The Effect of Aesthetic on the Usability of Data Visualization

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Abstract

Aesthetic seems currently under represented in most current data visualization evaluation methodologies. This paper investigates the results of an online survey of 285 participants, measuring both perceived aesthetic as well as the efficiency and effectiveness of retrieval tasks across a set of 11 different data visualization techniques. The data visualizations represent an identical hierarchical dataset, which has been normalized in terms of color, typography and layout balance. This study measured parameters such as speed of completion, accuracy rate, task abandonment and latency of erroneous response. Our findings demonstrate a correlation between latency in task abandonment and erroneous response time in relation to visualization's perceived aesthetic. These results support the need for an increased recognition for aesthetic in the typical evaluation process of data visualization techniques.

Keywords--- **User/Machine Systems: Human Factors, Information Interfaces: Graphical User Interfaces.**

1. Introduction

Aesthetics is a concept that relates to the beauty in both nature and art, as something that enlivens or invigorates both body and mind, awakening the senses. Aesthetics can be better understood by investigating general preferences in art [1], from interpreting results in experimental psychology [2] or by assuming that the subjective world is of a logical, mathematical nature [3]. Aesthetics is also tightly integrated in current society, as our environment contains an abundant amount of artifacts that were specifically designed with aesthetic criteria in mind. Ranging from historical buildings to modern software applications, the integration of aesthetics typically aims to stimulate the desire, positively influence the first impression, encourage repeated usage or even overwhelm its audience.

Aesthetic has already been investigated in related fields, including user experience, product design and human computer interaction. To date, the most relevant aesthetic measures in the data visualization field have been described in the study of graph drawing, the automatic generation of network diagrams. This research delineates the minimization of *bends*, *edge crossings* and the maximizing of *angles*, *orthogonality* and *symmetry* as effectors on aesthetic style [4]. Here, aesthetics is investigated as a directly measurable and quantifiable entity, rather than the reflection of personal judgment. Within the graph drawing discipline, as well as in most of the data visualization field, aesthetics is primarily considered for its potential positive influence on task effectiveness, as there seems less concern for the experiential nature of aesthetic judgment.

Other research projects demonstrate the advantages of aesthetic design on interactive systems [5-8]. Tractinsky [9] illustrates the importance of investigating whether a user discriminates between systems based upon aesthetic, in that beauty and usability represent a special type of relationship. More specifically, aesthetic judgment has shown to improve the *efficiency* and *effectiveness* of task performance reflected by a reduced completion time and error rate [7, 10, 11]. Chen [12] states aesthetic to be one of the most important problems that the data visualization field faces today. We further believe there is a need to understand why users find specific visualizations visual attractive, and how such judgment can influence task performance. Aesthetic plays a role in a system's overall attractiveness [13], as an significant incentive for initial use. Accordingly, the popularity of data visualization can only benefit by embracing aesthetic as a persuasive medium.

As research considers effectiveness and efficiency as important factors in judging visualization techniques, aesthetic quality should equally be considered. However, aesthetic is often seen as an add-on, implemented at the very end of the development process. In fact, aesthetic in the context of data visualization is still not methodically defined, and seems underrepresented in today's typical evaluation study methodologies [12]. This research attempts to fill this gap by investigating the relationship between aesthetic in data visualization and measures of effectiveness and efficiency, here supplemented with task abandonment and erroneous response time metrics.

2. Background

This study should not be considered a popularity or 'beauty contest' of different methods of visualization. Nor is it to be perceived as a competition staged to find the fastest and most accurate technique. Instead, this study investigates the correlation between task abandonment, erroneous response times and perceived aesthetic. Error rate and completion time measurements are well known in data visualization evaluations [11, 14]. *Task abandonment* is a metric of usability primarily referenced within the field of *web analytics*, the studying of user behavior on the Internet. The focus of statistical investigation for web analytics has matured from the basic counting of website visitors to deeper insight behind the metrics generated by long-term user behavior. As companies publish an inordinate amount of information on their websites, the potential increases for visitors (and potential customers) to exit due to a feeling of frustration. A user-centered perspective on a website's usability is critical to prevent lost revenue. Analytic applications place emphasis to isolate potential '*bottlenecks*', delays in progress for tasks such as multi-part form completion. It has been proven that removing such bottlenecks reduces the number of abandoning visitors. Duration and rate of task abandonment indicates to what duration a user is willing to persist with an interface before giving up altogether.

