Preferred citation: L.M. Cormier. Quantitative mottle measurement based on a physical model of the spatial contrast sensitivity of the human visual system. In **Advances in Paper Science and Technology**, *Trans. of the XIIIth Fund. Res. Symp. Cambridge, 2005*, (S.J. I'Anson, ed.), pp 1155–1189, FRC, Manchester, 2018. DOI: 10.15376/frc.2005.2.1155.

QUANTITATIVE MOTTLE MEASUREMENT BASED ON A PHYSICAL MODEL OF THE SPATIAL CONTRAST SENSITIVITY OF THE HUMAN VISUAL SYSTEM

Lyne M. Cormier

Pulp and Paper Research Institute of Canada (PAPRICAN), 570 Boulevard St-Jean, Pointe-Claire, Quebec, H9R 3J9, Canada

ABSTRACT

Print non-uniformity, or mottle, is an important factor in print quality. The ultimate judge of print quality is the printer or print buyer, so print quality measurement should be representative of human perception. Most methods that are currently available to systematically quantify print mottle do not consider eye response in the calculation. Instead, the user has to select appropriate scales for the analysis by comparing with separate visual ranking experiments for each new set of prints.

We developed a method to process digital images of mottled black prints to provide a mottle index that takes into account eye response. The mottle indices obtained for a range of paper and board grades were compared with the results of separate visual rating experiments, and there was very good agreement between them. The mottle index outperformed other parameters also used for the quantification of mottle. Based on these results, the mottle index is deemed reliable enough to decrease the need for separate visual assessments by panels. The mottle index algorithm removes the need for the operator to make subjective choices on the appropriate analysis scales for sample sets where print uniformity is the dominant quality criterion.

The proposed mottle measurement method allows systematic and objective quantification of mottle. The method can easily be implemented to analyze test prints using the analysis software we developed, and an appropriate desktop scanner that will require calibration to relate the greyscale to reflectance values.

INTRODUCTION

Uniformity of solid prints is an important aspect of print quality. The ultimate judge of print quality is the printer or print buyer, so an instrumental print quality measurement should be representative of human perception. Print non-uniformity has been described by many terms, including mottle, speckle, graininess, or cloudiness. These different terms reflect the various scales and intensities of the same phenomenon: the local variation of the reflectance of the print. In this paper, the term 'mottle' will be used as the general descriptor of the reflectance variation. Ink properties, paper properties and the printing process itself can all participate to create mottled prints. The purpose of this work was to obtain a systematic method to quantify print non-uniformity, to serve as a tool in subsequent studies investigating the causes of mottle. Specifically, the objectives were: (i) to obtain a mottle index that would reflect human perception, that would not require a separate visual rating experiment for comparison every time, and would minimize inputs of arbitrary values in the analysis; and (ii) to obtain a parameter that could describe the mottle of prints on different paper grades on a common scale.

BACKGROUND

Mottle measurement values that are obtained by commercially available instruments quantify the variation of reflectance in multiple ways, but most lack a built-in human perception component. With these systems, a parallel visual rating experiment usually has to be performed for every new sample set to determine if the parameters used in the analysis were the appropriate ones. Mottle parameters are often calculated at several scales and the most appropriate set of parameters is empirically selected from the best fit with the visual assessment data obtained separately. Since the resolution and the scales selected for analysis are somewhat arbitrary, if the values are not compared to visual rating data, there is a chance that the values obtained will correspond to variations at scales that are not relevant to perception. This is why certain instruments provide very good correlations for certain types of samples and are ineffective for others. One of the goals of instrumental mottle measurement is to avoid the need to perform a visual rating experiment every time, and to obtain data in a form that would help establish links between paper properties and observed mottle.

The idea behind the proposed mottle measurement is simple: obtain an image of the mottled print and process it numerically by simulating the human visual system (HVS). The full implementation of this concept would be quite ambitious due to the complexity and the many unknowns of HVS processing, but simulating selected aspects of the HVS may be sufficient to yield a practical measurement of mottle. In vision research, the functions of the HVS are often separated into low and high level vision. As its name implies, low level vision is characterized by relatively simple psycho-physical phenomena whereas high level vision might involve complex processing in the higher regions of the visual cortex. High level vision involves the organization of all the information contained in the image to be interpreted by the brain, e.g. identifying an object from a few lines. Low level vision includes phenomena such as lightness perception, contrast and pattern sensitivity, and colour coding. The mottle index proposed here is based on a model of low level vision describing perceived contrast.

The mottle measurement consists in obtaining a reflectance image of the print, separating the contributions to the contrast by spatial frequency, determining if the contrast at each spatial frequency is detected by the HVS, weighting the different contributions to the contrast of the image by a function based on the physiology and optical response of the eye, and summing all the contributions according to results of psychophysical experiments on perception. The function used to weight the different contributions to the contrast of the image is called the Contrast Sensitivity Function (CSF) and will be discussed in details in the next section. The general form of the mottle index can be summarized as:

$$MI = \sum_{u} f(detected\ image\ contrast(u) \times CSF(u))$$

where u is the spatial frequency of the mottle features in cycles/degree of visual angle.

The mottle index calculation for digital images of prints is presented in Appendix A.

Intensity discrimination, visual acuity and contrast

Intensity discrimination is the ability to distinguish between light and dark. Visual acuity is the precision with which we can see the details of a pattern. The perception of the contrast of a mottled print combines these two phenomena. If the variations in luminance (grey levels) between the areas of the print are too small to be detected by the eye, the print will appear uniform. Similarly, the contrast can be large, but if it occurs at such a fine scale that the eye cannot detect it, it will also appear uniform. Halftoning is based on this principle for example. The mottle index attempts to integrate the two phenomena by having a contrast term that gives the variation in grey levels and the contrast sensitivity term that reflects the texture detection.

Contrast sensitivity depends on the spatial frequency of the displayed information and on the luminance or print density of the image. Figure 1 can help illustrate the phenomenon. It contains three images displaying bands that increase in frequency horizontally and that decrease in contrast vertically. Figure 1-b), labelled the reference image [1], is the test image first introduced by Campbell and Robson [2] to illustrate the CSF in an intuitive manner. The other two images were added to emphasize the contributions of average luminance (L) to contrast perception and will be discussed shortly. For each band, there is a point where it becomes undistinguishable from its neighbours. This point is defined as the modulation threshold (M_t). The inverted-U shaped function that describes the inverse of the modulation threshold for each spatial frequency is called the contrast sensitivity function (CSF) and as the reader can readily observe, the apparent peak changes position as the viewing distance changes. The effect of the average luminance of an image is illustrated by Figure 1. Figures 1-a) and 1-c) were generated by adding and subtracting 50 grey levels from the reference image while keeping the difference in grey levels (ΔL) between the bands constant. There are some artefacts at the extremes in luminance at the bottom of the images as the reference image was already spanning the full 256 grey levels available in 8-bit digitization, but the observation of the rest of the images makes it clear that even if the difference in luminance over each horizontal line is the same for all three images, the perceived contrast is different[1]. Contrast defined as $C = \dfrac{\Delta \text{ Luminance}}{\text{average Luminance}}$ (Weber's law) appropriately describes this phenomenon for images containing only 2 grey levels[2].

[1] Results will vary depending on the rendering of the output-display or the printer.

[2] Ernst Henrich Weber (1795–1878) discovered that the change in a stimulus that will be just noticeable is a constant ratio of the original stimulus. Weber's law is one of the fundamentals in psychophysics.

