Perceptual Usability: Predicting changes in visual interfaces & designs due to visual acuity differences

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ABSTRACT
When designing interfaces and visualizations how does a human or automatic visual interface designer know how easy or hard it will be for viewers to see the interface? In this paper we present a perceptual usability measure of how easy or hard visual designs are to see when viewed over different distances. The measure predicts the relative perceivability of sub-parts of a visual design by using simulations of human visual acuity coupled with an information theoretic measure. We present results of the perceptual measure predicting the perceivability of optometrists eye charts, a webpage and a small network graph.

Categories and Subject Descriptors
H.5.2 [**Information Interfaces and Presentation**]: User Interfaces

General Terms
Evaluation/methodology, Screen design, Theory and methods

1. INTRODUCTION
Interactive dynamic visual displays are becoming increasingly pervasive [6, 2]. As display research and materials technology advances we can expect clothes, floors, tabletops, buildings, human skin and many other physical surfaces to continue getting turned into realtime visual displays. The implications of this are that an increasingly important facet of visual interface design will be catering to viewing interfaces and visualisations in a range of changing environments [14]. An advantage of turning previously static signage and materials into displays is that it offers the ability to improve the usability of visual interfaces and designs. Visual designs can be adapted in realtime to a viewer's perceptual abilities. Before a visual design is adapted we need measures of its current perceptual usability

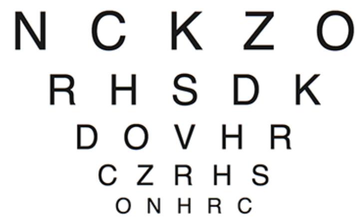

Figure 1: ETDRS chart for measuring visual acuity.

In this paper we present a perceptual usability measure of how easy or hard visual designs are to see when viewed at different distances due to blur. As viewers move away from a display their ability to perceive the display content decreases as a function of distance [7]. Distance is equated with a perceivers ability to perceive visual detail. The measure predicts the relative perceivability of sub-parts of a visual design by using simulations of human visual acuity coupled with an information theoretic measure.

2. RELATED WORK

2.1 Human Visual System Modeling
Human-Computer Interaction researchers have applied specific human vision system (HVS) models to evaluating and developing interfaces [12]. For example Rosenholtz et al's clutter measurement [11] for evaluating information density in interfaces and visualisations. In order to establish how visual designs and interfaces would appear to perceivers we require methods for modeling optical aberrations in the HVS [4, 10]. An optical aberrations model is needed to transform the visual designs into visual patterns people could see. The optical aberration we simulated was optical blur - since we hypothesized it would have a large effect on the perceivability of a visual design.

2.2 Visual Acuity
Spatial visual acuity is the smallest spatial detail that can be visually detected, discriminated, or identified [8]. Studies have experimentally demonstrated that there is a correspondence between a person's visual acuity and their ability to perform everday tasks [13].

Optometrists commonly measure visual acuity by taking psychophysical measures of a person's ability to identify and discriminate optotypes (Figure 1). Optotypes, such as let-

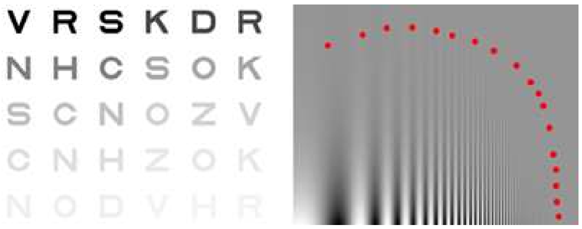

Figure 2: Pelli-Robson (left) and Campbell-Robson (right) Contrast Sensitivity charts. Dots plot Contrast Sensitivity Function.

ters, are presented on eye charts, such as the Snellen, Landolt C, Bailey-Lovie and ETDRS charts [3].

