Gloss Uniformity Attributes for Reflection Images

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Abstract

Gloss uniformity is an important image quality attribute for high quality reflective color images. One of the most important gloss uniformity sub-attributes is "differential gloss". Differential gloss[1] of printed images (of various image content) on substrates of wide ranging gloss values was studied. The preference levels of gloss and differential gloss were obtained for EP prints. A novel method to correlate image content to differential gloss was described. The mapping functions between subjective responses and the objective measurement were obtained and reported in this study.

1.0 Introduction

A picture, either it's a nature scene, a still life, a portrait or an action shot, usually consists area of different color and shade. Distinctive area with different amount of colorant when printed via a printing process often results in different amount of image gloss (differential gloss). Depending upon the printing technology used, adopted colorant could be dyes or pigments and their contribution to image gloss varies. Moreover, depending on the type of chosen imaging algorithm (continuous tone, binary halftone, multi-level halftone[2], stochastic screens etc), the amount of visible substrate changes in the highlight area and the corresponding image gloss can vary accordingly. Figure 1 shows examples of G60 gloss value as a function of colorant coverage on 3 different types of paper produced by an electrophotographic system.

2.0 Experiment Design

The purpose of this experiment is to study observer's preference levels of gloss and differential gloss. The psychophysics experiment of category scaling was utilized to collect observer's response and a statistical method of categorical analysis was used to analyze the collected data. Three paper stocks with different levels of gloss were used. They are Enso 4CC Silk 130gsm, Lustro Laser 118gsm, and Chromolux 700 300gsm. The 4CC is a coated matte paper with an average paper gloss of 5 when measured with a BYK Gardner gloss meter at 60° geometry. Lustro Laser is a coated glossy paper with an average paper gloss of 35. And Chromolux 700 is also a coated paper with paper gloss of 70. These three papers represent the range of paper gloss encountered in most of the commercial print job.

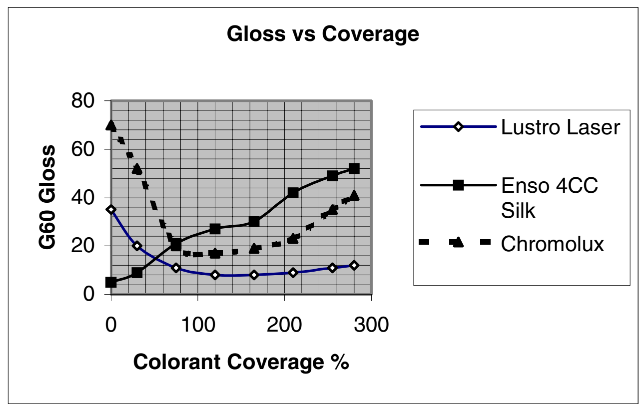

Figure 1, Gloss vs. Coverage for different papers

The test target used in this experiment consists of two color pictures, two paragraphs of black text, and eight columns of color patches. Pictures and text were included for the purpose of subjective visual evaluation, and color patches are provided for gloss measurement. The total image element covers 76% of a printed page, and the rest 24% of the paper surface remains unprinted. The two pictures are a high-contrast still life of metal parts and a portrait of a lady with brown hair. The still life picture covers mostly the two ends of the tone range with some area of mid-tone. The tone range of the portrait is from mid-tone to shadow.

Text font is 12 points Times in normal style. Single-color patches used are C, M, Y, and K tone steps of seven each. There are twenty-one steps of two-color overprint patches of R, G, and B. The number of three-color overprint patches is also seven. They were created by equal amount of C, M, and Y. The total number of color patches used is fifty-six. This test target was printed on three selected papers using a digital printing press. An off-line fuser was utilized to obtain different levels of image gloss on the sample prints. A set of nine prints was obtained for each paper. The total number of sample prints for this experiment was twenty-seven with G60 image gloss ranging from 5 to 94.

3.0 Psychophysics Experiment

Twenty-two normal vision observers were chosen from the fields of Electrophotography, Commercial Printing and Marketing. Age span is from 20's to 50's. The experiment was conducted in a viewing room of neutral surrounds with D5000 lighting. Observers first had a preparation session in which they were given a set of instructions to read. The meaning of differential gloss was explained and example prints were also shown.[3,4]

A total of nine categories were used and they were listed in the following:

1. Like extremely
2. Like very much
3. Like moderately
4. Like slightly
5. Neither like nor dislike
6. Dislike slightly
7. Dislike moderately
8. Dislike very much
9. Dislike extremely

Each observer took turn to evaluate twenty-seven prints, one print at a time. Three questions were asked, and they were (1) gloss uniformity within pictures, (2) gloss difference between text and paper, and (3) overall impression of gloss on this print (image gloss versus paper gloss). One adjective was chosen for each question. The response was then recorded for data analysis. Observers were allowed to hold the prints in their hands and adjust the viewing angle freely. Instructions were also given to ignore any image artifact.

