The XAOS Metric – Understanding Visual Complexity as Measure of Usability

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Abstract. The visual complexity of an interface is a crucial factor for usability, since it influences the cognitive load and forms expectations about the subjacent software or system. In this paper we propose a novel method that uses entropy, structure and functions, to calculate the visual complexity of a website. Our method is evaluated against a well known approach of using the file size of color jpeg images for determining visual complexity. Both methods were applied on a dataset consisting of images of 30 different websites. These websites were also evaluated with a web survey. We found a strong correlation for both methods on subjective ratings of visual complexity and structure. This suggests both methods to be reliable for determination of visual complexity.

Keywords: Visual Complexity, Entropy, User Experience, Usability.

1 Introduction

Defining and measuring 'Visual simplicity' and its opposite 'Visual complexity' is originally one of the main goals of psychologists working in gestalt tradition. The 'principle of simplicity' or 'maximum homogeneity' goes back to Hochberg [1] who states that a gestalt good organization is a simple organization. The Gestalt theorists followed the basic principle that the whole is greater than the sum of its parts, which means that the whole carries a different and bigger meaning than individual parts.

Individual parts can be considered as design elements and both the construction and the perception of any bigger object, respectively interface, will involve several of them (e. g. planes, fonts, lines, color, etc.) as well as the principles how to apply and combine them best.

These principles include unity, contrast, balance, proportion, etc. [24]. Consequently, the design elements are the individual parts that make up an interface, while the design principles are general rules of perception that describe and suggest the

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optimal relationships between parts of an interface. An example for this may be the principle of unity, which refers to a congruity among the single parts. Unity describes that they are perceived as if they belong together, respectively the viewer senses some kind of visual connection beyond mere chance which causes the parts to come together [24].

When components are comprehended as a ‘whole’, an elementary cognitive process takes place. This process is the attempt to visually and psychologically generate order out of chaos. The creation of harmony and structure from apparently disconnected bits of information. It is obvious that this process depends in many ways on the visual complexity of a stimulus. Consequently by being able to shape and adapt visual complexity of a stimulus means to shape and adapt the mental effort of the user.

Harper et al. investigated the visual complexity of websites and proposed using the measure of visual complexity as implicit marker of cognitive load [2]. Used this way measures of visual complexity will ultimately support the design of interfaces which are easier to interact with. A further work on

Interaction with computers relies on human perception and cognition [3]. The perception of a website is the determining factor for the emotions evoked in the user, which will evidently affect the extent of the pleasure. According to Berlyne's theory of aesthetic response [4], viewers' pleasure in response to an object is connected to the complexity of this object. Taking this into account, measures of visual complexity can support shaping the user experience of a website.

In this paper we propose a novel method for measuring the visual complexity of websites. Different to existing approaches for measuring visual complexity, like using the size of compressed images, the structure of our formula reveals the real issues of high visual complexity. The revelation of these issues and the principles they are based on, will support designers to increase the usability of interfaces.

2 Theoretical Background

This chapter describes Berlyne’s theory of aesthetic response and gives an overview on some measures of visual complexity.

2.1 Berlyne’s Theory of Aesthetic Response

The word "aesthetics," is used in reference to something beautiful, as well as to a branch of philosophy that deals with the nature of beauty, fine arts, taste and also with the appreciation and creation of beauty. Aesthetics is derived from the Greek word "aisthetikos" which means "pertaining to sense perception" or "perceive, sense, feel". The German philosopher Alexander Baumgarten was the first who introduced the term in the 17th century.

He chose the word in order to express the experience of beauty and art as a field of concrete knowledge communicated in sensory form, compared to the strict reasoning or logical knowledge [4].

Human perception is unconsciously sensitive to such things as proportions or unity of elements. An example is the "golden section" which describes a special ratio of length to height (1.6:1) that can be found very often in nature. It is said that this proportion is visually pleasing for the viewer. So far it played a prominent role in art and architecture throughout history [4]. The golden section provides a good example of how a design principle is unconsciously acquired through mere exposure to the environment. As people encounter this principle in nature very often, they find it appealing and so it works also in arts and designed artifacts [4]. This also applies to other design rules. Consequently the users have subjective views of aesthetics as a result of personal, social and cultural development.

Berlyne's (1971) theory of aesthetics proposed a Wundt-curve function, which linked the preference for a stimulus with the level of arousal. He suggests that only moderate increments in the arousal potential of a stimulus are perceived pleasurable, while sharp rises in arousal are experienced as being unpleasant and punishment. Fig. 1 depicts the proposed relationship.