2.3 Contrast Sensitivity

Measurements of spatial contrast sensitivity are another important predictor of a person's ability to see visual detail. Over the years it has been demonstrated that contrast sensitivity plays a very important part in people's abilities to resolve visual detail and carry out everyday tasks [9, 13, 5].

Contrast sensitivity can be measured by using a Pelli-Robson chart (Figure 2, left) or a Campbell-Robson Contrast Sensitivity chart (Figure 2, right). In a Pelli-Robson chart the contrast between the optotypes and the background decreases as a function of optotype distance from the top left of the chart. For further details on measuring Contrast Sensitivity Functions (CSF) please consult Norton et al [8].

3. MEASURING PERCEPTUAL CHANGES

3.1 Algorithm Overview

Our method for predicting the perceptual usability of a visual interface due to a viewer's position works as follows (Figure 3). A static image of the interface undergoes repeat transforms (convolutions). Each transform incrementally blurs the image. At each incremental blur information theoretic measures of the blurred image are calculated. Graphs of the information theoretic measures are then created. Users of the perceptual usability measure can then examine the graphs. The rate of change of the graphed information theoretic measures tells them how different parts of an image change due to the increasing blur. Changes in blur are treated as a function of distance [7]. As distance increases, image blur increases and as distance decreases, image blur decreases.

3.2 Modeling Blur With PSF

To simulate the drop in visual detail due to increasing distance from a display the display contents are incrementally blurred. We use a standard 2D Gaussian function (Eqn. 1) to generate multiple Point Spread Functions (PSF) for use as image convolution filters. The PSF simulates the ambiguity in the path a point of light takes through an aberrant optical system.

$$h_g(x,y) = e^{-(x^2+y^2)/(2\sigma^2)}$$

$$h(x,y) = \frac{h_g(x,y)}{\sum_x \sum_y h_g} \quad (1)$$

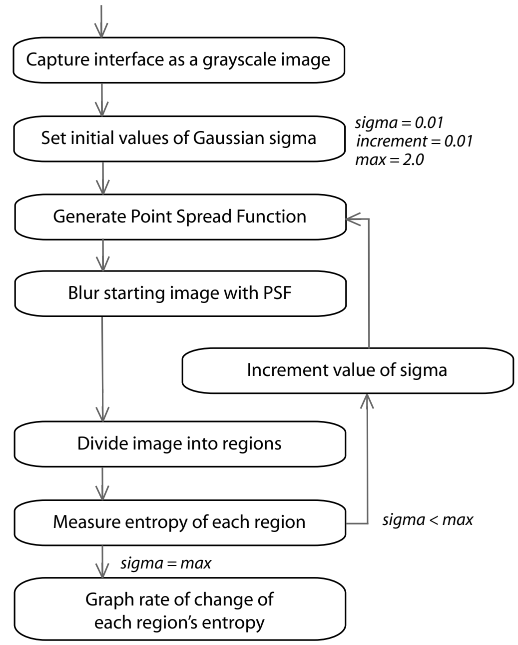

Figure 3: Algorithm measuring blur rate of change.

Slowly increasing the value of the Gaussian filter's σ sigma means the amount of image blur slowly increases. The higher the sigma the more image blur. The rate of change of sigma controls the sensitivity of the perceptual test. Similarly the range of sigma controls how much blur, and indirectly over what distances, we test.

3.3 Measuring Change With Entropy

When considering the eye and HVS as a communication system we hypothesized that elements of Shannon's Information Theory could be a potential measure. Information theory for sensory coding has been researched and applied to vision modeling and statistical image analysis [1]. Initially we used the rate of change of Shannon's entropy over multiple blurs (Eqn. 2) for our analysis, where each unique pixel colour counted as a discrete symbol x_i .

$$\frac{d(-\sum_{i=1}^{n} p(x_i)\log_2 p(x_i))}{d(Blur)} \quad (2)$$

Using Eqn. 2 to analyse the effects of blur in natural images gave what initially seemed meaningful predictions. Unfortunately when using it to analyse images of interfaces there was a problem. The problem arose due to the general structure of the images. Natural images are complex, while interfaces are sparse images. With complex images the entropy tended to decrease due to increasing blur. With sparse images the entropy increased as the blur increased, and eventually the entropy decreased but the point at which it decreased depended on the starting image.