4.0 Data Analysis and Results

4.1 Category Scaling Method

The "Torgerson's law of Categorical Judgment" was implemented to convert the originally ordinal scales into interval scale[3]. Visual preference is assumed to be normally distributed on a psychological continuum, and the given preference categories results from an unknown decision criterion. Hence, the following equation can be devised where B_j is the upper boundary of category ***J***, S_i is the preference scale of the sample ***I*** and σ_i, σ_j are the standard deviation of S_i and B_j respectively [3]:

$$B_j - S_i = Z_{ij}\sqrt{\sigma_i^2 + \sigma_j^2 - 2\rho\sigma_i\sigma_j}$$

"Condition B" where σ_i is assumed to be constant and σ_j be different among various categories is chosen in our model because the condition that σ_i and σ_j being equivalent and constants is too restrictive in this case. The sum of mean squared error of the above equation can be written as following[3]:

$$\min\{\ \sum_{i=1}^{m}\sum_{j=1}^{n}\left(S_i - B_j + a_i Z_{ij}\right)^2\}$$

It can be reformulated into a quadratic matrix form: *min{(Ax)'(Ax)}*. By limiting the solution in the range of *A*, solution *x* can be derived as the right singular vector with the smallest singular value in which category boundary is also obtained.

4.2 Neural Network based Picture Gloss Estimation

The current gloss measuring technique requires a lower limit on the size of an image patch to produce a reliable gloss measurement. Moreover, the measured gloss is the average reflection contributed from a large printed area. These factors pose a constraint to obtain reliable gloss reading from printed images across which toner percentage coverage varies significantly.

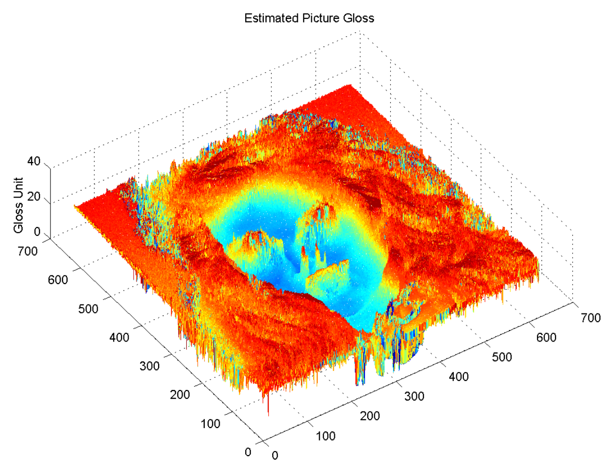

Figure 2. Estimated Image Gloss

Assuming image gloss reading, *g*, is a function of toner percentage coverage, p_c, p_m, p_y and p_k, i.e., $g = f(p_c, p_m, p_y, p_k)$, an indirect gloss estimation algorithm first obtains sample patches within the color gamut as well as their corresponding gloss reading. A back-propagation neural network is then designed to uncover the underlying mapping function *f*. Note that other techniques like high-degree polynomial regression, and radial basis function network can also serve this objective[5]. Nonetheless, the number of available sample patches limits the degree of the chosen multi-dimensional polynomial and it is difficult to handle local variations without affecting the overall fitting.

In our gloss estimator, a two-layer back-propagation neural network is designed with twenty nodes in the hidden layer with hyperbolic tangent activation functions and one output node with a linear activation function. The underlying mapping function f should be smooth based on observed training data, hence, we should avoid selecting a large hidden layer to avoid significant generalization error. An example estimated gloss associated with the lady image is presented in Figure 2. Corresponding histograms of total percent coverage and estimated gloss are illustrated in Figure 3 and 4. They are readily observed to be bi-modal distribution and identified as the face and hair region respectively from Figure 2. The estimated gloss using this method agrees well with the actually measured large area gloss around those regions. As a result, the needed measurement in the following log-linear models can be derived directly from this gloss estimation result.

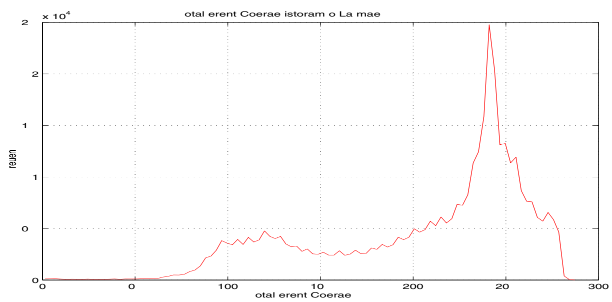

Figure 3. Histogram of Total Percent Coverage

4.3 Log-linear Gloss Preference Model

S. Stevens in 1957 proposed that a psychophysical scale S is related to physical stimulus T via a power law, $S = \alpha T^{\beta}$ where α and β are determined by psychophysical experiments[6]. Take logarithm on both sides, and it is transformed into a linear form: $log(S) = \alpha + \beta log(T)$. We can assume that human visual preference against gloss also satisfies the above log-linear model with different factors in various aspects. In our experiment, picture differential gloss, text differential gloss and overall gloss in visual preference are investigated and explained in the ensuing subsections.