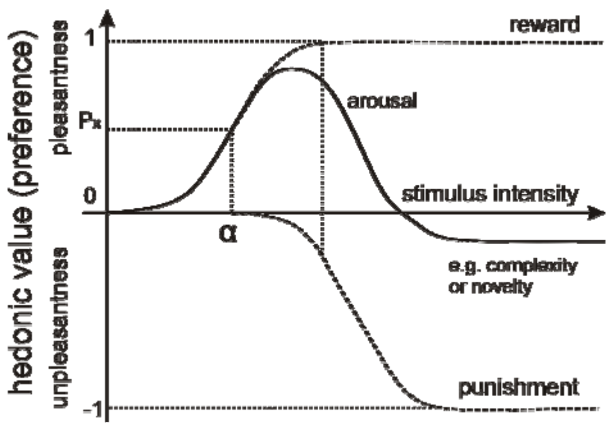

Fig. 1. Berlyne's proposed Wundt-curve function

'. . .aesthetic patterns produce their hedonic effects by acting on arousal. . . positive hedonic values can come about in either of two ways, namely through a moderate increase in arousal. . . or through a decrease in arousal when arousal reached an uncomfortably high level. . .' [4].

In software development, aesthetics has to be considered in regard of interface design and fortunately there are empirically measurable benefits of the application of principles of aesthetics [27, 28]. The sense of aesthetic is said to be influenced by visual complexity [9]. The visual complexity of an object depends on the amount of constituent elements and the diversity of these elements. This means the more single elements are perceived on an interface e.g. a website, the more increases the subjective impression of complexity of this site.

Berlyne considered visual complexity as subjective and also objective. Subjectivity comes from afore mentioned process of individual development resulting in relative views on complexity from subject to subject. Objectivity takes the physical constraints of the objects into account, as they are all the same for all subjects. He described complexity as an objective property of an object and defined relative complexity according to the number of elements within the objects [11].

The theory of aesthetic response states that a viewers' pleasure in response to an object will increase with increased complexity, to an optimal level. With further increasing complexity, pleasure begins to decline. So users don't like objects that are either too simple or too complicated. Consequently users will prefer objects, respectively websites that are moderately familiar and will be averse to the novel and the over familiar. The theory is expressed in an inverted U-shaped curve for pleasure, with a linearly increasing line for complexity, as can be seen in fig. 2.

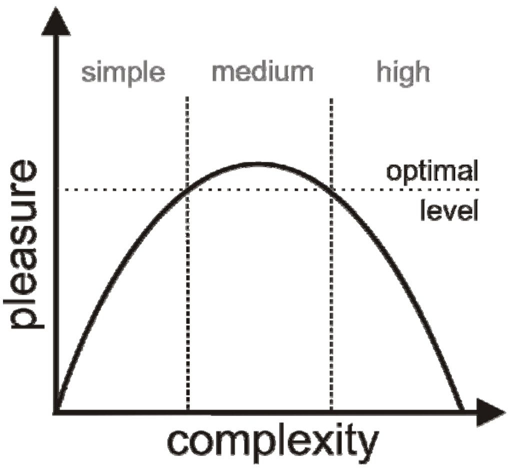

Fig. 2. Curve depicting the theoretical relationship between the hedonic value and visual complexity

The curve predicts that by adjusting visual complexity to an optimal level, viewers' pleasure of an object will increase. The influence of website complexity on user attitudes is supported by several recent studies [6],[7]. Some support Berlyne's theory, such as Geisser et al. who found that consumers responded more positive towards websites which fell within a moderate range of perceived complexity [8]. Others did not directly support it [9],[10], as they found a negative correlation between visual complexity and website perception.

2.2 Aesthetic Measures

Birkhoff was early to publish on measures of aesthetic. He aimed at determining the aesthetic effect of different objects e.g. vases, tiles or polygons.

Therefore he proposed that different classes of objects could not be compared and thus limited the range of objects. Birkhoff found out that also the aesthetic effect was subjectively dependent and thus he also limited the number of observers and conducted his experiments on a restricted group of subjects [29]. The model for aesthetic measures proposed by Birkhoff is based on three steps of perception.

The first step is the effort needed to focus the attention on an object, which relates proportional to the objects complexity, denoted as (C). In the second phase the reward for this effort is a feeling of value, which Birkhoff denotes as aesthetic measure (M).

