EG UK Theory and Practice of Computer Graphics (2013)
Silvester Czanner and Wen Tang (Editors)

The Evaluation of Perceptual Effectiveness of Isosurface Rendering-based Uncertainty Visualization Techniques for Volumetric Scalar Data

Ji Ma[†1,2], David Murphy[1], Gregory Provan[1], Cian O'Mathuna[2], Michael Hayes[2]

[1]Department of Computer Science, [2]Tyndall National Institute,
University College Cork (UCC), Ireland.

Abstract

Many techniques have been proposed to convey uncertainty in visualization. However, little research has been reported on the evaluation of their effectiveness. We present a user study that evaluates the perceptual effectiveness of six (four new and two existing) isosurface rendering-based uncertainty visualization techniques. For every technique, we consider its four effectiveness aspects: identification of the data, identification of the uncertainty, visual overload and brightness. There are thirty users participated in the user study and statistical analysis has been made for this study. Our analysis suggested that the two existing uncertainty visualization techniques appear to be the most advantageous in all the evaluated techniques. Both of them have high scores in all the four aspects of the effectiveness. In terms of the new techniques, the transparency technique appears to be the most promising. Whilst the remaining three new techniques may have some utility in certain aspects of the effectiveness, they are less useful in other aspects of the effectiveness. Additionally, a surprising result we have found is that adding auxiliary grid lines as background is not guaranteed to enhance the participants' perception to the errors depicted by the transparency. Conversely, it may lead to visual overload that increases the difficulty to recognize data. We believe that these findings can be useful for future uncertainty visualization design.

Categories and Subject Descriptors (according to ACM CCS): I.3.m [Computer Graphics]: Miscellaneous—

1. Introduction

Uncertainty is an inherent part of all data sets. For example, it can be found in Computational Fluid Dynamics (CFD) data sets, bioinformatics data sets, environmental science or geospatial data sets, to name just a few [DKLP02]. It can be introduced into the data at various stages. For example, Pang et al. [PWL97] identified three stages that can introduce uncertainty: data acquisition, data transformations and the visualization.

Visualizing the uncertainty in data is very significant as this will prevent the visualization from running in a risk that misleads viewers' interpretation of data, or drawing incorrect conclusions or decisions from data. Over the past few years, a variety of techniques have been proposed to convey the uncertainty in visualization. However, little research has been conducted to evaluate and compare their perceptual effectiveness. This could prevent the further development of new uncertainty visualization techniques as no valuable knowledge and guideline is summarized and formulated from the existing solutions. In this paper we address the issue by presenting a formal user study that evaluates the perceptual effectiveness of six isosurface rendering-based uncertainty visualization techniques. We present our study design as well as report the corresponding findings. We believe that these findings can provide useful guidance for future uncertainty visualization design.

The remainder of this paper is organized as follows: Section 2 introduces the related work. Section 3 presents our study design. Section 4 reports the initial findings from this study. Section 5 presents the methods used for statistical analysis. Section 6 reports the results from the statistical

† ji.ma@tyndall.ie

DOI: 10.2312/LocalChapterEvents.TPCG.TPCG13.025-032

analysis. Finally Section 7 draws conclusions and discusses future work.

2. Related Work

Some of the earliest research for uncertainty visualization started in the Geographic Information System (GIS) community [Mac92] [WF93]. That work was mainly concerned with representing the error in terrain models. Later on some early researchers in the visualization communities started to investigate the depiction of uncertainty in 3D surfaces [PWL97] [LSPW96].

Uncertainty visualization started to gain momentum when its significance was pointed out by several leading researchers [JS03] [Joh04] [Che05] [JMM*06] [LK07]. Djurclov et al. [DKLP02] developed two DVR based approaches termed inline DVR and post-processing to visualize uncertainty in an ocean model. Rhodes et al. [RLBS03] proposed two isosurface rendering-based methods, namely hue and texture opacity, to visualize the uncertainty in Multiresolution (MR) data. Lundstrom et al. [LLPY07] explored a probabilistic animation method to illustrate the classification's uncertainty in medical volume renderings. Foulks et al. [FB09] presented a series of techniques including color maps, semi-transparency overlays and different rendering algorithms to depict the uncertainty between different MR data sets.

