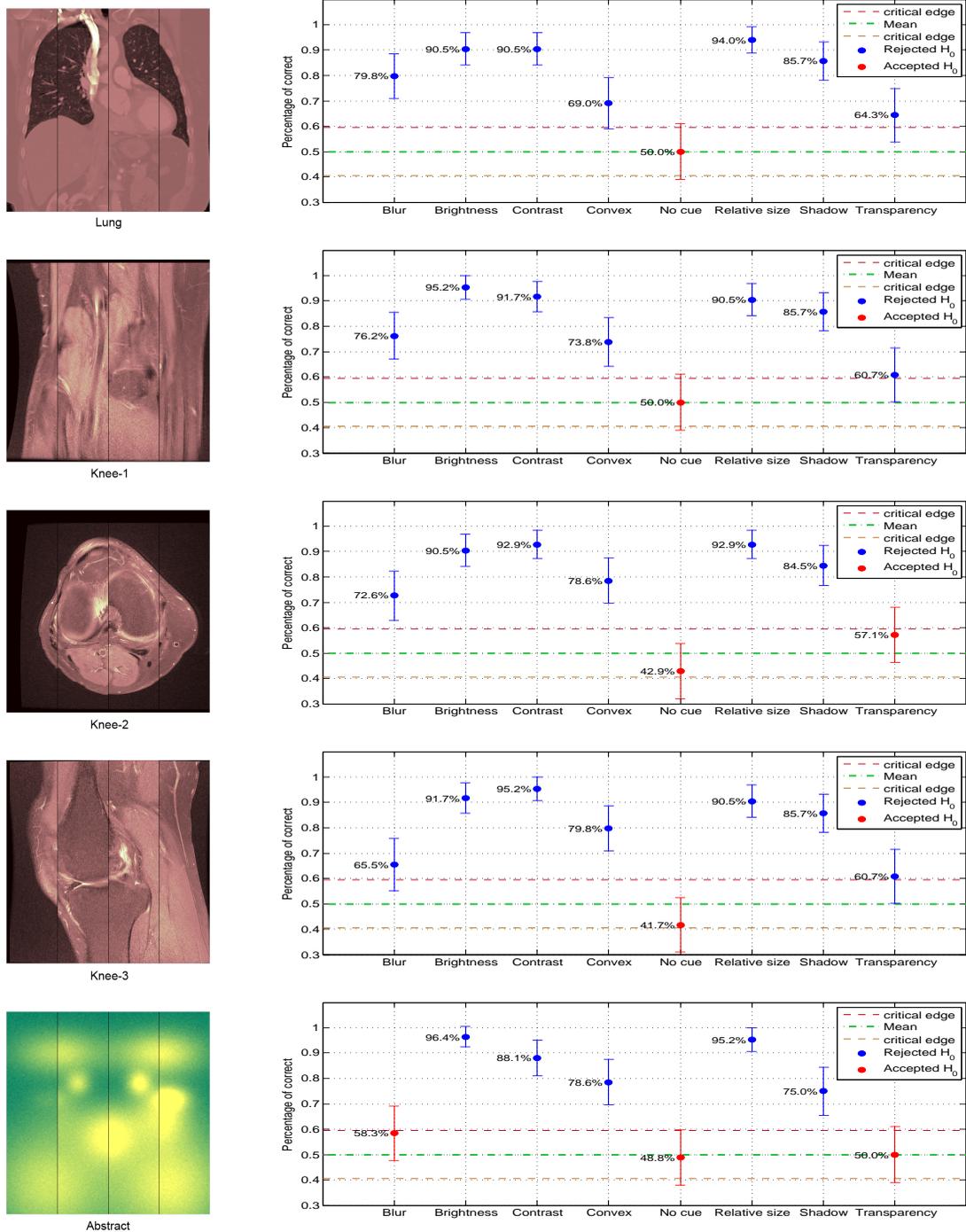


Fig. 11. Percentage of correct depth ordering judgments for each monocular cue. The error bars show 95% confidence intervals. The data points marked in red indicate no statistically significant effect of a given cue on the depth ordering performance. ACM Transactions on Applied Perception, Vol. 2, No. 3, Article 1, Publication date: July 2013.

The convex cue yielded a success rate of 75.96%. This lower than expected success rate can be explained by the nature of the volumes, which resulted in slices of very similar color. To show the effect of convex contour on the depth perception, Bertamini and Marko [2006], Bertamini and Lawson [2008], Bertamini and Croucher [2003] and Vecera et al. [2002] used two contrasting colors to separate the two layers. There was no such color difference in our stimuli.