Finally in the third step the aesthetic measure is verified and influenced by a harmony metric, describing symmetries and order. From this Birkhoff derived the following formula:

$$\mathbf{M = O/C}$$

The relationship of the components can be interpreted such that a rising complexity (C) in combination with disorder (O) creates an unpleasant reaction of the subject, thus the aesthetic measure (M) variable will be low. On the opposite a higher level of order, respectively symmetry will result in a more pleasant experience for the subject, respectively in a higher value of aesthetic measure. However recent studies suggest the perceived aesthetic value of users is curvilinear related to Birkhoffs aesthetic measure (M), peaking at a moderate M value [26].

The aesthetic measure seems to be useful for interface designers; however questions remain how to effectively measure metrics like order and complexity. Some input to this question comes from the field of algorithmic information theory (AIT), which will be covered in the next chapter.

2.3 Algorithmic Information Theory (AIT)

A recent approach to the measurement of visual complexity comes from algorithmic information theory (AIT). AIT provides a mathematical link between distributional rules used to produce a set of forms and the complexity code for a single form. This is done by measuring the probability of a string of symbols and linking it to the probability of the complexity of this symbol string. The string of symbols is generated by translating the form e.g. scanning and identifying the pixels that reproduce the form [13].

AIT provides a direct connection between the concepts of simplicity, respectively complexity and probabilistic measures. It thereby connects two principles about the organization of visual perception, namely the "likelihood principle" and the "simplicity principle".

The likelihood principle describes that a given visual sensory input will lead to the perception of the most likely distal object, which puts visual perception into a hypothesis-testing framework. Thereby the "hypotheses" are the possible distal objects representing the input, while the "data" is the actual visual input. This allows formulating the visual perception as a Bayesian probability decision [13]:

$$\mathbf{p(H/D) = p(D/H) \bullet p(H) / p(D)}$$

H denotes the perceptual hypothesis; D is the sensory input data. The visual system then fixes as the percept generated by sensory input D and maximizes the perceptual hypothesis H. In order to calculate this, the visual system needs probabilities for H, D/H and D. Thereby H is the probability of possible perceptual hypothesis, D is the probability of the current visual input and D/H are the probabilities of the data D given each hypothesis H.

The "simplicity principle" in AIT assumes that the human visual system chooses a perception based on Bayes' theorem, where the complexity of a possible perception (H), given the sensory input (D), will equal the complexity of the perception (H) added to the conditional complexity of the data (D) given the percept (H), minus the complexity of the data D.

$$\mathbf{I(H/D) = I(H) + I(D/H) - I(D)}$$

The perceptual hypothesis to be chosen has to minimize the complexity function. To solve the equation one will need the complexities of H, D and D/H.

The likelihood principle and the simplicity principle are connected as probability and complexity are directly linked. Thus the most probable perception is the least complex, and the least probable perception is the most complex. AIT shows that, given the input, the visual system either minimizes the complexity of a perception or maximizes the probability of the perception [13].

Another promising approach of using information measures to describe visual complexity was done by Klinger & Salingaros [16]. They propose two pragmatic measures, termed temperature (T) and harmony (H). The temperature describes symbol variation, whereby harmony measures the correlations of subunits via symmetries. Interestingly they link the results of their measure to Russel's circumplex Model of affect [17], which supports Berlyne's theory on the relationship between complexity and arousal.

2.4 Visual Complexity Measures

Visual complexity can be determined either by subjective user ratings, or by objective measurements. Subjective user ratings can be obtained by questionnaires or web surveys. Objective measurements can be the number of elements, dissimilarity of elements, or the degree to which several elements are responded to as a unit [11].

A present-day approach from Harper et al., which is applicable for websites, is using the number of each structural element on the page (density), the number (variety) of different structural elements and information presented (diversity) and the layout of the structural elements (position) [2].

A really easy and reliable way to assess the visual complexity is the utilization of digitized image compression. The File sizes of digital images after compression (e.g. JPEG, TIFF, GIF) can provide a measure of complexity. Thereby larger files indicate a higher complexity. In the same way complexity can be measured as the number of bytes preserved after compression [12]. There is strong evidence that the file size measure predicts the subjective complexity rating of images [14, 15]. Although digital image compression is not directly linked to theories of visual perception, it is connected to information theory. From the previous mentioned ideas and studies we derived our own measure of visual complexity, which was used in the present study. Our formula for visual complexity (X) consists of three factors:

1. Number of possible interactions, which can be considered as functional elements or just actions (A)
2. Number of higher level structures or gestalt groups, in short organizational elements (O)
3. Summed Entropy of RGB values (S).

$$\mathbf{X = A \bullet O \bullet S}$$

As functional elements we consider all kind of links and active GUI elements like buttons, drop boxes, checkboxes etc. Organizational elements are all kind of binding boxes, pictures, in short everything that fulfills the gestalt laws for grouping. The entropy measure should provide us with information on contrast.