Picture Differential Gloss Preference

Images become targets of which gloss observers were asked to judge upon. Therefore, it is reasonable to assume that surrounding paper influence is minimized and gloss discrepancy within images plays a major role in visual preference. Let D equal to $[D_{1p} \ \ D_{2p}]^T$, where D_{1p} and D_{2p} are the predominant gloss difference in the corresponding two images. The estimated gloss histograms show that area with the highest occurrence is the most noticeable and is demoted as G_h, the dominant gloss level in images. All gloss measurement is derived from estimation result noted in the previous section. We observed that both factors contribute to the picture differential gloss preference. As a result, the postulation regarding picture differential gloss preference P_{p_d} can be formulated as following:

$$\log\ P_{p\_d} = \alpha_p + \beta_p \log \|D\| + \gamma_p \log\ G_h$$

Equation 1. Picture Differential Gloss Preference Model

Figure 5 illustrates the calculated preference scale for each print, and the fitted surface based on the selected model. The discrepancy between the data and model prediction is less than 10% in 20 out of 24 sample prints. The acceptance percentage for these four samples with larger prediction error is all less than 50%. This model demonstrates that visual preference decreases along with increasing predominant differential gloss and the dominant gloss within the image.

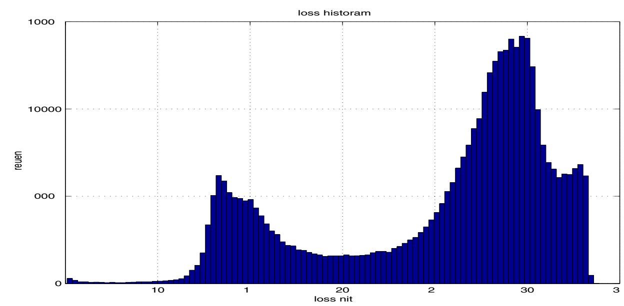

Figure 4. Histogram of Estimated Gloss

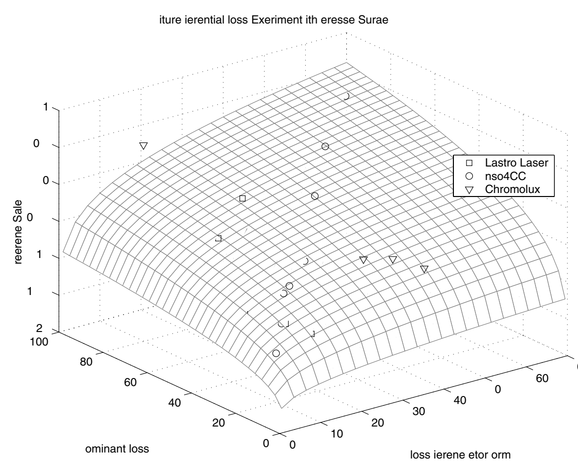

Figure 5. Picture Differential Gloss Preference

Text Differential Gloss Preference

Text is printed with 100 percent black coverage; hence, the gloss difference between paper and text can be considered as the major contributor toward text differential gloss preference. Let D_k be the difference between measured gloss on the patch with 100 percent black coverage and paper gloss, and we propose the following model relating the text differential gloss preference P_{t_d} and D_k:

$$\begin{cases} \log\ P_{t\_d} = \alpha_t + \beta_t \log\ D_k\ , & Gloss_{paper} < Gloss_{bk} \\ \log\ P_{t\_d} = \alpha_t' + \beta_t' \log\ D_k\ , & Gloss_{paper} > Gloss_{bk} \end{cases}$$

Equation 2. Text Differential Gloss Preference Model

Data and fitted model are shown in Figure 6, and it indicates that gloss matching (at low to intermediate substrate gloss) achieves the highest preference and matte finishing text is more preferable than glossy finishing overall.

$$\begin{cases} \log P_o = \alpha_o + \beta_o \log G_{ip}\,, & Gloss_{paper} < Gloss_{image} \\ \log P_o = \alpha'_o + \beta'_o \log G_{ip}\,, & Gloss_{paper} > Gloss_{image} \end{cases}$$