Similar success rates observed for the shadow cue, through all volumes except the abstract, suggests that it is not affected by the content within the volume. The shadow produced success rate of 83.32%. The false ordering, in the case of shadow, was most likely caused by the ambiguity between shadow and shading; the observer may see the “shadow” as if it was shading of a curved surface. Because of this ambiguity, the observer may assume that the volume is illuminated from the right, consist of curved surfaces and the order of the slices is opposite to the intended order (refer to Figure 12(b)). Another weak point of adding shadow is that less details could be visible in the shaded parts of an image.

The contrast, brightness and relative size cues have the highest ratio of correct judgment with the average of 91.68%, 92.86% and 92.62% respectively. Relative size is a very strong cue that could be used with any type of display device. However, it requires that the presented phenomena contains the features of common or known size. In our case, it was the equal size of the volume slices. It also requires perspective rather than orthogonal projection, which may be less suitable in some applications. Brightness and contrast cues provide intuitive depth ordering independently of the content or shape of the visualized volume. This supports our hypothesis that an HDR display can be useful in visualisation applications. From these two cues, the brightness cue could be more universal as it does not affect the contrast of the displayed data.

Contrary to our expectations, some cues, such as transparency and blur, resulted in very poor performance in the depth ordering task. Also, convex overlap and shadow cues were not as strong as we expected. Such a result could be specific to our data set, which consists mostly of abstract CT images, often lacking strong edges, and 4 discrete depth layers. We also expected the relative size to result in the highest probability. However, surprisingly, the brightness cue resulted in very comparable performance.



Fig. 12. An example of some possible ways to generate shadows. In (a) the shadow generated as a result of occluding lights by the layers on the top and the light source, in this case, will be in the left side, whilst in (b) the shadow is the result of a curved layers shade and the light source is in the right side.

## 5. CONCLUSIONS AND FUTURE WORK

The focus of this study was to test which monocular depth cues are the most effective in applications that require visualisation of abstract 3D data. We found that each individual cue increased a likelihood of correct depth ordering beyond a chance; however, such probability varies greatly between the cues.

Although transparency is probably the most commonly used mean to visualize multi-layered data, it was the least effective with the lowest percentage of correct order judgments. Low success rate was also observed for the blur and convex cues. The shadow cue provided a better success rate but not as much as expected. Unsurprisingly, the relative size cue resulted in high success rate. However, such cue could be much less effective if the visualized data did not contain elements of common size. The most interesting observation was high success rate for two cues that utilized the extended dynamic range of an HDR display: contrast and brightness. Their success rate was comparable to the best performing cue — relative size. This indicated a potential of using HDR displays in visualization applications.

The results of our study apply to the case of parallel slices of CT scans and more experiments need to be done to confirm whether these findings generalize to more complex cases. For example, altering brightness of a complex shape may result in interpreting the brightness change as shading due to surface curvature rather than discontinuity in depth. This ambiguity can be partially addressed by introducing steep luminance change on an HDR display, which will be interpreted as illumination discontinuity rather than shading. However, a significant luminance contrast in an image may result in disability glare (scattering the light in eye's optics and on the retina) and reduce the visibility of details in dark regions. In our future work we will experiment with such complex cases and test whether the current results carry over to more natural settings. Furthermore, we wish to experiment with a combination of monocular depth cues, as such a combination is expected to improve the accuracy and speed of depth detection [Mather and Smith 2004].