3 Methods and Materials

This chapter covers the used dataset, methods and results. It describes the experiment as well as the analysis.

3.1 Hypothesis and Research Question

Due to the possible affective impact of visual complexity on users, this study strived at investigating the elements of website complexity by generating a novel measure called XAOS metric. The XAOS metric had to be tested against established objective measurements and also against subjective user ratings. For this test we expected to find high correlations between the user ratings, traditional measures and the XAOS metric (H1).

Taking into account the idea of compressed images, expressing visual complexity, we were interested in testing this against uncompressed images. Following the suggestions of Donderi, we expected to find no or just weak correlations between the user rating item complexity and the file size of uncompressed (PNG) images (H2).

With Berlyne's theory in mind we expected to find correlations between the objective measures of visual complexity and subjective valence ratings (H3).

3.2 Dataset

The dataset for the present experiment consisted of 30 different screenshots of website landing pages. Coming from an e-learning context, we chose start pages of different Learning Management Systems (LMS). Real websites were chosen in order to ensure ecological validity.

All screenshots were taken in uncompressed PNG format, with a resolution of 1024x768 pixels. They showed just the website without the browser interface. The interface elements would have influenced the perception of the users, as they had to be embedded in the web-survey. Thus a replication of the browsers navigational elements would have biased the results.

3.3 Methods

For the comparison with the XAOS metric we chose the JPEG file size method for determination of visual complexity [14][15], as it seemed to be the fastest and most reliable. For the JPEG files a compression ratio of 70% was used. The file sizes of the JPEG and PNG files of the dataset were collected.

3.3.1 XAOS Metric

The generation of the XAOS metric was a little more exhaustive as we had to calculate the entropy of the screenshots, which was done with a MatLab script. The number of actions and organizational elements of each website was elaborated empirically, following the gestalt laws. However for a website this could also be done automatically with a parser for functions and computer vision techniques for analyzing the structure.

3.3.2 Websurvey

Finally a web-survey was implemented, which showed one screenshot at a time. This can be considered a typical passive viewing test. In a pilot study we used iFrames linking to the real websites, however this proved to be distracting and error-prone. The participants were asked to rate their first impression of the shown website, concerning complexity, structure, color, contrast and valence. The dimensions were arranged on a seven point semantic differential, whereof an example can be seen in fig. 3. The scores for each dimension ranged from 1 to 7.

Fig. 3. Example for used seven point semantic differential

The semantic differentials were expressed as shown in following table 1. Although it was tested, we disclaimed using a more elaborative questionnaire. Due to the voluntary nature and the amount of tested websites, we didn't want to risk participants aborting the survey.

Table 1. Shows the used semantic differentials for describing first impression

color	dreary	colorful
complexity	simple	complex
structure	Empty	overloaded
contrast	low-contrast	high-contrast
valence	Pleasant	unpleasant

A22 participants took part in the web survey, with the age ranging from 19 to 42 (mean ~ 28). 12 of them were familiar with the concept of Learning Management Systems (LMS). 11 out of 22 had already used an LMS. The Internet expertise of the participants ranged from 4 to 7 (mean ~ 5,86), which suggests that there were lots of experts.

3.4 Analysis

For the subjective user rating the results for each webpage and item were averaged over participants, so that every page finally had five averaged scores of subjective measures (complexity, structure, color, contrast and valence). The objective metrics were calculated, so that every page had three objective scores. These were 'PNG file size', 'JPEG file size' and XAOS metric.

3.5 Results

The first hypothesis asked for a comparison of a reliable traditional method with our novel proposed XAOS metric and with the subjective user rating. Therefore the results of the three metrics were normalized in order to make it comparable. For visual simplicity reasons we just show the trend lines of the metrics in fig. 4. The trend line of the XAOS metric matches the JPEG file size method and both objective methods almost match the subjective user rating of visual complexity. Table 2 shows the correlations between the compared metrics.

For testing hypothesis H2, the PNG file size and the JPG file size were compared against the user rating of visual complexity. As expected the JPG measure correlated much higher (r=.79) with the user score, than the PNG measure (r=.33). That data can be seen in fig. 4 and tab. 2.