Tractinsky et al. [15] have validated results of an aesthetic perception study for web interfaces by implicitly measuring response latencies. In this study, we isolate the *erroneous response latency* as the length of time taken by a participant who generates an incorrect answer. Independent from the *efficiency* metric, an erroneous response latency indicates the level of investment a participant is willing to take for an seemingly difficult task. We considered this measure in conjunction with the above mentioned task abandonment response, as participants can terminate their 'struggle' at any point in time, but some instead choose to extend their search, pertaining in finding the correct answer.

In this study, these measures, originally defined for website evaluations, have been leveraged in the assessment of data visualization. Drawing analogy from the linear task of an online shopping cart with an information retrieval function within data visualization, the core of the *efficiency* and *effectiveness* metrics are similarly applicable. Our hypothesis is that aesthetic will have an effect on extending the latency of task abandonment and duration of erroneous response time. This is potentially important because these factors correlate with a level of *user patience*, the duration in which interaction occurs before either completion or abandonment. As data visualization continues to commercialize, so does its exposure to the greater masses, making further understanding of the holistic user experience all the more crucial.

3. Methodology

As illustrated in Figure 1, this study is based on 11 different data visualization techniques that were chosen on following grounds: general availability, whether the application software is relatively easily obtainable, installable and configurable by non-experts, and visualization technique diversity. Accordingly, the chosen set contains visualization techniques ranging from traditional TreeMaps and network diagrams to more elaborate, or creative, floral-inspired representations. All data visualizations represent an identical hierarchical dataset.

3.1. Dataset

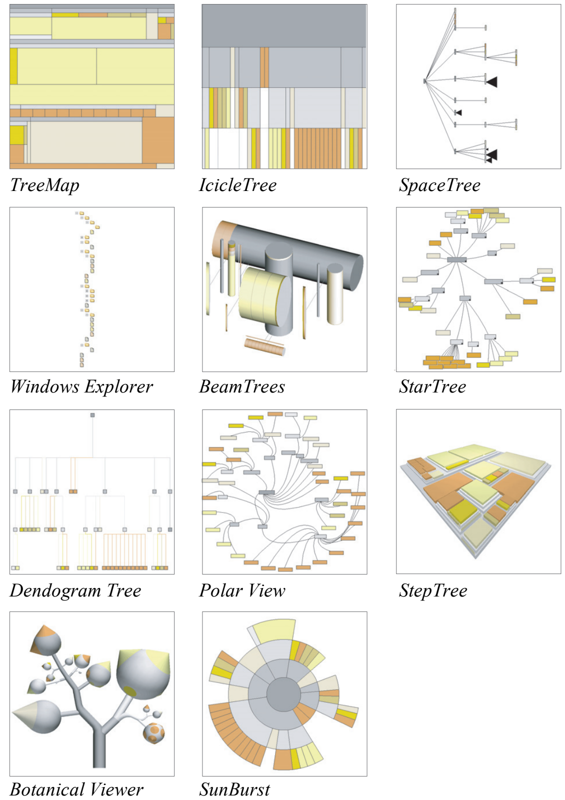

Figure 1. Tested data visualization methods (see Appendix for authors and affiliations).