More recently, there are some researchers who have combined various visualization techniques into multiple linked windows to explore uncertainty visualization. For example, Potter et al. [PWB*09] presented an Ensemble-Vis, which consists of a collection of overview and statistical displays, linked through a high level of interactivity, to enable scientists to gain key insight into the uncertainty within scientific simulations. Sanyal et al. [SZD*10] proposed a framework called Noodles, which consists of coordinated views of ribbon, spaghetti plots, isopressure color maps, data transect plots etc. to visualize the uncertainty in ensemble data.

While most research has been focused on univariate uncertainty data, little work has been reported on uncertainty visualization in multivariate data. Xie et al. [XHWR06] describe two approaches to visually explore multivariate data with variable quality. He et al. [HYX11] presented approaches to improve the existing parallel coordinates and star glyph methods for uncertainty visualization in multivariate data.

Although uncertainty visualization is now an active research area in the visualization community [Pot11] and many techniques have been proposed, only a little work [KPH01] [LB00] [Wec03] has been reported on the evaluation of their effectiveness. Newman et al. [NL04] presented a user study which evaluates the effectiveness of eight isosurface rendering-based uncertainty visualization techniques. They synthetically generated the errors whose distribution is controllable for the volumetric data. In particular, seven of their techniques can be classified as overloading approaches, and one technique can be classified as seamless integration approach [PWL97]. In contrast to their study, all the techniques described in this study belong to the seamless integration approach. Sanyal et al. [SZB*09] performed a user study that compares four commonly used uncertainty visualization techniques for both 1D and 2D data sets. The novelty of their work is that they designed a controlled synthetic-data generation scheme that is not only specific enough to provide immediate insight into geosciences uncertainty representation, but also generic enough to potentially have other applications.

3. Study Design

This section presents the study design of this evaluation. This includes the uncertainty data modeling and quantification, chosen uncertainty visualization techniques, participant pool and user study tasks, interface design, participant training, the trial run and finally the main study.

3.1. Uncertainty Data Modeling and Quantification

A necessary step of uncertainty visualization research is to model and quantify the uncertainty data. In this paper we use the MR modelling technique, in particular the Haar Wavelet Transform to model the uncertainty. This procedure can be summarized as the following two steps: First, we applied the Haar Wavelet Transform to the original volumetric data cube by cube (cube refers to a small volume where the Haar Wavelet Transform is applied to. In 3D case, a cube must incorporate the power of 8 voxels) to generate its coarse resolution data. Second, we quantified the error within each cube between the original volumetric data and any one of its low resolution data using the Standard Deviation, as illustrated in formula 1:

$$e = \sqrt{\frac{1}{n}[(V_1-\overline{V})^2+(V_2-\overline{V})^2+\cdots+(V_n-\overline{V})^2]} \quad (1)$$

As a result, each voxel in the low resolution data is associated to two values calculated from the original volumetric data: a mean that represent the "certain" data, and a Standard Deviation that represents the "uncertain" data. For clarification, we formally define the uncertainty as errors that are quantified between the original volumetric data and any one of its low resolution data.

3.2. Uncertainty Visualization Techniques Chosen for Evaluation

Six uncertainty visualization techniques are presented in this section, and they are all seamlessly integrated into the extended Marching Cubes (MC)-based algorithm [RLBS03].

3.2.1. Hue

This is a known techniques proposed by Rhodes et al. [RLBS03], and it uses the hue component of Hue, Saturation and Lightness (HSL) to indicate the presence and degree of errors. Figure 1 illustrates a result of this technique after applying it to a volumetric data of lobster, which has been used in our main study. It is clear from Figure 1 that the errors have been mapped to five discrete hue values. The smaller errors correspond to the hue values that appear more yellow, and the bigger errors correspond to the hue values that appear more reddish. Other errors correspond to the hue values with colors in-between.

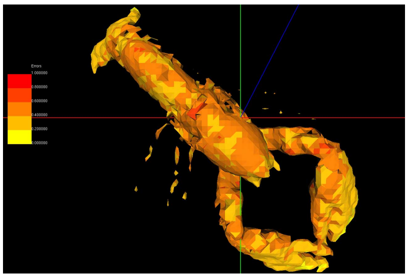

Figure 1: *Errors are mapped to the hue.*

3.2.2. Blurred Textures

This is a new technique that indicates the presence and degree of errors by the blurred textures. Although using blur to depict uncertainty is not new [PWL97] [GR04], to our knowledge, integrating the blurred textures into the MC to depict the errors has not been used. Figure 2 illustrates a result of this technique. The blurred effects used here are from Gaussian Blur. It is clear from Figure 2 that the errors have been mapped to five discrete blurred textures. The smaller errors correspond to less blurred textures, and the bigger errors correspond to more blurred textures. Other errors correspond to the blurred textures in-between.