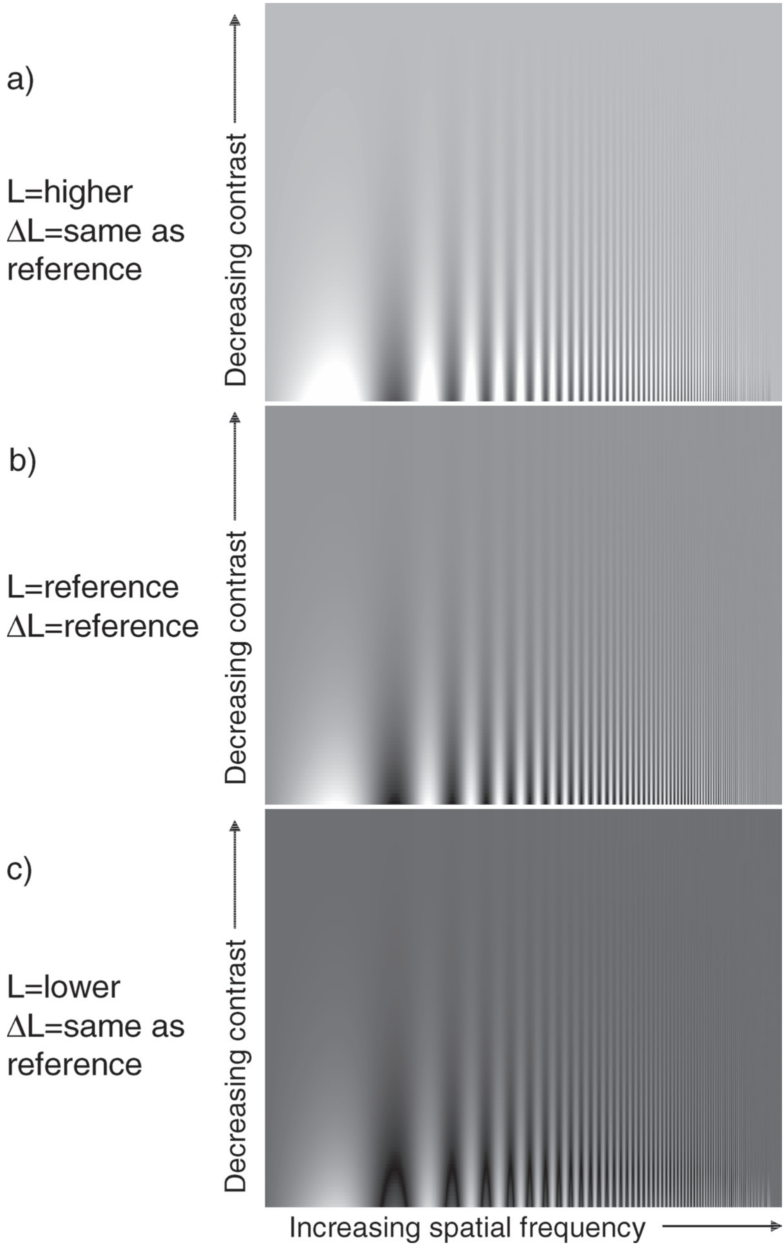

Figure 1 Campbell-Robson Charts displayed for different luminance levels.

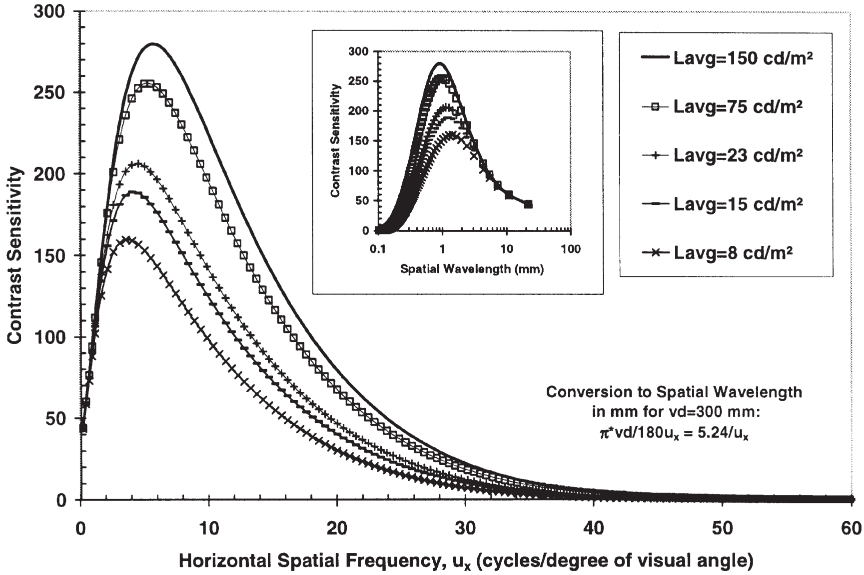

Figure 2 Contrast sensitivity Function calculated using Barten's model for 4 cm^2 prints viewed at a distance of 30 cm.

Many expressions have been proposed for the CSF [3]; all yield the same general shape (see Figure 2) of maximal sensitivity at 2–6 cycles/degree of visual angle and were defined under different experimental conditions. A good survey of the CSF obtained by various authors is given in reference [3]. When the image presents contrasts that are higher than the detection threshold, i.e. suprathreshold, some authors have reported that the decrease of sensitivity with increasing spatial frequency is not as pronounced as would be indicated by the contrast sensitivity function (contrast constancy) [4–6], but the CSF is still widely used as an indicator of the trend of the eye response above threshold [7]. The contrast sensitivity model of Barten [3] was chosen because it is based on the physical structure of the eye and its efficiency as a photodetector. The mathematical description of the CSF proposed by Barten is found in Appendix A (Equations (4) to (7)). The model agrees very well with experimental data obtained from independent studies using different experimental conditions [3,6]. The model is also amenable to computer implementation where parameters such as the image size, resolution, viewing distance and luminance level can be varied. Figure 2 plots the CSF based on Barten's model for 4 cm^2 images of different print densities viewed under office lighting condition at a distance of 30 cm. The contrast sensitivity is usually defined for spatial frequencies expressed in cycles/degree of visual angle because the HVS collects from a cone whose truncated apex is the pupil. The maximum extent of that cone is 12° [3], corresponding to a size of about 6 cm at 30 cm viewing distance. One degree of visual angle corresponds to different physical sizes on a print depending on the viewing distance, i.e. depending on where the 1° cone is intersected. The insert of Figure 2 shows the same CSF curves plotted against spatial wavelengths calculated for a viewing distance of 30 cm. As can be observed from the graph, the maximum sensitivity at that distance is found for wavelengths of about 1–2 mm (i.e. features of 0.5–1 mm), depending on the darkness (luminance) of the print. This can explain why some reported mottle measurements based solely on this wavelength range performed well under some conditions, but were less successful when the viewing distance was increased and thus the waveband best-fitting the visual rating results had changed [8,9]. Isolating the waveband to which the eye is the most sensitive for analysis has certain logic, but the determination of a proper width for that band would change depending on the luminance of the print.

Contrast sensitivity is dimensionless as it is the inverse of the modulation threshold determined for alternating dark and light bands at a given frequency, i.e. if the modulation threshold is 0.005, contrast sensitivity is 200. The contrast sensitivity decreases at low and high frequencies and with decreasing luminance entering the eye.

At high wavelength (low frequency), the model predicts that the modulation threshold does not change much with luminance, which respects experimental observations [6,10].

The mathematical description of the perceived contrast of a complex image is still an area of active research [11]. A complex image is defined here as an image containing more than two grey levels whose spatial distributions are not periodic. The contrast definitions of Michelson [12] or Weber (see above) which are commonly used for images displaying simple periodic bands, such as those of Figure 1, are not suitable for the description of contrast in complex images because they only take into account the highest and lowest luminance values of the image. Aside from lacking a general definition for the physical contrast for these images, other concepts such as adaptation luminance, or contrast constancy, come into play for the perception of a given physical contrast. The definition of contrast (see Equation (3) in Appendix A) used by Hess *et al.* [13] was selected for inclusion into the mottle index. By this definition, the contrast is the amplitude of the Fourier transform of the image calculated at each spatial frequency divided by the average luminance. The spatial dependence of the eye response prompted the frequency decomposition format of the contrast. The contrast at each spatial frequency can be convoluted with the contrast sensitivity function which is also defined in terms of spatial frequency.