The chosen dataset comprises of a file directory structure containing subfolders, vacation images, and text files. This particular dataset was chosen to achieve an identifiable level of familiarity to the user, who should focus on the representation, instead of on the dataset's meaning. Visualizations in the survey dataset were normalized according to the following criteria:

- *Color* – all color palettes were generated from a single, identical set of 11 colors, selected from the default palette used in the folder icon of *Windows Explorer*.
- *Size, Scale & Positioning* – For each technique, a single screenshot was generated, measuring 600 by 600 pixels. Data visualizations were centered on both a horizontal and vertical axis. Each visualization was scaled in size to the maximum that legibility would allow.
- *Typography* – Text labels were replaced by an identical black colored, 10 point Arial font face in all visualization techniques.

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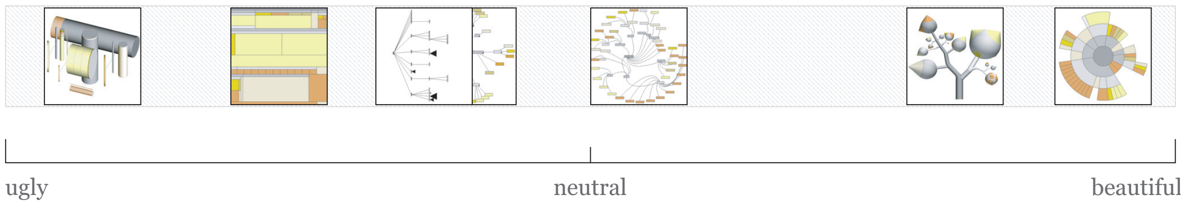


Figure 2. Online survey interface element used to evaluate the relative level of aesthetic appearance for different information visualization techniques as a group.

- *Conveyance* – All data visualization techniques conveyed the same information of the identical hierarchical dataset of 53 files and folders. In the case of *SpaceTree* and *Windows Explorer,* some folders needed to be collapsed, due to vertical space constraints.
- *Interaction* – All data visualization techniques could be perceived only as static images, as no interaction was allowed. This was to deliberately avoid any influence of the interaction metaphor on the visual judgment of beauty, and to focus solely on the display as a sort of 'art painting'.

3.2. Online Survey

The findings published in this paper are based on an online survey and part of a larger study on the role of aesthetic within data visualization [16]. The online survey method was utilized for the following reasons:

- *Validation* - A large number of participants were needed due to a desire to validate both a diverse set of different displays methods along with a number of corresponding usability metrics, and the expected variability of aesthetic subjective judgment throughout age groups, psychosocial factors and cultures. With 11 different methods randomized against 14 questions of varying difficulty, the minimum amount of participants needed for a valid random dispersal of questions to visualizations was 154.
- *Native delivery method* - the majority of the native delivery methods for data visualizations are through use of a computer screen or a plug-in displayed within a desktop-based application.

Registration pages collected personal information regarding the age, gender, design experience, primary and secondary languages, computer application usage, and preferred computing platform of each participant. It is expected that these identifiers may provide further insight into subjective aesthetic of data visualizations in accordance to demographic and psychosocial factors. Participants were recruited via online message boards, mailing lists and weblog postings across a variety of different demographic targets. Each survey was designed to require about twenty-five minutes, while participants offered no direct or indirect compensation. The web browser dimensions were mandated to be a minimum of 1024x768 pixels in dimension through the use of Javascript. All images were pre-loaded during the registration process to ensure instantaneous display.

3.3. Procedure

The online survey consisted of two separate sections, prefaced with small textual descriptions and simple examples beforehand. These two sections, labeled *aesthetic ranking* and *task performance* were presented to users in a randomized order. This format follows an order-varied ANOVA method in order to sensitize against results from one section affecting the other. Each participant received a unique ID, which tracked the order of sections as well as their randomized set of visualization techniques and corresponding task retrieval questions. Instead of using the full set of 11 visualizations, randomized subsets of 7 were selected for each participant, which were also varied in their order of display. A typical subset, with two retrieval questions per visualization technique, was limited to 7 in the interest of reducing the required survey completion time, as well as not to overwhelm the participant's cognitive capacity.