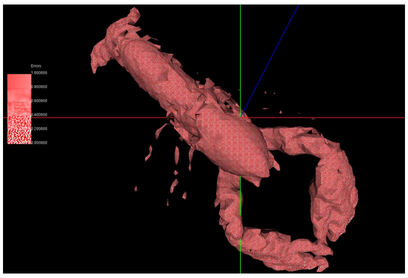

Figure 2: *Errors are mapped to the blurred textures.*

3.2.3. Glyph Textures with Different Number of Edges

The new technique indicates the presence and degree of errors by different edge numbers of the glyph textures. Although using glyphs to depict uncertainty is not new [PWL97] [NL04], to our knowledge, integrating the glyph textures with different edge numbers into the MC to depict the errors has not been used. Figure 3 illustrates a result of this technique. It is clear from Figure 3 that the errors have been mapped to five discrete glyph textures, with each one being associated to a glyph with different number of edges. The smaller errors correspond to the glyph textures with fewer edges, while the bigger errors correspond to the glyph textures with more edges.

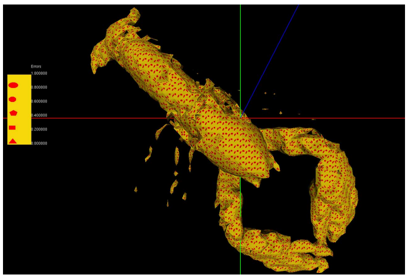

Figure 3: *Errors are mapped to the glyph textures with different number of edges.*

3.2.4. Transparency

The new technique indicates the presence and degree of errors by the transparency of the isosurface. Although using transparency to depict uncertainty has been explored for many times [DKLP02] [PWL97], integrating the transparency into the MC to indicate the errors has not been used. Figure 4 illustrates a result of the technique. It is clear from Figure 4 that the errors have been mapped to five discrete scales of transparency. The smaller errors are mapped to more transparent, and the bigger errors are mapped to less transparent. Other errors are mapped to transparency in-between.

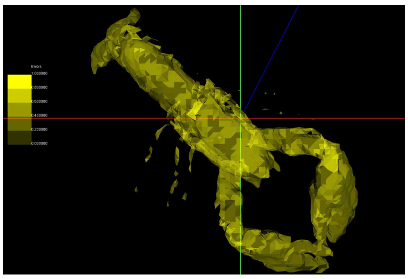

Figure 4: *Errors are mapped to the transparency.*

3.2.5. Transparency with Enhanced Grid Background

This technique is similar to the technique as described above except that extra grid lines were added as the background.

We want to test whether such a cue is helpful for users to distinguish the errors depicted by the transparency, as suggested in [DKLP02]. Figure 5 illustrates a result of this technique.

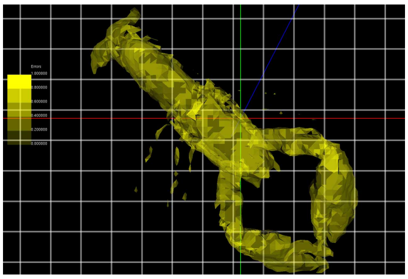

Figure 5: *Errors are mapped to the transparency with enhanced grid background.*

3.2.6. Texture Opacity

This is a known technique proposed by Rhodes et al. [RLBS03]. It indicates the presence and degree of errors by the texture opacity. Figure 6 illustrates a result of this technique. It is clear from Figure 6 that the errors have been mapped to five discrete opacity of a texture. The smaller errors correspond to the less opaque textures, while the bigger errors correspond to the more opaque textures.