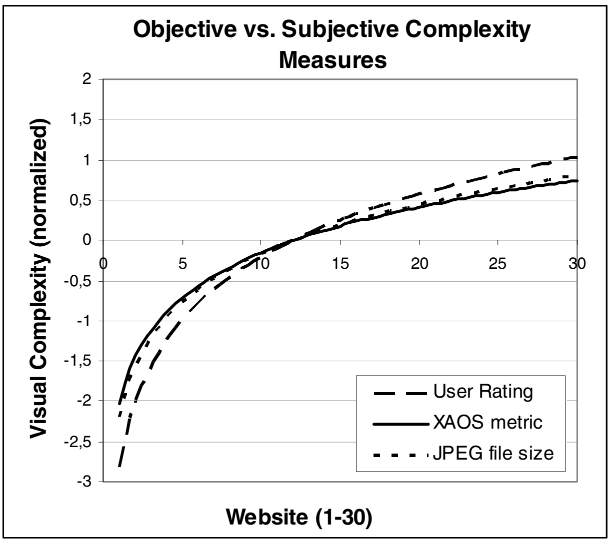

Fig. 4. The XAOS metric matches the JPEG file size method and user ratings

Table 2. Shows the correlations between the complexity metrics

	User rating	JPEG file size	XAOS metric	PNG file size
User rating	1,00	0,79	0,77	0,33
JPEG file size	0,79	1,00	0,68	0,51
XAOS metric	0,77	0,68	1,00	0,31
PNG file size	0,33	0,51	0,31	1,00

For testing hypothesis H3, the objective and subjective measures of complexity were first compared to the subjective valence score. As tab. 3 shows there are no significant correlations. So far this study does not support Berlyne's theory.

Table 3. Color Harmony of best vs. worst

	User rating	JPEG file size	XAOS metric	PNG file size
Valence	0,25	0,21	0,27	0,50

Mentionable at this point may be that the most influencing factors on the valence score were the subjective ratings on contrast (r = .68) and color (r = .69). So far color variables can be considered as an important factor for valence.

4 Discussion

The XAOS metric has proven to be reliable, also the JPEG method showed good performance for predicting subjective user ratings of the visual complexity of websites. However JPEG prediction does not work with uncompressed images, as this method depends on the compression algorithm.

4.1 Validation of the XAOS Metric

Based on the results of this study the proposed XAOS metric is applicable as a measure of visual complexity for websites. The underlying factors, namely number of interactions, organizational elements and the entropy of the image are influenced by the ideas of the Gestalt psychology and algorithmic information theory and have proven to be reliable. The metric could be enhanced, taking into account variables like size and position of objects, or by other measures of color and contrast. Further development should include the complete automatic derivation of all factors of the formula. Testing should include different kind of software interfaces.

The XAOS metric can be used directly in the design process, by just simple multiplication of functional elements with organizational elements. We found that the entropy part of the formula is not necessary for the prediction of visual complexity. However it raises the correlation of the result for valence (r+.24) and contrast (r+.20). With this simplification and Berlyne's theory in mind it should be possible to systematically develop an applicable scale for visual complexity with a connection to valence.

4.2 Validation of JPEG Method

The JPEG file size method can be considered as reliable, as the present study replicated a high correlation (r = .79) between JPEG file size and subjective user ratings of complexity. The technical background on this phenomenon is that the JPEG compression algorithm cause larger compressions depending on image features like details, contrast, color and redundancies [21]. In addition other research has found the file size of images like charts, web images and photos to correlate highly and significantly (0.82) with human judgments of visual complexity [15][22]. This makes file size a suitable general measures of the visual complexity of images.

4.3 Validation of Berlyne's Theory

The outcome of the present study does not support Berlyne's theory of an inverted U-shaped relationship between pleasure and a linearly increasing complexity. None of the applied methods was able to reproduce the proposed relationship. This may be due to the limited variance in visual complexity of the shown websites. An artificially constructed dataset with sufficient variance is able to reproduce the theory of aesthetic response [8].

4.4 Limitations

The limited variance in complexity resulted from choosing the dataset out of real–life websites. Furthermore the uncontrolled real life setting of the web survey may bias the results. The last shortcoming is the small number of 22 participants as base for the subjective ratings.

5 Conclusion and Future Research

Visual complexity analysis provides a quick way to review a visualization design before any user study can be conducted. It's also applicable in the design cycle.

Although our data does not support the theory of aesthetic response, there is evidence that visual complexity should be considered as important metric for usability and user experience [8] [18], as it is indeed influencing emotions [20]. Further more it can be considered as extraneous load [19], influencing the cognitive load and mental effort of the user [2], [30], [31].

Further work may want to investigate the idea of Wolfram, that the perceived complexity of an image is a function of the most complex structure in the image, detectable by humans [23]. Finally, using visual complexity as metric offers the challenge of integrating it into design cycles of software engineering. It seems likely that understanding and application of shaping the visual complexity of information systems will improve usability and user experience. Ultimately it is a tool for cognitive performance support.

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