After examining why the entropy in sparse images was increasing we found that it was because there was an increase in the number (n) of colours (x_i). That is the entropy was changing due to a change in the number of unique colours (n) in an image as well as a change in the distribution $p(x_i)$ of the colours. By subjecting entropy to the rate of change

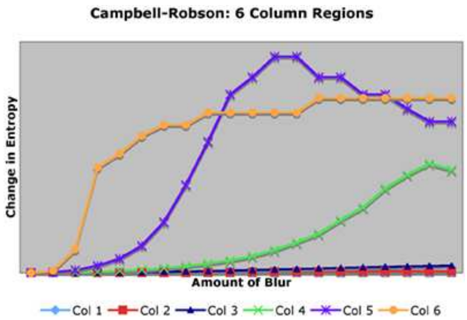

Figure 4: Results Campbell-Robson Contrast Sensitivity Chart. Divide into 6 equal column regions with column 1 starting on the left.

of blur we were effectively measuring the entropy of a series of unique communication channels, each of which has its own set of symbols. To eliminate the change in entropy due to the increase and decrease of symbols between blurred images (communication channels) we normalised Shannon's entropy equation:

$$NormEntropy = \frac{-\sum_{i=1}^{n} p(x_i)\log_2 p(x_i)}{n}$$

$$ChangeMeasure = \frac{d(NormEntropy)}{d(Blur)} \qquad (3)$$

By dividing Shannon's entropy measure by n, we sought to control the change in the number of colours between images while still allowing for the change in the distribution of colours.

4. EVALUATION

Interfaces and visualisations can visually vary significantly so we sought to establish a ground truth for the performance of our measure. We hypothesized that if our perceptual measure worked it would make predictions consistent with very well established human performance on eye charts [8].

4.1 Results

4.1.1 *Campbell-Robson Contrast Sensitivity Chart*

Figure 4 shows the results where we tested the Campbell-Robson Contrast Sensitivity Chart by dividing it into 6 column regions of equal width. As you can see from the graph the perceptual measure predicted Col 6 would change the most initially, then Col 5, Col 4, and so on. This result conforms to how people see CSF charts. You can also see that Col 6 stopped changing but the other columns continued changing due to blur. The entropy of Col 6 does begin to decrease, this may be due to normalization working imperfectly (Section 3.3) though it may also be due to how the gray scale colours are quantized into symbols.

4.1.2 *Pelli-Robson Chart*

We tested the Pelli-Robson Chart (Figure 2, left) by dividing it into four regions of equal size. Figure 5 shows the results. In this case the results are not as clear as with the Campbell-Robson Contrast Sensitivity Chart. Early on in the blur we see that the lower left (red line) and right (green line) regions change fastest, that is they become harder to

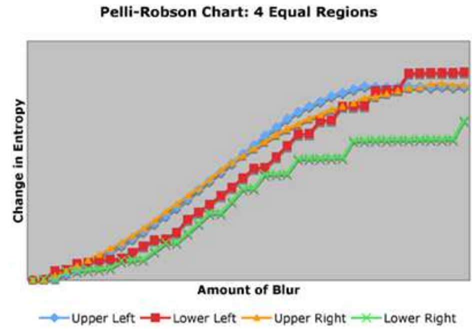

Figure 5: Results Pelli-Robson Contrast Sensitivity Chart. Divided into 4 equal regions.