3.3.1. Aesthetic Ranking – The aesthetic ranking section of the survey was comprised of two individual evaluation tasks. This section was limited to the visual representation only, as all typographic labels were removed from the display. Participants were asked to perform the following rankings:

- *Individual ranking* – For the individual ranking task, participants were first asked to pause for six seconds to "reflect on the aesthetic quality of the image" as they "would with a painting or illustration", while looking at a visualization with all text labels removed. After this specified duration of reflection, the interface elements for the survey were presented alongside the display. Using keyboard or mouse, each participant was then asked to rate the perceived beauty of the shown visualization display by using a slider bar interface (see Figure 3). In order to provide a more instinctual experience, while no numeric indication of this input was shown.

- *Group ranking* – Subsequently, participants were requested to perform a relative group ranking. This relational method was chosen to evaluate visualizations against one-another. It allowed participants to directly compare visualization techniques within a self-chosen group, and even permitted for similar assessments to overlap when participants deemed different techniques as equally aesthetic. This approach specifically aimed to detect clustering and commonalities between multiple visualizations, grouping them accordingly. Participants were invited to rank and group displays by dragging and dropping thumbnails on a horizontal scale (see Figure 2) based on their perceived, relative level of aesthetic quality. The extremes of this scale were labeled '*ugly*' and '*beautiful*', similar to the ends of the slider bar in the individual ranking task. However, using the 'drag and drop' method, participants were more encouraged to group together different visualization techniques because of perceived similarities or reasoning.

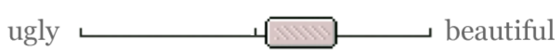


Figure 3. Survey interface element for determining quantitative individual aesthetic.

3.3.2. Task Performance – In addition to the subjective aesthetic response questions, a series of question and answer tasks were asked of each participant. These queries centered around 14 structure and attribute-related questions of the dataset consisting of a standardized file and folder hierarchy.

The 14 questions were randomized in order and application towards the 7 different visualization techniques, with each display being used to answer two queries. This randomization was required to eliminate a display performing poorly due to variations in the difficulty of questions. All visualizations thus needed to contain sufficient information to answer all possible questions. Each question was displayed along with a multiple-choice selection of 6 answers, including a '*cannot tell*' option, which specifically aimed to measure the abandonment response. Participants were instructed to complete each task as quickly as possible, as their response times were being recorded.

4. Results

An eight-week testing period resulted in 285 valid participants (n=285). A participant's results were omitted if they were considered as duplicate, indicated by the combination of the provided name and the recorded IP address. Participants who did not complete all sections or questions within the survey, regardless of order, had their results removed. Any responses that took under three seconds or over 100 seconds were removed, to avoid rushed answers or responses that were possibly influenced by external disturbances. Over 50% of the total online survey visitors canceled their process once reaching the registration page. Subsequently, approximately 45% of the successfully registered survey participants were removed due to duplication, process abandonment or response impropriety. The 285 valid participants originated from 37 different countries as diverse as Peru, Nepal and Sweden. The call for participation had been spread heavily amongst those with formal design backgrounds, due to selected postings amongst information architecture and design community websites. However, due to the viral nature of the Internet, the occupation of participants ranged widely and participants have shown an interest in visualization from typical data-related research fields ranging from Epidemiology and Economics to Library Sciences. The survey continues to run until July of 2008 in order to provide further data from an increasingly varied pool of participants.

4.1. Aesthetic Ranking

Aesthetic ranking was calculated on a scale of 0 to 100, with 100 indicating an optimal aesthetic value (rightmost of either scale in Figures 2 and 3, previous page). An individual mean and group mean of aesthetic rank was calculated for each of the 11 visualizations, as illustrated in Figure 4. The confidence interval of .05% determined the validity and variance of each visualization response set, a previously unreported measure of aesthetic preference investigations.