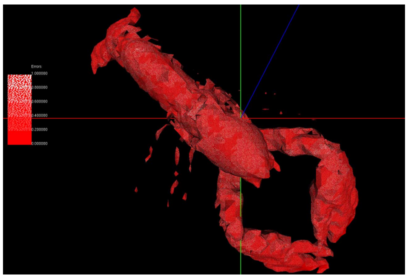

Figure 6: *Errors are mapped to the texture opacity.*

3.3. Participant Pool

In total we had 30 participants, of which 2 participated in a trial run, and the remaining 28 participated in the main user study. More specifically, there were 8 participants who are researchers in UCC. And there were 4 participants from our industrial partner. The remaining participants are postgraduate students in UCC. Among these participants, 10 are female and 20 are male. None of them are color-blind. All of them claimed that they use graphs and charts for day-to-day activities and they typically use a computer more than 21 hours per week.

3.4. User Study Tasks

Different methods have been proposed for the usability and effectiveness studies. Some [NL04] [RR00] employed subjective user ratings of effectiveness for their evaluation. Some [SZB*09] used task completion time and accuracy as their evaluation. In this work, we employed the former and each participant was asked to rate four effectiveness aspects for each uncertainty visualization technique (with 10-point scale): (1) how easy it is to identify the data? (2) how easy it is to identify the error? (3) do you feel visual overload? (4) how do you feel about the brightness? In addition, each participant was asked to answer an open question about his impression to the technique. Some basic personal information i.e., do you use charts/graphs for day-to-day activities? is also collected from each participant.

3.5. Interface Design

Keeping the real world scenario in mind that scientists like to look at the entire data first and then focus on a region of interest [SZB*09], a simple interface was designed to facilitate the participants' evaluation. Figure 7 shows this interface and it is clear that it consists of three parts. The first part is the 3D display area located in the middle. It is intended to display both the isosurface rendering and the scale bar that are associated to one uncertainty visualization technique. Please note that only an uncertainty visualization technique can be displayed in this area at one time, and it appears on the screen in a random order. The second part is the interaction area located on the right. It facilitates the participants' exploration and observation to the data by the two functionalities of translation and zooming in or out. Consequently the participants can easily navigate to their region of interest. Once they completed the evaluation to an uncertainty visualization technique, they can go to the next technique by clicking the “Next Vis. Technique” button. The last part of this interface is a status bar located at the bottom, and it informs the name of currently displayed technique to the participants. This interface is configured under the full screen mode to avoid unexpected user behaviour of untimely termination.

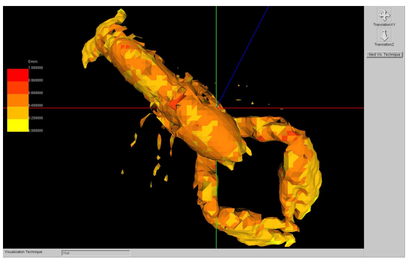

Figure 7: *User study interface.*

3.6. Participant Training

A training process was given to the participants before the main user study. This is to make sure they are familiar with the evaluation and feel confident to take on the main user study. We typically spent about 5 to 10 minutes to give participants an overview of the user study. This involves getting them understanding the concept of uncertainty visualization, its significance, as well as the purpose of the user study. After that, each participant was assigned to a computer which runs a training module that is similar to the main study, but uses a different data set (the data set we used in the training module is CT scan of engine, available at *http://www.volvis.org/*). And the participant was asked to complete the corresponding tasks in the training module. Coupling with this process, we spent about 10 to 15 minutes explaining the participants the 6 different uncertainty visualization techniques, the user interface as well as the four user rating tasks expected from them. We believe that organizing the explanation along with the training module is a better idea than those methods to separate them, because this could better the participants' understanding with living examples. After the participants completed the training, we entered the "question and answer" stage where we answered all questions that were unclear to them. Finally they went to the main study where they performed all tasks independently.

3.7. The Trial Run

A trial run has been conducted to identify the weakness of the user interface. Two participants have taken part in this procedure. One is a postgraduate student who has a good understanding of uncertainty visualization. Another one is a senior researcher who has rich experience in user study design. Based on the trial run we have identified a weakness of the user interface: initially, our interface included a rotation functionality which aims to assist the participants to gain more comprehensive observation. While this idea is good for data and error identifications, it dramatically increases the time that the participants spent on the evaluation. Therefore we removed the rotation functionality from the final interface.

3.8. The Main Study

The data set we used in the main user study is CT scan of a lobster (available at *http://www.volvis.org/*), as illustrated in Figure 7. We had a total of 28 participants who took part in the main user study and we only selected feedback from 25 of them for the analysis. We excluded the feedback from the other 3 participants is because they seemed unmotivated and completed the tasks in a rush, or their rating answers are inconsistent with their answers for the open question. In order to avoid the interplay between participants, we only run the user study on one participant at a time. We kept all participants in the similar environment to eliminate the impact from the environment.