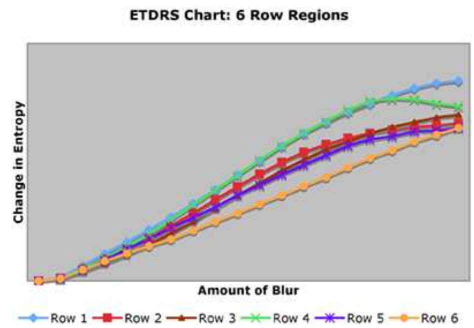

Figure 6: Results ETDRS Chart. Divided into 6 equal row regions with row 1 starting at the top.

Figure 7: Small network graph (left) and webpage (right) that were analysed.

see quicker. Though the rate of change of the top of the chart quickly surpasses the bottom of the chart. The letters at the top of the chart continued changing for longer at a faster rate because they can undergo a greater amount of blur before becoming indistinguishable blobs. The larger letters are more perceptually robust, while the rate of change of the smaller letters slowed down because the letters had lost so much detail relative to their size.

4.1.3 *ETDRS Chart*

Figure 6 graphs the results of the perceptual measure evaluating an ETDRS chart (Figure 1). The results are as we would expect, row 1 with the largest letters is the most robust and can change longest while row 6 changes at a slow rate because it has less detail to lose. Of concern is row 4, which appears to perceptually robust - this is an artifact of white space and how the chart was segmented into regions. In future work a smart region segmentation approach will be taken to help avoid such issues.

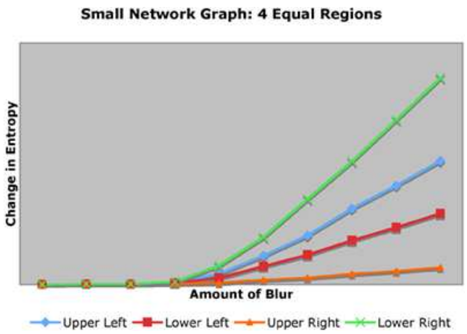

Figure 8: Results of the small network graph analysed with the perceptual measure.

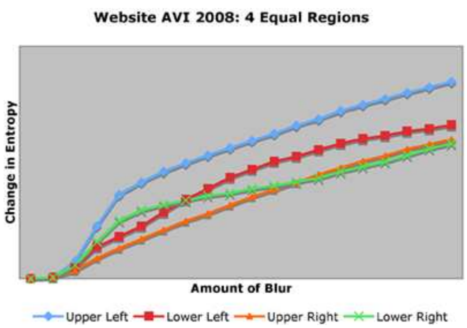

Figure 9: Results of the perceptual measure evaluating the AVI 2008 website.

4.1.4 *Small Network Graph*

The small network graph (Figure 7, left) was divided into four equal regions and the perceptual measure was applied. For this analysis the increment value of sigma was set low. As can be seen the results (Figure 8) were as expected. The lower right hand region (green line) changed the most due to blur, and the mostly empty upper right region (orange line) changed the least.

4.1.5 *Webpage*

Shown in Figure 9 are the results of the perceptual measure evaluating the AVI 2008 front webpage (Figure 7, right). The results are also as expected, the rate at which the lower right hand region (green line) changes quickly decreases as the amount of blur increases. The upper left hand region (blue line) initially looses detail fastest because it has the most detail to loose due to the text and the logo. For a brief while near the midpoint of the blurring the amount of detail lost is faster in the lower left hand region (red line).

5. CONCLUSIONS & FUTURE WORK

In this paper we have presented a first approach to quantifying the perceptibility of a visual design when viewed over different distances. We implemented the perceptual measure and evaluated its performance on a range of eye charts. The results showed the perceptual measure does predict the perceivability of visual designs and, with further research, the accuracy of the perceptual predictions are open to improvement. We also demonstrated the measure predicting the perceivability of a visual design commonly found in graph visualisations, while also providing the results of it analyzing a web page. Further experimental analysis of the perceptual measure outlined in this paper is ongoing. Especially with regards to testing it on a wide range of interfaces.

6. ACKNOWLEDGMENTS

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