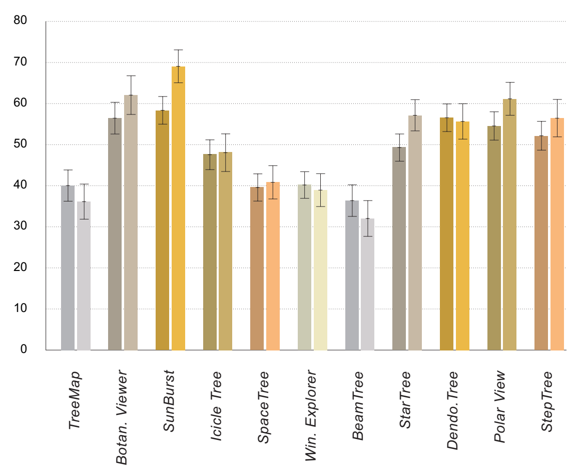


Figure 4. Individual (leftmost of each pair, darker) and group aesthetic (rightmost, lighter) rankings, with overlaying confidence intervals.

The *SunBurst* method was associated to the highest level of perceived beauty, averaging a ranking of 58 and

69 of a possible value of 100 for the individual and group ranking tasks, respectively (see Figure 4). On the other end of the spectrum, *BeamTrees* averaged 36 and 32 for each aesthetic ranking task. Logical groupings of visualization techniques by categorical appearance did not necessarily occur. For example, rankings for the *three-dimensional* visualization methods (those which utilize a perspective of depth, e.g. – *Botanical Viewer*, *StepTree*, *BeamTrees*) were inconsistent. In addition, *TreeMap* and *IcicleTree*, similar in their orthogonal, space-filling technique, received significantly different average rankings, with *TreeMap* scoring continually toward the bottom of the pack in both ranking queries. Additionally, the similar graph node-linking techniques of *SpaceTree* and *PolarView* did not appear as like elements in the participant responses.

The highest discrepancy in confidence interval was detected in *Botanical Viewer* (±3.86, ±4.86) for both individual and group ranking, although existing on an insignificant scale. This consistency in results might be explained by the relatively short time span between the individual and group aesthetic ranking tasks. The slightly higher scores for the group ranking tasks are likely due to conceptual differences in the interface elements (e.g. allowing overlap) that were used to rate the visualization techniques.

	Rate of Correct response (%)	Correct response time (seconds)	Error response time (seconds)	Rate of Abandonment (%)	Abandon. Response time (seconds)
TreeMap	.32	35.0	37.3	.38	34.5
Botan.Viewer	.43	39.6	40.6	.32	35.3
SunBurst	.84	23.2	47.1	.07	37.8
IcicleTree	.81	22.0	41.2	.12	42.4
SpaceTree	.73	20.8	40.9	.06	52.1
Win. Explorer	.79	21.8	38.0	.08	38.6
BeamTree	.28	27.7	35.6	.55	29.9
StarTree	.81	23.4	43.5	.07	50.8
Dendo.Tree	.74	25.7	43.2	.11	43.2
Polar View	.69	27.6	37.2	.15	35.0
StepTree	.42	39.0	40.6	.35	29.6

Table 1. Measures of effectiveness, efficiency, erroneous response and task abandonment.

The visualization technique showing the widest range of discrepancy (although not evident in averaged ranking) between the group and the individual metric is the *SunBurst*, showing an 8% increase between the individual and group ranking averages. In the individual ranking, where the interface of a slider bar was used (Figure 3), the extreme Low ranking for all 11 visualizations reached an absolute of 0, compared to none of the collective rankings. This extreme in ranking was on the High end of the scale as well, with 4 visualizations receiving an optimal 100 score a total of 15 times. In contrast, the group evaluation method proved to be more susceptible to reach an absolute minimum or maximum value.