Studies involving contrast perception have mostly used images containing features occurring at one frequency. How the different contrasts occurring at the various frequencies in a complex image add up to produce the total perceived contrast is still unknown. The proposed expressions relating the physical and perceived contrast are generally non-linear, with a log-like or saturation behaviour [5,14–16]. The application of square root integral (SQRI) proposed by Barten [17–19] has reportedly given excellent results in psychophysical experiments. Details about the SQRI are in Appendix A.

EXPERIMENTAL

Samples

Four sets of samples were evaluated. The detailed description of the samples with optical properties is in Appendix B.

Set A: uncoated woodfree fine paper, 4-colour black prints from a commercial heatset offset press. Set A is a subset of the samples previously examined in reference [20].

Set B: coated board, cover grade, 4-colour black prints from a commercial sheetfed offset press.

Set C: surface sized and dry finish, solid bleached and white top board, printed on a laboratory flexographic proof press. Sets C and D were evaluated in reference [21].

Set D: coated and surface sized, solid bleached and white top board, printed on a laboratory flexographic proof press. The coated samples of set D were of a lower grade than those of set B. The surface sized samples are common to both sets (C and D) but were visually ranked twice, once with each sample set.

Visual rating experiments to validate measured mottle index

Visual rating experiments were performed on sample sets of different paper grades to serve as a basis for comparison with the mottle index obtained with the proposed method.

Each set of samples was evaluated using the Proscale method [22]. The judges were asked to rank the samples based on a quality criterion and assigned a high number for a good sample and a low number for a bad sample. In Proscale, the values assigned are proportional to the degree of perceived quality of the samples. The samples are first grouped by similarity and then graded, so the outcome might be different if the dominating feature that separates the families is different from the variable intended for the study. The question asked to the judges can affect the results and their interpretation. The sample sets were rated as part of different studies, so the question varied slightly from one set to the other. Sets A and B were rated specifically for print uniformity and mottle respectively, and sets C and D were rated for quality without additional specifications. As described in reference [22], judges also assigned a cut-off rating, which is the lowest score that they would still find acceptable as consumers. In Appendix B, this cut-off rating is given as the % Accepted – that is the percentage of the judges who accepted the sample.

Data acquisition and analysis

The images of the prints used for analysis were 1024 × 1024 pixels in size at 1200 dpi resolution, each pixel representing a length of 21.17 μm and the total area measured was 2.2 cm × 2.2 cm. The spatial resolution for the measurement was judged sufficient by observing that contrast sensitivity for the range of luminance involved here is negligible for frequencies greater than about 40 cycles/degree (i.e. features smaller than 65 μm). Except for set B whose samples did not permit it, 4 areas were measured and the mottle index was the average of the indices of the 4 areas. The images were acquired on a desktop scanner, HP Scanjet 6300 C that has a bit-depth of 8 (256 grey levels) with all the automatic settings for image enhancement (e.g. sharpening) disabled. The greyscale of the scanner was calibrated by measuring photographic prints of solid squares of known reflectance. The reflectance of the reference prints was measured with an Elrepho 2000 densitometer. The calculation of the mottle index for all the samples was implemented as a Matlab® program.

RESULTS AND DISCUSSION

Performance of mottle index

The results of the mottle measurements and the visual ratings for all the samples examined are shown in Figures 3 to 18. The values of the mottle index are tabulated in Appendix B. For each set of samples, 4 graphs are included to compare the performance of the proposed mottle with the other metrics chosen to forecast visual ratings. The first graph shows the subjective rating assigned to the prints by the panels plotted against the mottle index

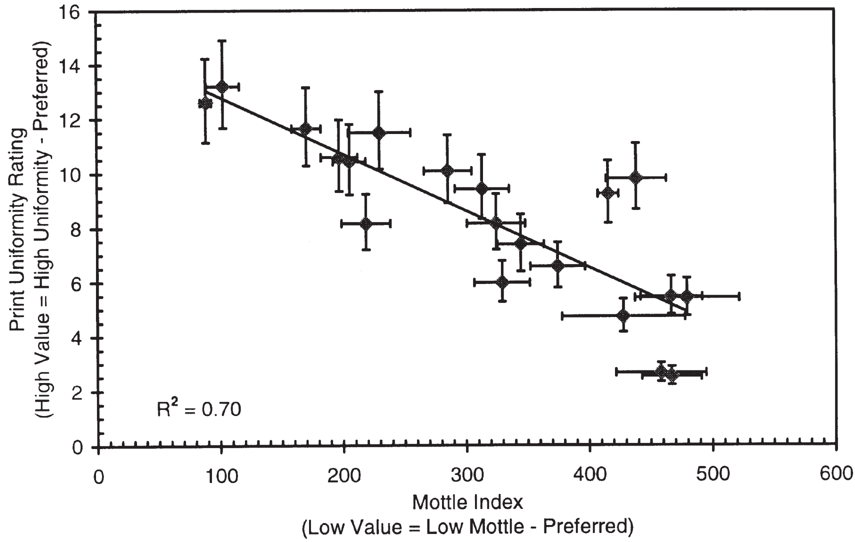

Figure 3 Prediction of Print Uniformity Rating of Uncoated Woodfree Fine Paper Prints (Set A) using COV of the Scanned Reflectances.

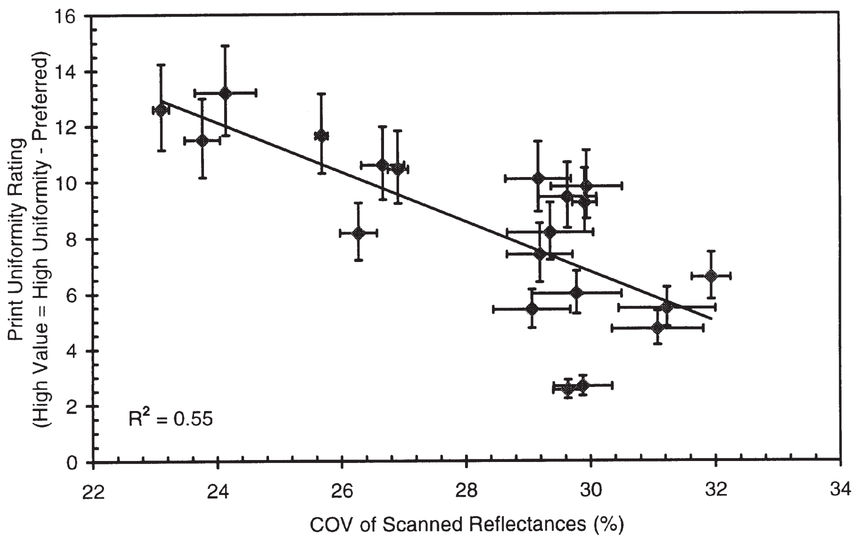

Figure 4 Prediction of Print Uniformity Rating of Uncoated Woodfree Fine Paper Prints (Set A) using Proposed Mottle Index.