4. Initial Findings

The initial findings found from the user rating results are reported in this section (the 4 figures involved in this section can be found in *http://csvcg.blogspot.ie/2013/07/the-evaluation-of-perceptual.html*).

4.1. Data Identification

Figure 8 presents the average scores of the data identification rated by the participants for the six uncertainty visualization techniques. It is clear that both existing hue and texture opacity techniques have the highest average scores (above 9 points), which indicates they are the best practice among the six techniques to identify the data. On the contrary, the two transparency-related techniques have the lowest average scores (below 7 points), which indicates they are difficult for the participants to identify the data. However, both their average scores are more than 5 points, which means it is still possible to use them to identify the data. As for the other two techniques, they have the medium average scores (between 8 and 9 points), which indicate a good ease to identify the data. We attribute the reasons for the low scores of these two transparency-related techniques to the partial missing of the data caused by the transparency or semi-transparent rendering.

4.2. Error Identification

Figure 9 illustrates the average scores of the error identification for these techniques. It is obvious that the hue technique has a highest score (nearly 9 points), which indicates it is the best method to identify errors. On the contrary, the glyph textures with different edge numbers technique has the lowest average score (below 2 points), which indicates its uselessness to identify errors. As for the remaining four techniques, whilst it is possible to employ the texture opacity and the both transparency-related techniques to identify errors, it is relatively difficult to use blurred textures to identify errors. In addition, one surprising finding from the study was that adding auxiliary grid lines as background is not guaranteed to enhance the participants' perception to the errors depicted by the transparency. Conversely, it appeared to lead to visual overload that increases the difficulty to recognize data, as described in the following section.

It is clear from Figure 9 that the mean of the glyph textures with different edge numbers technique is dramatically lower than any other techniques. We believe the reason is because that our visual system is more sensitive to the clustering patterns [TLFL04] rather than the non-clustering ones, and this technique failed to provide us with the clustering patterns. In addition, distortion occurred during the process of texturing, which may cause perceptual difficulties to identify the glyph shapes of the textures. Also, it is clear from Figure 9 that the mean of the blurred textures technique is relative low (below 5.0 points).This proves that blur is not a good metaphor to depict the uncertainty [Kos11].

4.3. Visual Overload

Figure 10 illustrates the average scores of the visual overload for these techniques. It is clear that both of the glyph textures with different edge numbers and the transparency with enhanced grid background techniques have the highest average scores (slightly above 6 points), which indicates their difficulties for the participants to make a clear observation. The hue technique has the lowest average score (below 2 points), which indicates its ease for the participants to make an observation. The remaining three techniques have average scores more than 2.5 and less than 4.5 points, which reveals their usefulness for a clear observation.

4.4. Brightness

Figure 11 illustrates the average scores of the brightness for these techniques. It is clear that the overall average scores of these techniques are quite similar (close to 5 points), which indicates they all have appropriate brightness for the participants' observation.

5. Methods of Analysis

Our analysis followed a common, classic statistical approach. First, a one-way (since we have only one independent variable, which is our uncertainty visualization techniques) multivariate analysis of variance (MANOVA) [lsb] was conducted to test the hypothesis that all the 6 uncertainty visualization techniques have the same mean on the 4 effectiveness aspects. If the result is true, we will accept the hypothesis and stop our analysis. If not, we will continue our analysis with 4 (since we have 4 effectiveness aspects) univariate analysis of variance (ANOVA). In particular, considering that each participant was exposed to the 4 effectiveness aspects and having to response to each of them, we employed the univariate ANOVA's RM form [lsa]. And for each univariate RM ANOVA, it is associated to an individual effectiveness aspect and used to test the hypothesis that all the 6 techniques have the same mean on that aspect. If the hypothesis is true, we will accept the hypothesis and draw our conclusions. If not, standard post hoc test will be performed to test the significant difference between any one pair of these techniques in regard to that effectiveness aspect. In particular, we employed the Bonferroni post hoc test in this analysis. And since we have 6 different techniques, in total there are 15 pairwise comparisons.