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#### REFERENCES

- Edward H. Adelson and Padmanabhan Anandan. 1990. *Ordinal characteristics of transparency*. Vision and Modeling Group, Media Laboratory, Massachusetts Institute of Technology, Massachusetts, USA. <http://books.google.co.uk/books?id=gP7DHAAACAAJ>
- James T. Aks, Deborah J.; Enns. 1996. Visual search for size is influenced by a background texture gradient. *Journal of Experimental Psychology: Human Perception and Performance* 22:6 (1996), 1467–1481. DOI:<http://dx.doi.org/10.1037/0096-1523.22.6.1467>
- B. L. Anderson. 1997. A theory of illusory lightness and transparency in monocular and binocular images: the role of contour junctions. *Perception* 26, 4 (Jan. 1997), 419–454.
- Louis Bavoil and Kevin Myers. 2008. Order Independent Transparency with Dual Depth Peeling. *NVIDIA Corporation* 107, February (2008), 22020–5.
- J. Beck, K. Prazdny, and R. Ivry. 1984. The perception of transparency with achromatic colors. *Perception & psychophysics* 35, 5 (May 1984), 407–422.
- Marco Bertamini. 2006. Who owns the contour of a visual hole? *Perception* 35, 7 (2006), 883–894. DOI:<http://dx.doi.org/10.1068/p5496>
- Marco Bertamini and Camilla J. Croucher. 2003. The shape of holes. *Cognition* 87 (2003), 33–54. DOI:[http://dx.doi.org/10.1016/S0010-0277\(02\)00183-X](http://dx.doi.org/10.1016/S0010-0277(02)00183-X)
- Marco Bertamini and Rebecca Lawson. 2008. Rapid figure-ground responses to stereograms reveal an advantage for a convex foreground. *Perception* 37, 4 (2008), 483–494. DOI:<http://dx.doi.org/10.1068/p5728>
- Shane G. Blackburn and Robert P. O. Shea. 1994. Contrast as a Depth Cue. *Vision Research* 34, 12 (1994), 1595–1604.
- D. Cunningham and C. Wallraven. 2011. *Experimental Design: From User Studies to Psychophysics*. AK Peters, Ltd., Natick, MA, USA.
- J. E. Cutting and P. M. Vishotn. 1995. Perceiving layout and knowing distances: The integration, relative potency, and contextual use of different information about depth. (*W. Epstein & S. Rogers, Eds.*) *Perception* 5(3), 3 (1995), 1–37.