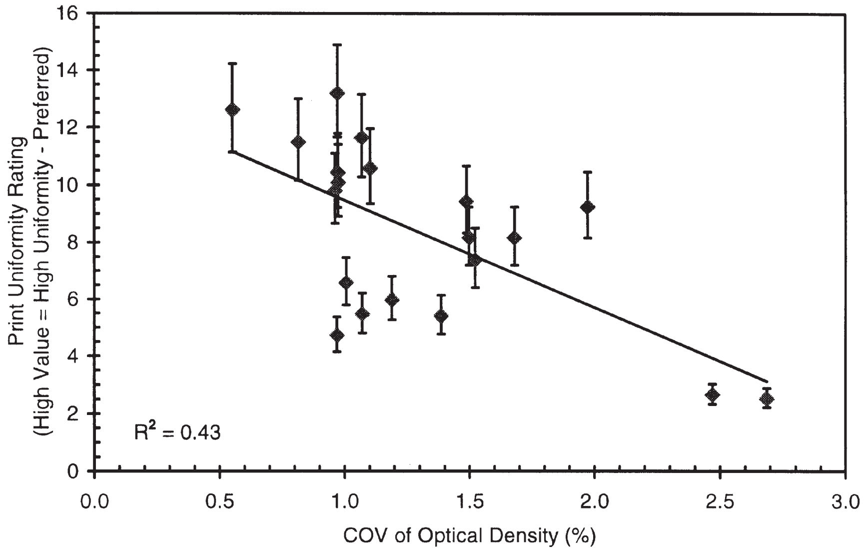

Figure 5 Prediction of Print Uniformity Rating of Uncoated Woodfree Fine Paper Prints (Set A) using COV of Optical Density Measured with a 5-mm Aperture Spectrophotometer.

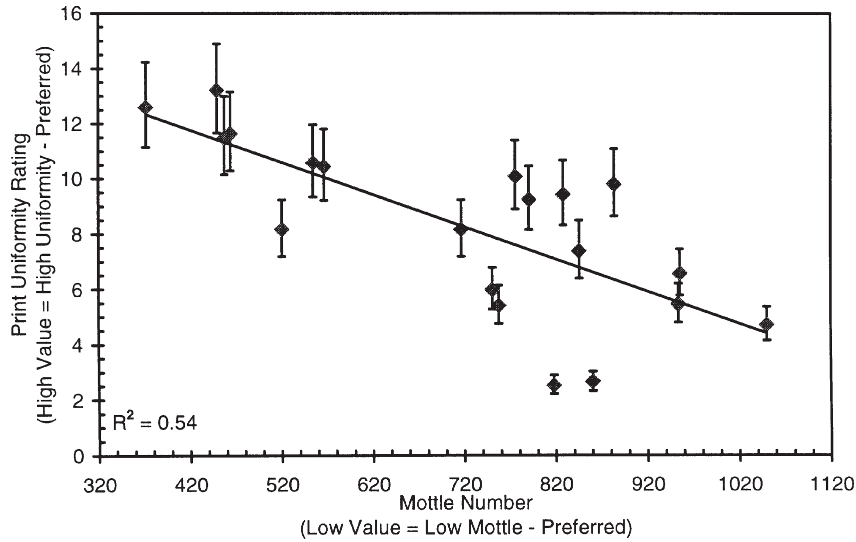

Figure 6 Prediction of Print Uniformity Rating of Uncoated Woodfree Fine Paper Prints (Set A) using the Software of a Commercial Mottle Measuring Instrument.

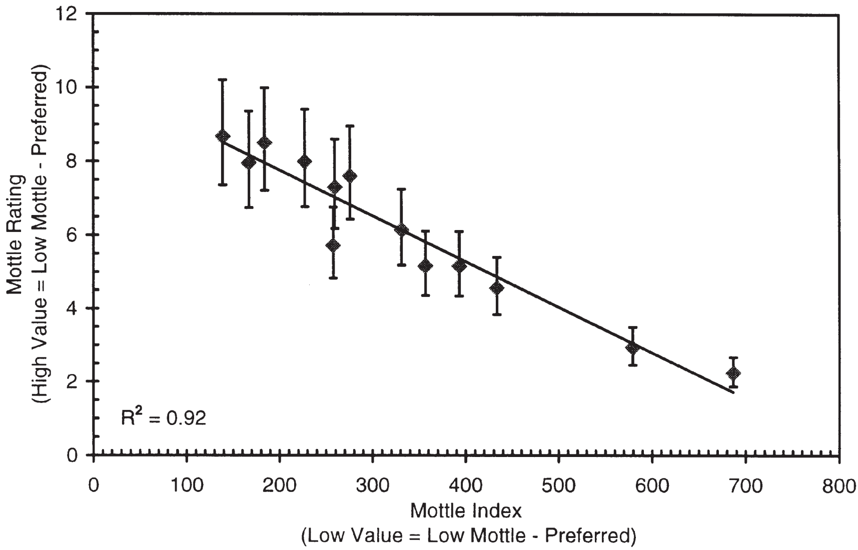

Figure 7 Prediction of Mottle Rating of Coated Board Offset Prints (Set B) using Proposed Mottle Index.

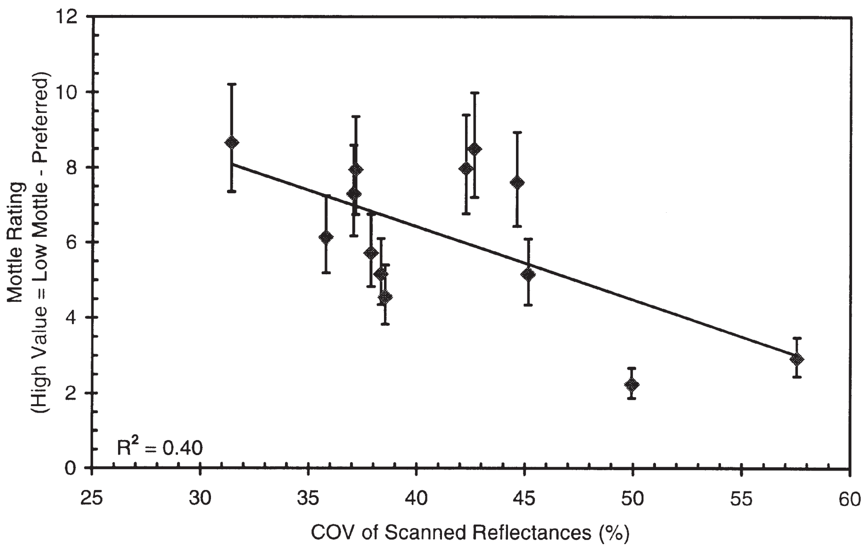

Figure 8 Prediction of Mottle Rating of Coated Board Offset Prints (Set B) using COV of the Scanned Reflectances.

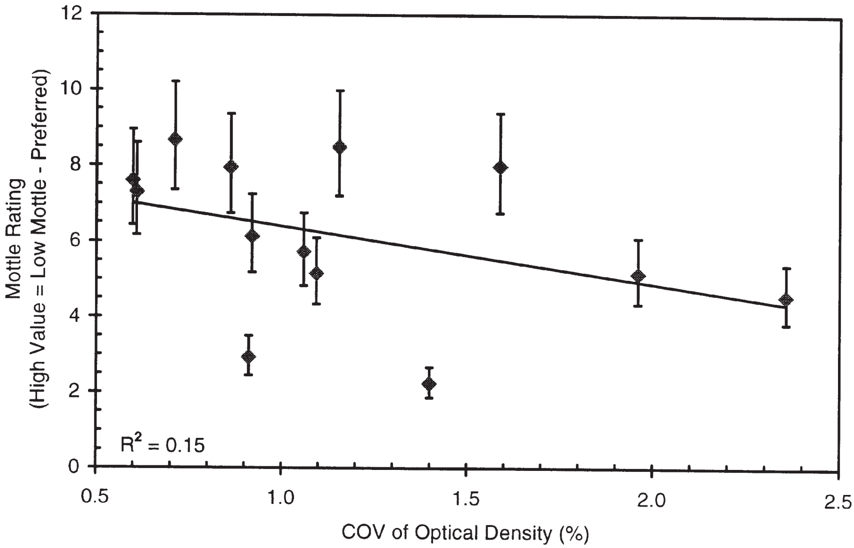

Figure 9 Prediction of Mottle Rating of Coated Board Offset Prints (Set B) using COV of Optical Density Measured with a 5-mm Aperture Spectrophotometer.