Table 1: *Statistically significant difference between the 6 techniques on the aspect of data identification.*

		Hue	BT.[a]	GT.[b]	Tra.[c]	TGB.[d]	TO.[e]
Mean	Hue				**	**	
(bigger)	TO.[e]				**	**	
↓	BT.[a]				**	**	
	GT.[b]				*	**	
(smaller)	Tra.[c]						
Mean	TGB.[d]						

* indicates significance at the 0.05 level.
** indicates strong significance at the 0.025 level.

[a] BT. is short for Blurring Textures technique.
[b] GT. is short for Glyph Textures with Different Edge Numbers technique.
[c] Tra. is short for Transparency technique.
[d] TGB. is short for Transparency with Grid Background technique.
[e] TO. is short for Texture Opacity technique.

6. Results and Discussion

The SPSS was used for the statistical analysis. It is indicated by the Wilks' Lambda row in the Multivariate Tests table that there is a statistically significant difference between the 6 uncertainty visualization techniques on all the 4 aspects of effectiveness ($F(20,468.594) = 15.323, p < 0.0005$). Therefore 4 univariate RM ANOVAs were conducted to analyze the significant difference between the 6 techniques on each of the 4 effectiveness aspects.

6.1. Data Identification

By analyzing both Mauchly's Test of Sphericity and Tests of Within-Subjects Effects tables from the univariate RM ANOVA we know that there is a strongly significant difference between the 6 techniques on the data identification aspect ($F(2.634,63.208) = 22.973, p < 0.0005$). Therefore we further performed Bonferroni post hoc test to find out the significant difference between any two of these techniques. Table 1 illustrates the results of the test. From Table 1 it is clear that there is a strong significance between the hue technique and the transparency technique. Also, the mean of the hue technique is higher than the mean of the transparency technique. Therefore, we can draw the conclusion that it is significantly much easier to use the hue technique than the transparency technique to identify the data. We applied the same method in the remainder of this section to summarize the results acquired from Bonferroni test.

From Table 1 it is also clear that there is a strong significance between the hue technique and the transparency with enhanced grid background technique. This indicates that the hue technique is significantly much superior to the latter in the data identification aspect. As for the texture opacity and

Table 2: *Statistically significant difference between the 6 techniques on the aspect of error identification.*

		Hue	BT.[a]	GT.[b]	Tra.[c]	TGB.[d]	TO.[e]
Mean	Hue		**	**	**	**	**
(bigger)	TO.[e]		*	**			
	Tra.[c]			**			
↓	TGB.[d]			**			
(smaller)	BT.[a]			**			
Mean	GT.[b]						

* indicates significance at the 0.05 level.
** indicates strong significance at the 0.025 level.

Table 3: *Statistically significant difference between the 6 techniques on the aspect of visual overload.*

		Hue	BT.[a]	GT.[b]	Tra.[c]	TGB.[d]	TO.[e]
Mean	Hue		**	**	**	**	
(bigger)	TO.[e]			**		**	
	Tra.[c]			**		**	
↓	BT.[a]			**			
(smaller)	GT.[b]						
Mean	TGB.[d]						

* indicates significance at the 0.05 level.
** indicates strong significance at the 0.025 level.

blurred textures techniques, they are all significantly much better than the two transparency-related techniques to identify the data. In terms of the glyph textures with different edge numbers technique, whilst it is significantly much easier than the transparency with enhanced gird background technique to identify the data, it is slightly easier than the transparency technique.

6.2. Error Identification

Based on both Mauchly's Test of Sphericity and Tests of Within-Subjects Effects tables from the univariate RM ANOVA we know that there is a strongly significant difference between the 6 uncertainty visualization techniques on the error identification aspect ($F(3.578, 85.874) = 47.415, p < 0.0005$). Thus we performed the Bonferroni test to compare the significant difference between any two of these techniques. Table 2 presents the results of the test.

From Table 2 it is clear that there is a strong significance between the hue technique and the remaining techniques. This indicates that hue is significantly the best technique to identify errors. As for the texture opacity technique, whilst it is significantly a little bit easier than the blurred textures technique to identify errors, it is significantly much easier than the glyph textures with different edge numbers technique to identify errors. In terms of the remaining three techniques, they are all significantly much better than the glyph textures with different edge numbers technique to identify errors.