- Scott Daly, Timo Kunkel, Xing Sun, Suzanne Farrell, and Poppy Crum. 2013. Preference limits of the visual dynamic range for ultra high quality and aesthetic conveyance. In *IS&T/SPIE Human Vision and Electronic Imaging*. International Society for Optics and Photonics, Burlingame, California, USA, 86510J–86510J. DOI: <http://dx.doi.org/10.1117/12.2013161>
- Franco Delogu, George Fedorov, Marta Olivetti Belardinelli, and Cees van Leeuwen. 2010. Perceptual preferences in depth stratification of transparent layers: Photometric and non-photometric factors. *Journal of Vision* 10, 2 (2010), 1–. DOI: <http://dx.doi.org/10.1167/10.2.19>
- James H. Elder, Sherry Trithart, Gregor Pintilie, and Donald MacLean. 2004. Rapid processing of cast and attached shadows. *Perception* 33, 11 (2004), 1319–1338. DOI: <http://dx.doi.org/10.1068/p5323>
- Mark B. Fineman. 1981. Complexity of context and orientation of figure in the corridor illusion. *Perceptual and Motor Skills* 53:1 (1981), 11–14.
- James J. Gibson. 1950. The perception of visual surfaces. *The American Journal of Psychology* 63.3 (1950), 367–384.
- RT. Held and EA. Cooper. 2010. Using blur to affect perceived distance and size. *ACM Transactions on Graphics* 29, 2 (2010), 1–33. DOI: <http://dx.doi.org/10.1145/1731047.1731057>
- Shigeru Ichihara, Norimichi Kitagawa, and Hiromi Akutsu. 2007. Contrast and depth perception: Effects of texture contrast and area contrast. *Perception* 36, 5 (2007), 686–695. DOI: <http://dx.doi.org/10.1068/p5696>
- Reza Kasrai. 2004. *On the Perception of Transparency: Psychophysics and Applications to Medical Image Visualisation*. Ph.D. Dissertation. McGill University, Canada.
- Jens Krüger, Jens Schneider, and Rüdiger Westermann. 2006. ClearView: An Interactive Context Preserving Hotspot Visualization Technique. *IEEE Transactions on Visualization and Computer Graphics (Proceedings Visualization / Information Visualization 2006)* 12, 5 (September-October 2006), 941–948. DOI: <http://dx.doi.org/10.1109/TVCG.2006.124>
- Hayden Landis. 2002. Production-Ready Global Illumination. *SIGGRAPH course notes* 16, 11 (2002), 87–101.
- Pascal Mamassian, David C. Knill, and Daniel Kersten. 1998. The perception of cast shadows. *Trends in Cognitive Sciences* 2, 8 (Aug. 1998), 288–95. DOI: [http://dx.doi.org/10.1016/S1364-6613\(98\)01204-2](http://dx.doi.org/10.1016/S1364-6613(98)01204-2)
- R. Mantiuk, R. K. Mantiuk, A. Tomaszewska, and W. Heidrich. 2009. Color correction for tone mapping. *Computer Graphics Forum* 28, 2 (April 2009), 193–202. DOI: <http://dx.doi.org/10.1111/j.1467-8659.2009.01358.x>
- J. Marshall, C. Burbeck, D. Ariely, J. Rolland, and K. Martin. 1996. Occlusion edge blur: a cue to relative visual depth. *Journal of the Optical Society of America* 13, 4 (1996), 681–688. DOI: <http://dx.doi.org/10.1364/JOSAA.13.000681>
- G. Mather. 1996. Image blur as a pictorial depth cue. *Proceedings. Biological sciences / The Royal Society* 263, 1367 (Feb. 1996), 169–72. DOI: <http://dx.doi.org/10.1098/rspb.1996.0027>
- George Mather and David R.R. Smith. 2004. Combining depth cues: effects upon accuracy and speed of performance in a depth-ordering task. *Vision Research* 44, 6 (March 2004), 557–562. DOI: <http://dx.doi.org/10.1016/j.visres.2003.09.036>
- J. M. Mendez. 2010. A Simple and Practical Approach to SSAO. In: *Graphics Programming and Theory*, gamedev.net. (May 2010). [http://www.gamedev.net/page/resources/\\_/technical/graphics-programming-and-theory/a-simple-and-practical-approach-to-ssao-r2753](http://www.gamedev.net/page/resources/_/technical/graphics-programming-and-theory/a-simple-and-practical-approach-to-ssao-r2753)
- Allan G Rempel, Wolfgang Heidrich, and Rafał Mantiuk. 2011. The role of contrast in the perceived depth of monocular imagery. In *Proc. of the ACM SIGGRAPH Symposium on Applied Perception in Graphics and Visualization*. ACM, NY, USA, 115–115. DOI: <http://dx.doi.org/10.1145/2077451.2077478>
- Helge Seetzen, Wolfgang Heidrich, Wolfgang Stuerzlinger, Greg Ward, Lorne Whitehead, Matthew Trentacoste, Abhijeet Ghosh, and Andrejs Vorozcovs. 2004. High dynamic range display systems. *ACM Transactions on Graphics* 23, 3 (Aug. 2004), 760. DOI: <http://dx.doi.org/10.1145/1015706.1015797>
- Manish Singh and Barton L. Anderson. 2002. Toward a perceptual theory of transparency. *Psychological Review* 109, 3 (2002), 492–519. DOI: <http://dx.doi.org/10.1037/0033-295X.109.3.492>
- R. Troy Surdick. 1994. Relevant cues for the visual perception of depth: is where you see it where it is? *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* 38 -19 (1994), 1305–1309. DOI: <http://dx.doi.org/10.1177/154193129403801912>
- Cassandra Turner Swain. 2000. Integration of monocular cues to improve depth perception. (2000). US patent 6,157,733.
- Shaun P. Vecera, Edward K. Vogel, and Geoffrey F. Woodman. 2002. Lower region: A new cue for figure-ground assignment. *Journal of Experimental Psychology: General* 131, 2 (2002), 194–205. DOI: <http://dx.doi.org/10.1037/0096-3445.131.2.194>
- Ivan Viola, Armin Kanitsar, and M. Eduard Gröller. 2005. Importance-driven feature enhancement in volume visualization. *IEEE Transactions on Visualization and Computer Graphics* 11, 4 (2005), 408–418. DOI: <http://dx.doi.org/10.1109/TVCG.2005.62>
- Robert Wanat, Josselin Petit, and Rafał Mantiuk. 2012. Physical and perceptual limitations of a projector-based high dynamic range display. In *Proc. of Theory and Practice of Computer Graphics*. Eurographics Association, Goslar, Germany, 9–16.

Lin Zheng, Yingcai Wu, and Kwan-Liu Ma. 2012. Perceptually Based Depth-Ordering Enhancement for Direct Volume Rendering. *IEEE Transactions on Visualization and Computer Graphics* 19, 3 (June 2012), 446–459. DOI:<http://dx.doi.org/10.1109/TVCG.2012.144>

# Online Appendix to: Evaluation of Monocular Depth Cues on a High-dynamic-range Display for Visualisation

HAIDER K. EASA, RAFAŁ K. MANTIUK and IK SOO LIM, School of Computer Science, Bangor University, UK

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