4.2. Effectiveness

The effectiveness of three-dimensional displays proves to be consistently low in comparison to two-dimensional displays. All three examples, *Botanical Viewer*, *StepTree* and *BeamTrees* are ranked in the lowest four displays in terms of task accuracy (43%, 42% and 28% correct, respectively). *TreeMap*, a long-established data mapping technique finished amongst this group with a correct response rate of 32%. Contrarily, *SunBurst* displays an accuracy rate of 84%, surpassing the mark of 81% received by *Windows Explorer*, disproving the notion that the familiarity of *Explorer* would result in the highest effectiveness of any method.

4.2.1. Order Variance – It is of note that the order variance of *SpaceTree's* perceived aesthetic ranking improved the most dramatically (+6.5%) when participants were presented with the data retrieval tasks first. We will revisit this finding in the analysis section of this paper.

4.3. Efficiency

Mirroring effectiveness, there proved to be correlations found in measures of efficiency. These metrics were averaged from all correct response times within the valid range of between 3 and 100 seconds. The three-dimensional layouts of *Botanical Viewer* and *StepTree* proved to be the slowest. Accordingly, these two specific techniques were likely the most affected by the total lack of user interaction.

The color-coded *IcicleTree*, performed 5.6 seconds faster to the structurally identical space-filling layout *Dendogram Tree*. The familiarity of *Windows Explorer*, neither made it the most effective nor the most efficient technique, with *SpaceTree* averaging a full one-second faster in correct response time (20.8 seconds). Data visualization techniquess that read top-to-bottom (i.e. *Dendogram Tree*, *Windows Explorer, IcicleTree*) were not found to be significantly slower than those reading left-to-right. Separation of demographics in accordance to the participant's primary language (those which read top-to-bottom versus left-to-right) and preferred technique has not yet been performed.

The particular swirling technique *PolarView*, similar in layout to the space-filling *StarTree*, measured 4.2 seconds longer for data retrieval, also resulting in a lower efficiency average of approximately 12%. This supports findings from the field of graph drawing, which recommends against the use of edge crossings [4] for optimal usability. Conversely, *PolarView* received a higher aesthetic rank, averaging second highest in the group ranking task.

BeamTrees, the technique that received the lowest subjective aesthetic ranking and effectiveness, participants recorded an average duration of 27.7 seconds per question. Amongst the dataset of 11 different data visualization techniques, this ranks as approximately an average time, placing *BeamTrees* in the middle of the pack in terms of efficiency.

4.4. Latency in Erroneous Response

Complimenting accuracy ratios are timings of erroneous response and speed of completion, measuring the duration in which a participant probed in expectation of retrieving the correct answer. The three-dimensional techniques of *Botanical Viewer* and *StepTree*, two of the more aesthetic, but lesser performing, visualization techniques, show above average erroneous response times of 40.6 seconds, which is comparable to methods nearly twice their effectiveness.

BeamTrees, which showed an average ranking in efficiency, displayed the shortest level of latency in erroneous response, 35.6 seconds. In contrast, participants were most inclined to spend time interacting with *SunBurst*, the visualization technique that held the highest rank of subjective aesthetic. *SunBurst* had the highest percentage of correct response (84%), but also a significantly longer duration (47.1 seconds) of erroneous response.

4.5. Task Abandonment

Given *SunBurst's* high accuracy rate, the rate of task abandonment is expectedly low at less than 1%. Reversing, over half the participants (55%) abandoned questions associated with the *BeamTrees* visualization. Participants attempted to decipher problems presented by *StarTree* (50.8 seconds) and *SpaceTree* (52.1 seconds) nearly twice as long as *StepTree* (29.6 seconds) or *BeamTree* (29.9 seconds) before selecting '*cannot tell*' as a conceding answer, showing a wide discrepancy in abandonment times.