6.3. Visual Overload

By analyzing both Mauchly's Test of Sphericity and Tests of Within-Subjects Effects tables from the univariate RM ANOVA we know that there is a strongly significant difference between the 6 uncertainty visualization techniques on the visual overload aspect ($F(3.546, 85.105) = 19.555, p < 0.0005$). Therefore we performed the Bonferroni test to test the significant difference between any two of these techniques. Table 3 illustrates the results of the test.

From Table 3 it is clear that there is a strong significance between the hue technique and the rest of these techniques but not the texture opacity technique. This indicates that the hue technique is significantly less visual overload than the other 4 techniques (blurred textures, glyph textures with different edge numbers and the two transparency-related techniques). As for both the texture opacity and the transparency techniques, they are strongly significant with the glyph textures with different edge numbers technique and the transparency with enhanced grid background technique. Thus we can summarize that they are significantly less visual overload than the latter two techniques. Also, it is clear from Table 3 that there is a strong significance between the blurred textures technique and the glyph textures with different edge numbers technique. This indicates that the former is significantly less visual overload than the latter.

6.4. Brightness

By analyzing both Mauchly's Test of Sphericity and Tests of Within-Subjects Effects tables from the univariate RM ANOVA we know that there is a slightly significant difference between these 6 uncertainty visualization techniques on the brightness aspect ($F(3.004, 72.097) = 3.191, p = 0.029$). Thus we continued the analysis with the Bonferroni test to find out the statistically significant difference between any two of these techniques. It turns out from the Bonferroni analysis that there is no statistically significant difference between any of these 6 uncertainty visualization techniques on the brightness aspect. However, this is inconsistent with the result from our univariate RM ANOVA. We attribute this to the conservatism of Bonferroni adjustment [GGQY07].

7. Conclusions and Future Work

We presented a user study regarding the participants' subjective ratings to 4 effectiveness aspects of 6 isosurface rendering-based uncertainty visualization techniques. Two existing and four new techniques have been investigated. The four chosen effectiveness aspects address the significant characteristics of uncertainty visualization and there is no weighting importance between them. Our analysis suggested that the two existing uncertainty visualization techniques appear to be the most advantageous. Both of them have high scores in all the four aspects of the effectiveness. In terms of the new techniques, the transparency technique appears to be the most promising. Whilst the remaining three new techniques may have some utility in certain aspects of the effectiveness, they are less useful in other aspects of the effectiveness. Additionally, a surprising result we have found is that adding auxiliary grid lines as background is not guaranteed to enhance the participants' perception to the errors depicted by the transparency. Conversely, it may lead to visual overload that increases the difficulty to recognize data. We believe that these findings can be useful for future uncertainty visualization design.

Two future works are planned. First, we want to utilize task completion times and accuracies to objectively measure the perceptual effectiveness of these evaluated techniques. Second, we want to evaluate the perceptual effectiveness for DVR-based uncertainty visualization techniques.

8. Acknowledgement

Many thanks to Philip O'Mahoney and Aodhan O'Leary from School of Mathematical Sciences in UCC for their generous help of the statistical analysis.

References

[Che05] CHEN C. M.: Top 10 unsolved information visualization problems. *IEEE CG&A* (2005), 12–16. 2

[DKLP02] DJURCILOV S., KIM K., LERMUSIAUX P., PANG A. T.: Visualizing scalar volumetric data with uncertainty. *Computers & Graphics* (2002), 239–248. 1, 2, 3, 4

[FB09] FOULKS A., BERGERON R. D.: Uncertainty visualization in the visit visualization environment. In *Proc. of Visualization and Data Analysis* (2009). 2

[GGQY07] GORDON A., GLAZKO G., QIU X., YAKOVLEVS A.: Control of the mean number of false discoveries, bonferroni and stability of multiple testing. 179–190. 7

[GR04] GRIGORYAN G., RHEINGANS P.: Point-based probabilistic surfaces to show surface uncertainty. 564–573. 3

[HYX11] HE H. Q., YANG L., XU Q.: Multidimentional uncertainty visualization with parallel coordinate and star glyph. 412–420. 2

[JMM*06] JOHNSON C. R., MOORHEAD R., MUNZNER T., PFISTER H., RHEINGANS P., YOO T. S.: *NIH-NSF Visualization Research Challenges Report*. IEEE Computer Society, 2006. 2