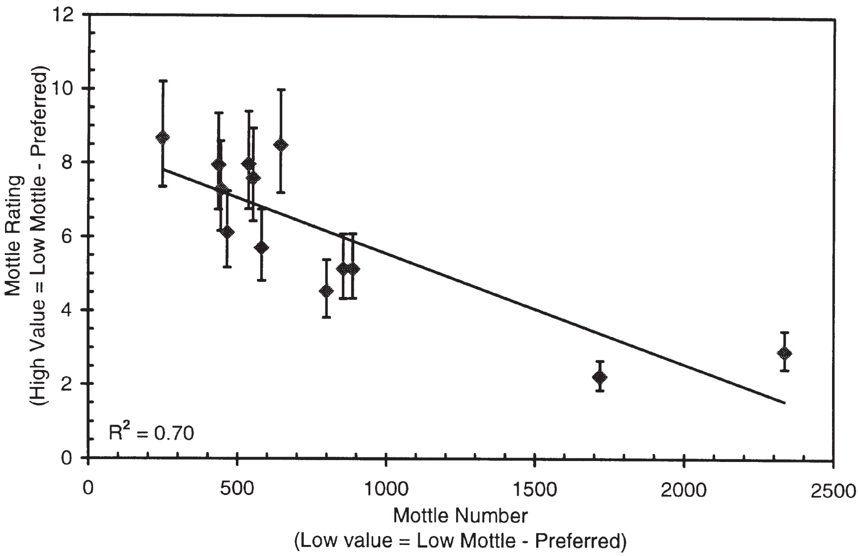

Figure 10 Prediction of Mottle Rating of Coated Board Offset Prints (Set B) using the Software of a Commercial Mottle Measuring Instrument.

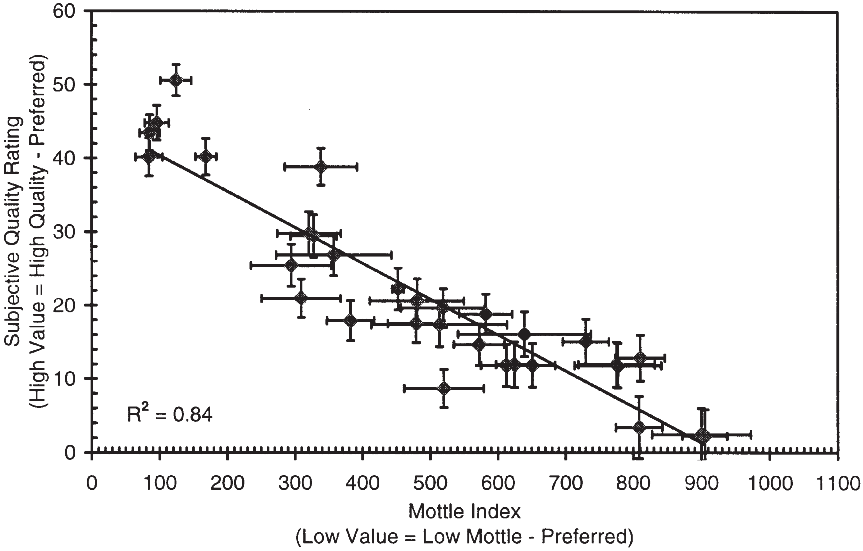

Figure 11 Prediction of Subjective Quality Rating of Surface Sized and Dry Finished White-Top and Solid Bleached Board Flexo Prints (Set C) using COV of the Scanned Reflectances.

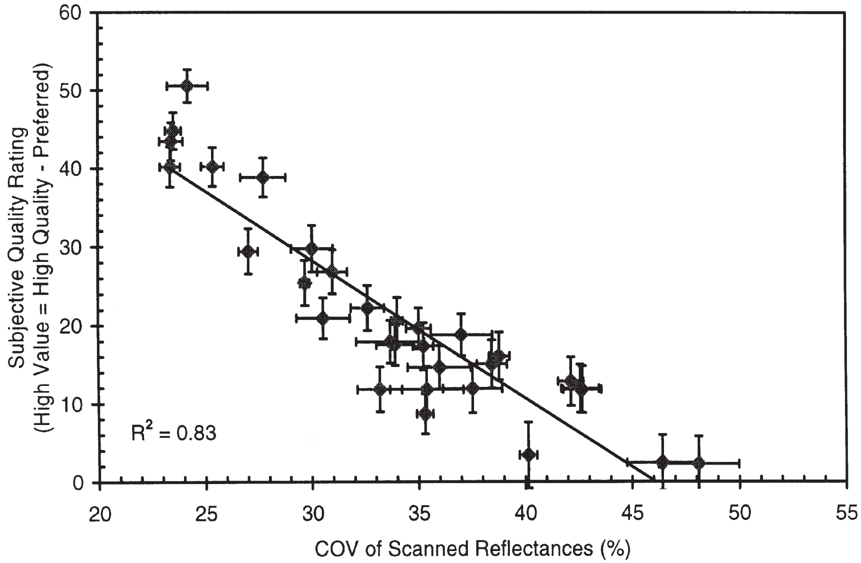

Figure 12 Prediction of Subjective Quality Rating of Surface Sized and Dry Finished White-Top and Solid Bleached Board Flexo Prints (Set C) Prints using Proposed Mottle Index.

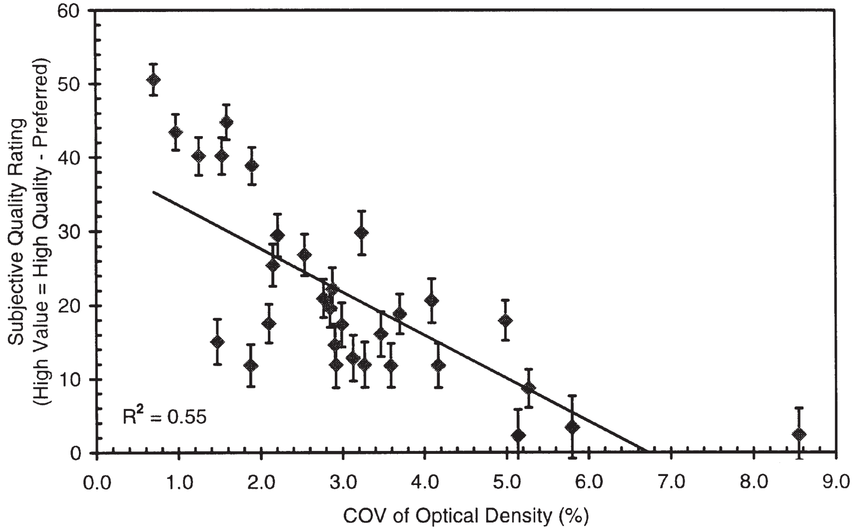

Figure 13 Prediction of Subjective Quality Rating of Surface Sized and Dry Finished White-Top and Solid Bleached Board Flexo Prints (Set C) using the Software of a Commercial Mottle Measuring Instrument.