5. Analysis

SunBurst exemplifies the notion that 'beautiful is indeed usable [9, 17, 18]. This technique ranks the highest in aesthetic and is one of the top performing visualizations in both efficiency and effectiveness. Conversely, visualization techniques that were both efficient and effective did not necessarily embody aesthetic beauty. *Windows Explorer* and *SpaceTree*, two of the fastest and most accurate displays, were amongst the lowest ranked aesthetically. In the case of *Windows Explorer*, previous exposure to this widespread technique may have created an element of bias in perceived beauty. Furthermore, *Botanical Viewer*, among the highest ranked visualization technique in terms of aesthetic, performed poorly in the data retrieval tasks. Participants took nearly twice as long in answering questions and averaged approximately half the accuracy rate of comparable techniques with similar aesthetic rank (i.e. *PolarView*, *SunBurst*, *StarTree*).

The order variation of the aesthetic ranking and task performance sections provided some discrepancy in results. As mentioned in section 4.2.1, *SpaceTree's* perceived aesthetic ranking displayed the most significant improvement (+6.5%) when participants were presented with the data retrieval tasks first. *SpaceTree* had the most efficient completion time of 20.8 seconds. Accordingly, both the time and rate of abandonment for this display method were highest and lowest, respectively. *SpaceTree* recorded an abandonment time of 52.1 seconds, with an extremely low abandonment rate of .06%.

The *SunBurst* technique received the highest score for both individual and group aesthetic ranking. In addition, *SunBurst* averaged the second lowest rate of task abandonment as well as the highest rate of correct response. These results prove that participants who did not immediately locate the correct answer felt encouraged to continue their task. In contrast, *BeamTrees,* the visualization technique with the lowest aggregate aesthetic rank, averaged the highest rate of task abandonment and was among the lowest in latency of erroneous response. More than half of all participants abandoned their task when confronted with *BeamTrees*. We believe that these findings are significant in that they correlate both a favorable and unfavorable aesthetic ranking with metrics of task abandonment and erroneous response.

6. Discussion

The notion that some data visualization techniques are better suited to the abstraction of a specific dataset type is worth exploring. For instance, *SunBurst* may not have faired so well in aesthetic rank if the hierarchy of files and folders had not been either so shallow or so balanced. Some specialized data visualization techniques have been shown to be capable to display datasets containing over 19 million nodes [19], a capacity not likely to be found amongst the chosen survey's data visualization set. Further work might include the investigation as to which display method is suitable for different dataset types (one, two, and multi-dimensional) as well as a varying number of nodes.

According to Tufte [20], the human eye finds nature's color palette harmonious, and thus advises the use of greens, blues, and browns for information displays. If the existing earth-toned color palette was not used in this online survey, results may not have been equal. Perhaps *BeamTrees* would have not faired so poorly in comparative aesthetic rank if the vibrant palette was removed and the survey limited to a more utilitarian greyscale.

Lastly, we acknowledge that the full advantage of these data visualization techniques is leveraged through the use of interaction. There exists both a joy and aesthetic in playful interaction with a system which raises the level of affect and emotion [16]. The availability of interactive features is also related to perceived usability. For instance, *BeamTrees*, which heavily relies on 3D navigation features to fully convey the data mapping metaphor, was at a clear disadvantage in its static, two-dimensional form. However, the technical complexity of implementing 11 different data visualization techniques in an online medium was deemed impracticable for this study, especially as it deliberately focused on the aesthetic quality of the data mapping techniques, and less on the usability of the according interaction methods. However, with the recent proliferation of online data visualization tools (i.e. *swivel.com*, IBM's *Many Eyes* project [21]), such endeavour could be imagined for future research.

7. Conclusion

In this paper, we have presented an online study that correlated aesthetic and usability measures in the context of data visualization. Through the subjective input from 285 participants, a quantitative ranking of data visualization techniques were established. In addition to determining relative beauty, participants were asked to fulfil comparable retrieval tasks forcing them to utilize these data visualization techniques. This methodology returned objective metrics of efficiency and effectiveness as well as measures of task abandonment and latency in erroneous response.