[Joh04] JOHNSON C. R.: Top scientific visualization research problems. *IEEE CG&A* (2004), 13–17. 2

[JS03] JOHNSON C. R., SANDERSON A. R.: A next step: Visualizing errors and uncertainty. *IEEE CG&A* (2003), 6–10. 2

[Kos11] KOSARA R.: *Blur and Uncertainty Visualization*. available at http://eagereyes.org/techniques/blur-and-uncertainty, 2011. 6

[KPH01] KOBUS D. A., PROCTOR S., HOLSTE S.: Effects of experience and uncertainty during dynamic decision making. 275–290. 2

[LB00] LEITNER M., BUTTENFIELD B. P.: Guidelines for the display of attribute certainty. 3–14. 2

[LK07] LARAMEE R. S., KOSARA R.: Future challenges and unsolved problems. In *Human-Centered Visualization Environments* (2007), pp. 231–254. 2

[LLPY07] LUNDSTROM C., LJUNG P., PERSSON A., YNNERMAN A.: Uncertainty visualization in medical volume rendering using probabilistic animation. 1648–1655. 2

[lsa] LAERD STATISTICS: *ANOVA with Repeated Measurements Using SPSS*. available at https://statistics.laerd.com/spss-tutorials/one-way-anova-repeated-measures-using-spss-statistics.php. 6

[lsb] LAERD STATISTICS: *One-way MANOVA Using SPSS*. available at https://statistics.laerd.com/spss-tutorials/one-way-manova-using-spss-statistics.php. 6

[LSPW96] LODHA S., SHEEHAN B., PANG A. T., WITTENBRINK C.: Visualizing geometric uncertainty of surface interpolants. In *Proc. of Graphics Interface* (1996), pp. 238–245. 2

[Mac92] MACEACHREN A. M.: Visualizing uncertainty information. 10–19. 2

[NL04] NEWMAN T. S., LEE W.: On visualizing uncertainty in volumetric data: Techniques and their evaluation. 463–491. 2, 3, 4

[Pot11] POTTER K.: Uncertainty visualization state of the art. In *USA/South America Symposium on Stochastic Modelling and Uncertainty Quantification* (2011). 2

[PWB*09] POTTER K., WILSON A., BREMER P. T., WILLIAMS D., DOUTRIAUX C., PASCUCCI V., JOHNSON C. R.: Ensemble-Vis: A framework for the statistical visualization of ensemble data. In *Proc. of IEEE International Conference on Data Mining Workshop* (2009), pp. 233–240. 2

[PWL97] PANG A. T., WITTENBRINK C. M., LODHA S. K.: Approaches to uncertainty visualization. 370–390. 1, 2, 3

[RLBS03] RHODES P. J., LARAMEE R. S., BERGERON R. D., SPARR T. M.: Uncertainty visualization methods in isosurface rendering. In *Proc. of Eurographics* (2003), pp. 83–88. 2, 3, 4

[RR00] RICKENBERG R., REEVES B.: The effects of animated characters on anxiety, task performance, and evaluations of user interfaces. In *Proc. of the SIGCHI Conference on Human Factors in Computing Systems* (2000), pp. 49–56. 4

[SZB*09] SANYAL J., ZHANG S., BHATTACHARYA G., AMBURN P., MOORHEADE R. J.: A user study to compare four uncertainty visualization methods for 1D and 2D datasets. 1209–1218. 2, 4

[SZD*10] SANYAL J., ZHANG S., DYER J., MERCER A., AMBURN P., MOORHEADN R. J.: Noodles: A tool for visualization of numerical weather model ensemble uncertainty. 1421–1430. 2

[TLFL04] TAO Y., LIU Y., FRIEDMAN C., LUSSIER Y. A.: Information visualization techniques in bioinformatics during the postgenomic era. 237–245. 5

[Wec03] WECHSLER S. P.: Perceptions of digital elevation model uncertainty by DEM users. 57–64. 2

[WF93] WOODS J. D., FISHER P. F.: Assessing interpolation accuracy in elevation models. *IEEE CG&A 13*, 3 (May 1993), 48–56. 2

[XHWR06] XIE Z. X., HUANG S. P., WARD M. O., RUNDENSTEINER E. A.: Exploratory visualization of multivariate data with variable quality. In *Proc. of IEEE Symposium on Visual Analysis Science and Technology* (2006), pp. 183–190. 2