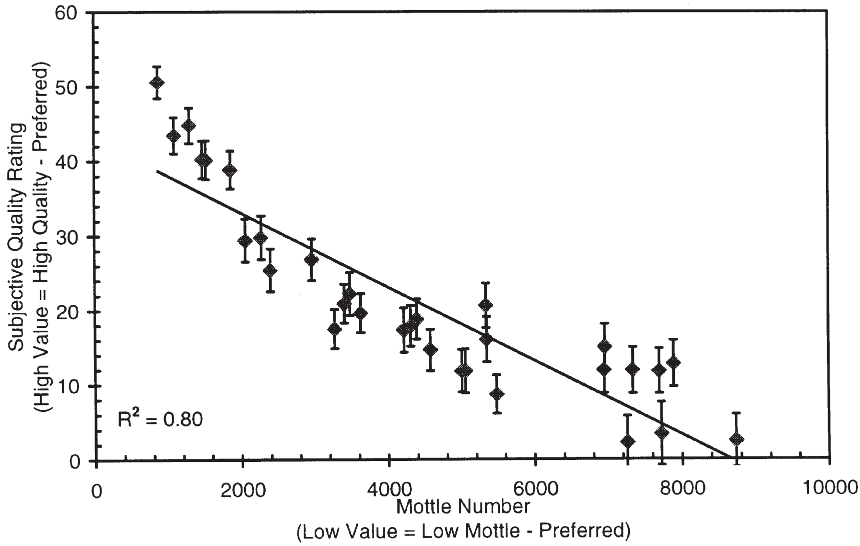

Figure 14 Prediction of Subjective Quality Rating of Surface Sized and Dry Finished White-Top and Solid Bleached Board Flexo Prints (Set C) using COV of Optical Density Measured with a 5-mm Aperture Spectrophotometer.

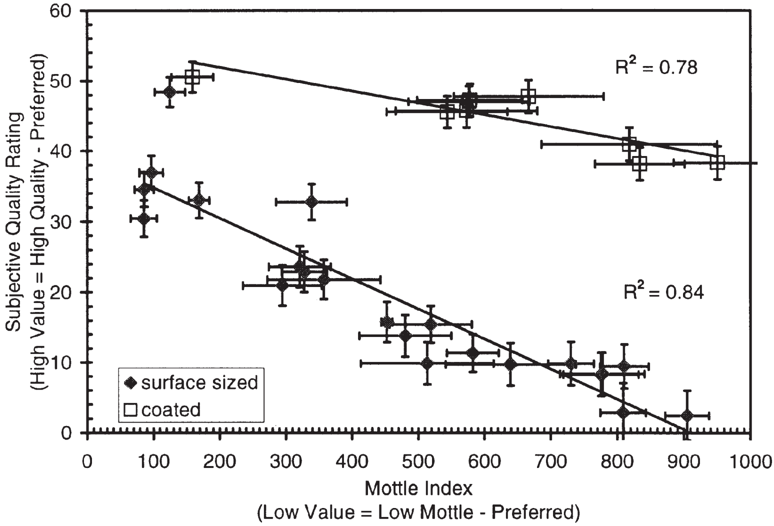

Figure 15 Prediction of Subjective Quality Rating of Surface Sized and Coated White-Top and Solid Bleached Board Flexo Prints (Set D) using Proposed Mottle Index.

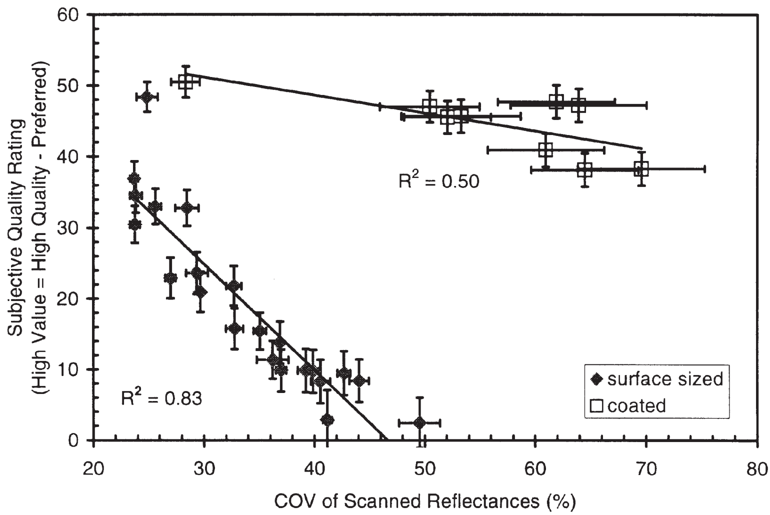

Figure 16 Prediction of Subjective Quality Rating of Surface Sized and Coated White-Top and Solid Bleached Board Flexo Prints (Set D) using COV of the Scanned Reflectances.

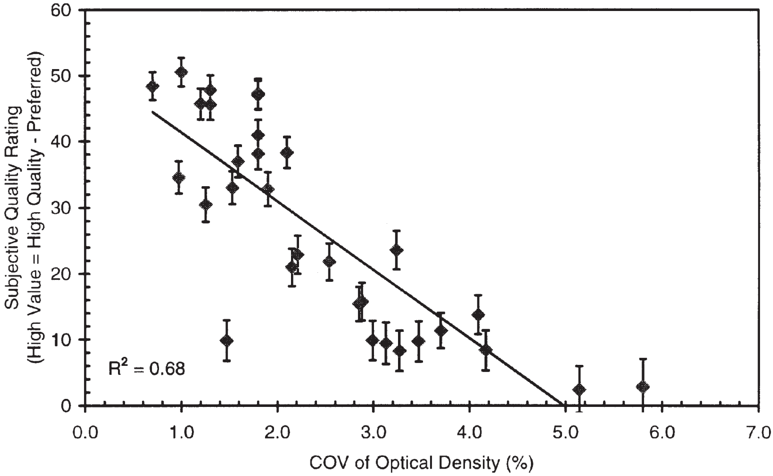

Figure 17 Prediction of Subjective Quality Rating of Surface Sized and Coated White-Top and Solid Bleached Board Flexo Prints (Set D) using COV of Optical Density Measured with a 5-mm Aperture Spectrophotometer.

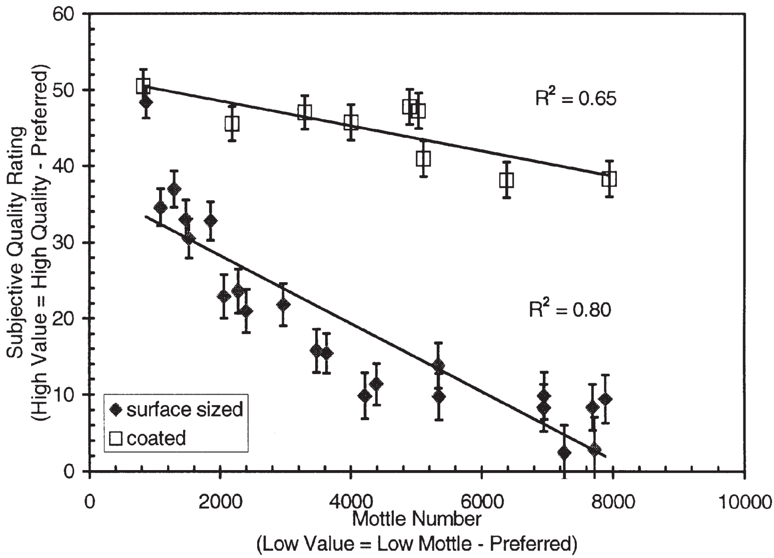

Figure 18 Prediction of Subjective Quality Rating of Surface Sized and Coated White-Top and Solid Bleached Board Flexo Prints (Set D) using the Software of a Commercial Mottle Measuring Instrument.

calculated by the method proposed in this paper. The criterion used for the subjective rating is indicated on the graphs. The second graph plots the subjective rating as a function of the coefficient of variation (COV) of the point-to-point reflectance values of the prints obtained by the scanner. This corresponds to the contrast term of the mottle index and is included to determine if there is a benefit to including the frequency-dependent contrast sensitivity term in the mottle index. The last two graphs of each set are for comparison with the performance of another Paprican method and a commercially-available method. The first one displays the subjective rating as a function of the COV of the optical density obtained with a 5-mm aperture spectrophotometer (SPECTRO/plus by Technidyne Inc.) which is a measurement that has been used occasionally at Paprican to quantify mottle [21]. The second one plots the results of mottle analysis from a commercial mottle instrument software. In this case, the same raw images as the ones used for the mottle index calculations were fed as inputs into the commercial software. The aim here was to compare the calculation methods for the quantification of mottle based on the same inputs. When displayed, the error bars represent the 95% confidence interval on the data. Table 1 shows the R^2 values required to have statistical significance of the regressions at 95% and 99% confidence levels [23] for each sample set, i.e. if the calculated R^2 is below these values the regression is not statistically significant.