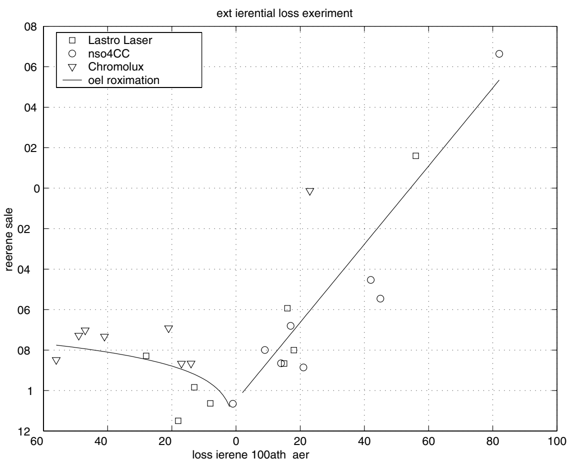

Figure 6. Text Differential Gloss Preference

Overall Gloss Preference

Observers were asked to give their preference based on the gloss level of the whole print. Because the two pictures occupy only a quarter size of the paper, the gloss influence of the surrounding substrate now have more significance. Hence, the perceived gloss difference between images and paper possesses the major contribution. Let this gloss difference be G_{ip}, and we can then model the overall gloss preference, P_o, to be as following:

$$\begin{cases} \log P_o = \alpha_o + \beta_o \log G_{ip}\,, & Gloss_{paper} < Gloss_{image} \\ \log P_o = \alpha'_o + \beta'_o \log G_{ip}\,, & Gloss_{paper} > Gloss_{image} \end{cases}$$

Equation 3. Overall Gloss Preference Model

Figure 7 is the fitted model and it shows that prints with extreme gloss difference toward that of adopted paper received lower preference than those with image gloss near the paper gloss.

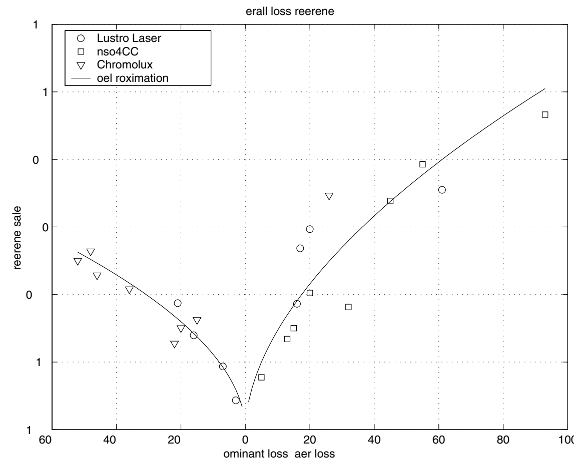

Figure 7. Overall Gloss Preference

5.0 Conclusion

Apply the back propagation neural network, picture gloss can be estimated based on samples in the *CMYK* color space. Visual preference toward differential gloss can be directly linked to the gloss distribution of an image. Base on log-linear models, we found that for pictures only, visual preference decreases along with increasing predominant differential gloss and dominant gloss within the image. For text only, gloss matching (at low to intermediate substrate gloss) achieves the highest preference and matte text is preferable than glossy text. For mixed images that have significant substrate exposed, prints with extreme gloss difference to that of the paper received lower preference than those with image gloss near the paper gloss.

References

1. C Jeffrey Wang, “Differential Gloss in Electrophotography”, *IS&T’s NIP15:*1999, pp. 406-407.
2. Yee S. Ng, Hieu T. Pham, Hwai T. Tai, and Eric Zeise, “Gray Level Printing Method with Embedded Non-Uniformity Correction Using a Multi-bit LED Printhead”, *IS&T’s 4th Annual Conference,* pp 622-625, 1994.
3. Peter G. Engeldrum, “Psychometric Scaling”, *Imcotek Press, Winchester, MA., 2000*
4. “Standard Guide for Designing and Conducting Visual Experiments”, *ASTM: E1808-96.*
5. Simon Haykin, “Neural Networks”, *Prentice Hall, 1999*
6. S. S. Stevens, “On the Psychophysical law”, *The Psychological Review,* **64**:153*, 1957*

Biography

Yee S. Ng is a Chief Engineer of NexPress since 1998. He was a Project Chief Engineer and Science Associate at Eastman Kodak Company before that. He received his Ph.D in Physics from Pennsylvania State University and joined Kodak Reserach Laboratory in 1980. His research interests are in image quality, image processing, Electrophotographic processes, electronic Writer and Image Data Path design. He was a Kodak Distinguished Inventor and holds > 80 U.S. Patents. He received the Carlson Memorial Award in 2000 from IS&T.

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C. Jeffrey Wang received a MS degree from Imaging Science of RIT in 1987. He worked at RITRC between 1987 and 1996. Had joined Eastman Kodak later in 1996. He has been working at NexPress as a Senior Scientist since 1998. Has published in IS&T and TAGA proceedings.