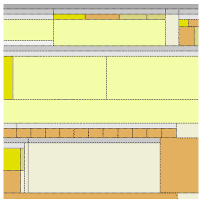
This research introduced metrics of task abandonment and erroneous response in correlation to a level of aesthetic preference, demonstrating that these new measures can be used to gauge user experience. It also shows that aesthetic correlates with these values, allowing for attractive visualizations to be looked at more closely displaying a higher level of user patience. This supports statements by Norman [22] in that, "it is only through our emotions do we unravel problems, as the human emotional system is intertwined with our cognitive abilities"; if the user finds a positive affection towards an object, our brains are encouraged to think creatively in order to solve any problem in which the object might present. Although Norman's theory was originally formulated towards the design of an industrial product, this study shows similar correlations in the field of data visualization. More specifically, the results illustrate that the most aesthetic data visualization technique also performs relatively high in metrics of effectiveness, rate of task abandonment, and latency of erroneous response. We argue that these results show that aesthetic should no longer be seen as a cost to utility.

The original purpose of this research was to increase the awareness of the positive role and purpose of aesthetic in the design of data visualization techniques. This paper focused on the effect in which data visualization's aesthetic has on specific measures of usability. As aesthetic affects usability, this research suggest that aesthetic should become an integral part of evaluating data visualization techniques.

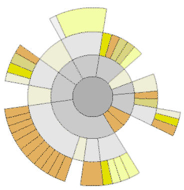
Acknowledgements

The authors would like to thank all participants who took this survey. We would also like to also acknowledge the authors of each visualization technique for making their work available for the purposes of this study. The online survey website can be visited at the location: **http://aesthetic-effect.com** until July of 2008.

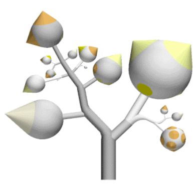
Appendix



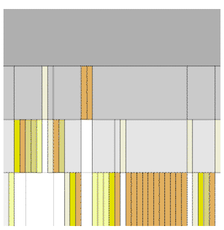
TreeMap
University of Maryland
C. Plaisant, B. Shneiderman, G. Chintalapani, A. Aris



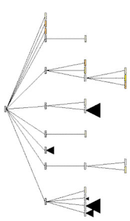
SunBurst
Georgia Tech University
J. Stasko



Botanical Viewer
Eindhoven University of Technology
E. Kleiberg, H. van de Wetering, J.J. van Wijk

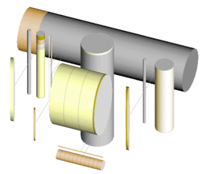


IcicleTree
INRIA Futurs/LRI
J. Fekete



SpaceTree
University of Maryland
J. Grosjean, C. Plaisant, B. Bederson

Windows Explorer
Microsoft Corporation
http://www.microsoft.com



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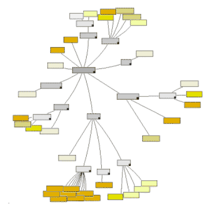
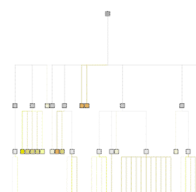
F. van Ham



StarTree
Inxight Software
http://www.inxight.com



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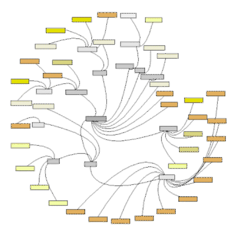
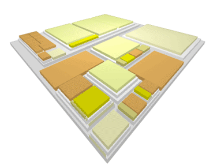
INRIA Futurs/LRI
J Fekete



Reingold Tilfer Polar View
INRIA Futurs/LRI
J. Fekete



StepTree
Lulea University of Technology
T. Bladh

11th International Conference Information Visualization (IV'07)
0-7695-2900-3/07 $20.00 © 2007 IEEE

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