For the four sets (A–D) measured, the mottle index performed very well, with good to excellent correlation with the visual ratings. The advantage of including a contrast sensitivity term in the index was observable for all sample sets, and the best illustration was set B where the COVs of reflectance were very similar but the spatial distribution of the variation differed across samples. When the spatial distribution of the mottle is similar within a

Table 1 R^2 values required for statistical significance of the regressions [23]

Sample Set	95% Confidence Level	99% Confidence Level
Set A	0.444	0.561
Set B	0.553	0.684
Set C	0.355	0.456
Set D-Coated	0.666	0.798
Set D-Surface Sized	0.433	0.549
Set D-Complete Set	0.374	0.479

sample set, the improvement in correlation is not as important, which could explain why taking only the COV of reflectance is still successful in some cases.

The mottle index outperformed the other two methods chosen to quantify mottle. The COV of optical density measured at a fixed aperture size clearly failed to quantify the coated board samples (set B), was borderline for set A, and was acceptable for the other two sample sets. The variation in performance of this parameter can be explained by the 5-mm aperture size succeeding or failing to capture the pertinent information describing the size of mottle. The commercial software gave acceptable results in general but gave lower correlations to the visual rating results than the proposed mottle index. For set B, the discrimination between samples was much weaker for the commercial software which clustered the samples as compared to the mottle index which distributed the samples.

The four sets of samples displayed a wide range of mottle characteristics and the mottle index captured them well without manual optimization of analysis parameters by the operator. The different contributions of the contrast are weighted using the CSF and then their square root is summed to obtain the total contrast of the image. The CSF is calculated taking into account the viewing distance, the resolution and the print density of each image. This way, the need to manually (often arbitrarily) exclude some wavelength components in the analysis is avoided, as the CSF represents the size sensitivity of the HVS.

The mottle index calculation produced two distinct families for the coated and surface sized board samples (set D). A few possibilities for explanation can be envisioned. A partial explanation could come from the fact that this set was rated for overall quality and not specifically for mottle. Since in Proscale, the judges sort the samples by families before grading them, in this case it appears that print density was the primary criterion to separate the samples at least into two main families. Support for this hypothesis comes from observing Figure 19 where print density values cleanly divides the sample set into two. No sample with a print density (PD) below 1.1 got a rating above 38 and all the samples that had a PD higher than 1.1 rated above 38. Within each range of PD, the judges then ranked the samples by uniformity. Combining the relative contributions of the print reflectance (PD) and the mottle index, the two families fall on the same line and the subjective quality rating can be predicted with a R^2 of 0.94 (Figure 20). The R^2 for the regression of the ratings and reflectance alone is 0.73. The subjective print quality of sample set D is determined by print density as well as by print uniformity, and the contribution of each factor can be quantified. At this point, the relative contributions of print density and print uniformity appear to be

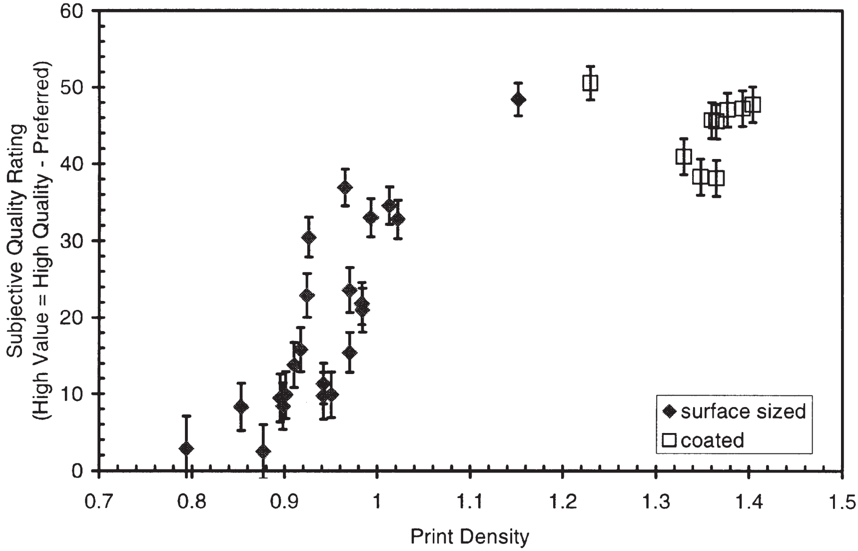

Figure 19 Prediction of Subjective Quality Rating of Surface Sized and Coated White-Top and Solid Bleached Board Flexo Prints (Set D) using Print Density.

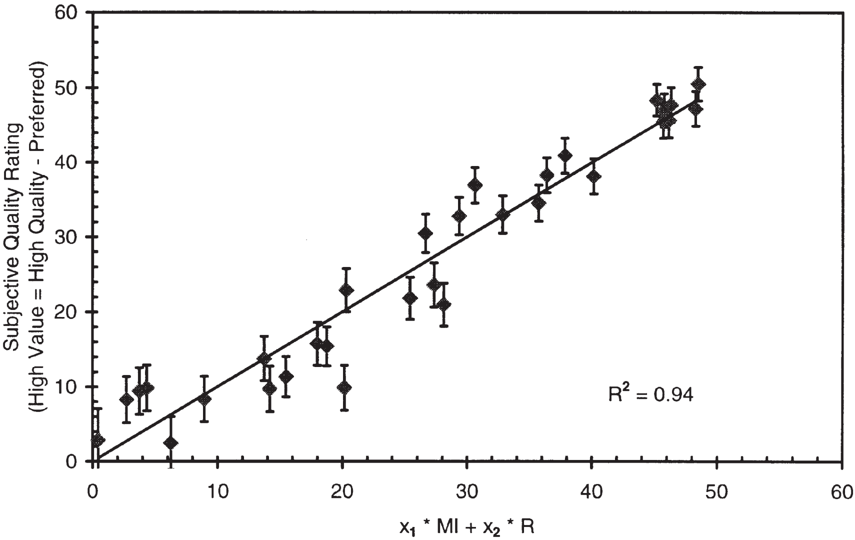

Figure 20 Prediction of Subjective Quality Rating of Surface Sized and Coated White-Top and Solid Bleached Board Flexo Prints (Set D) using a Linear Combination of Proposed Mottle Index and Average Reflectance of the Print.

specific to each sample set, and no generalization of this relationship could be established.

Another possible explanation for the results obtained when there are large differences in print densities (PD) is that the mottle index may overestimate the contrast perception at high PD as compared to lower PD because the contrast and contrast sensitivity terms incompletely describe the effect of average luminance on contrast perception. Possible improvements to the index on this aspect will be investigated.

The last possible explanation resides in what is actually quantified by the mottle index. The mottle index is an indicator of the number and magnitude of contrast differences in a print. The hypothesis is that the more contrast differences there are in a print the worse the perceived quality would be, but that may not necessarily be so when other factors such as print density or gloss come into play. For example, if two samples have the same or even different mottle indices, the darker or glossier sample would probably be preferred in the end. It is unknown at this point how much mottle would be tolerated to get a darker print or by how much print density requirements may be lessened in favour of a uniform print. Since such issues are often client-specific, it may be very difficult to establish a unique print quality scale.

Another limitation of the mottle index is that even if it includes a spatial component through the use of the CSF, the mottle index does not take into account how the contrast differences are spatially organized, a factor which also affects the mottle perception. For these reasons, two different looking prints can have similar mottle indices. Having similar mottle indices means that the mottle features are perceived to stand out equally from the background even though they may be in different print density ranges or display different sizes. The inclusion of a texture parameter in the mottle index to describe the coarseness of the pattern formed by the mottle was considered, but thus far the several parameters that were tested improved the correlations with visual assessments only marginally, if at all, while increasing the computation time. Since the mottle index in its current form performs very well in the majority of cases, it was decided not to include a texture parameter in the mottle index at this point, but leave it as a future refinement of the measurement with the development of new knowledge on this topic.

Experimental results have shown excellent correlation between the mottle index and the viewer's quality assessment when print uniformity was the dominant quality criterion. The user has to exert caution when using the mottle index calculation on a sample set displaying a broad range of gloss or print densities (e.g. set D) where the print uniformity may become a secondary rating criterion. In this case, the mottle index ranks the samples within different regimes, as was observed for set D, and may produce inconsistent

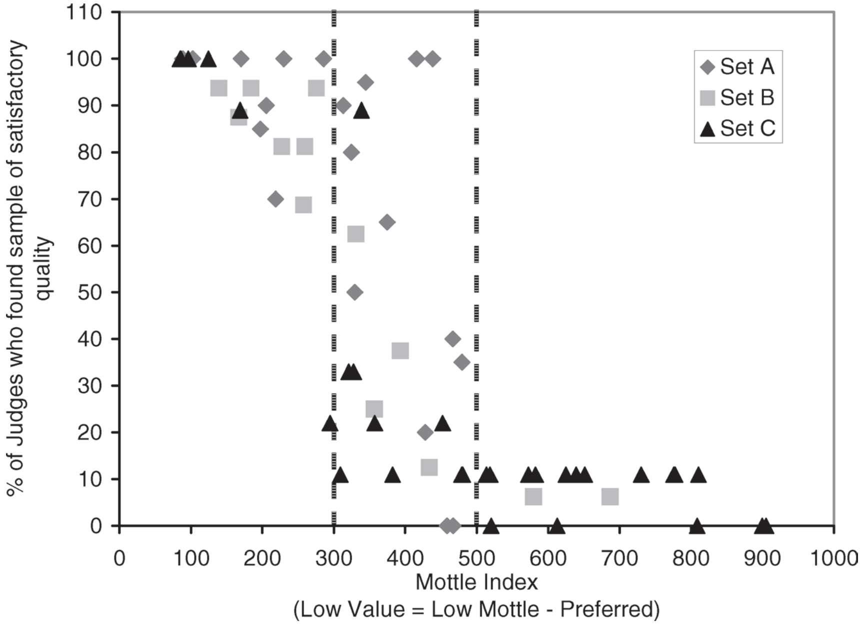

Figure 21 Prediction of Quality Acceptability Based on the Mottle Index.

results if the other properties are not taken under consideration. For such sample sets, a confirmation from a panel rating experiment may still be necessary. It is not clear at this point if there are threshold values for a certain parameter to become the dominant quality criterion. Future work will be aimed at exploring the possibility of establishing rules of preference with gloss, print density and mottle index as variables.

A common problem encountered in print quality assessments is the differentiation of samples that have similar average print density or average print gloss, but different uniformity. This is where the mottle index becomes most useful.

If the percentage of judges who found the samples of satisfactory quality (%Accepted in the tables of Appendix B) is plotted against the mottle indices of sample sets A, B, and C (Figure 21), a rough separation can be made of good and poor samples based on the mottle index[3]. A mottle index below

[3] The mottle indices of different sample sets will be directly comparable only if the acquisition size, resolution, and assumed viewing distances are the same.

would 300 indicate a sample that 70% or more judges would accept whereas a sample having a mottle index above 500 would be rejected by a majority of judges. The intermediate zone between 300 and 500 shows very different levels of acceptability and this probably has to do with the relative quality of the other samples of the set, and the difference in other optical properties as was discussed previously. Evidently, more sample sets need to be measured to establish more rigorous benchmarks, but these preliminary observations already show some trends. It should also be emphasized that since the absolute values for the mottle index would change if the resolution of the image and analysis size were different from those used here, the values of 300 and 500 are only valid for the current analysis conditions. Other analysis conditions would change the absolute values, but would not change the relative ratings of the samples unless these conditions are such that they exclude significant components of the mottle.

Extension to mottle of colour prints

The same principle of analysis as was used here could be applied to colour prints by decomposing the image in the appropriate colour channels and applying the CSF corresponding to each of these channels. The CSFs for colour are different from the CSF for luminance as the sensitivity is lower for colours than for luminance and the CSF has a low-pass behaviour rather than a band-pass behaviour as it does for luminance.

Paper performance troubleshooting

In terms of paper performance troubleshooting, since the contrast is decomposed by waveband before the summation in the mottle index calculation, the contrast distribution can be inspected to see if the contrast is higher at some wavelengths than others or if samples in a given set are more dissimilar in a certain range of spatial range frequencies. Similar analyses can be done on the structural properties of paper and links can potentially be established.

CONCLUSION

A method for predicting the mottle perception of solid black prints has been developed that incorporates a model of spatial contrast sensitivity of the visual system. The mottle index obtained by this method correlated very well with ratings from visual assessment experiments and outperformed the three other methods it was compared to. Apart from the luminance value for a perfectly white sample and the viewing distance where typical values were chosen but could have been measured more rigorously if required, the user did not need to make subjective choices of analysis parameters such as spatial frequency band, for example.

One of the goals of instrumental mottle quantification is to reduce the need for separate panel rating experiments. The results have shown the reliability of the mottle index for sample sets where print uniformity was the dominant quality criterion. Caution must be exerted when the mottle index is calculated for a sample set where print uniformity may not be the dominant quality criterion, e.g. when the prints show a broad range of print densities. In this case, a separate panel rating experiment may still be required to establish the order of precedence of the quality parameters. Further work will help establish if there are any quality sorting rules that can be generalized.

The proposed mottle measurement method is relatively easy to implement. The user needs to calibrate an appropriate desktop scanner to relate greyscale to reflectance values, and acquire images at a suitable resolution with no automatic enhancements. Once the calibration function is incorporated into the software, the mottle index can be calculated for each image measured with the viewing distance, the image acquisition resolution and size, and the lighting conditions as inputs into the software.

ACKNOWLEDGEMENTS

The author wishes to thank especially Maureen O'Neill for her competent technical assistance. Drs Byron Jordan, Tetsu Uesaka and Joseph Aspler are gratefully acknowledged for the many discussions. Anthony Manfred and Sylvie St-Amour are thanked for sample characterization. The author also thanks Mr. Roy Rosenberger from Verity IA for making his mottle analysis software available for comparative purposes.

REFERENCES

1. I. Ohzawa. http://www.bpe.es.osaka-u.ac.jp/ohzawalab/izumi/CSF/A_JG_Robson CSFchart.html
2. F.W. Campbell and J. G. Robson. Application of Fourier analysis to the visibility of gratings. J. Physiol. (London) **197**, 551–566, 1968.
3. P.G.J. Barten. Physical model for the contrast sensitivity of the human eye. Proc. SPIE, **1666**, 57–72, 1992, and references therein.

4. M.A. Georgeson and G.D. Sullivan. Contrast constancy: deblurring in human vision by spatial frequency channels. J. Physiol. (London), **252**, 627–656, 1975.
5. M.W. Cannon. Perceived contrast in the fovea and periphery. J. Opt. Soc. Am. A, **2**, 1760–1768, 1985.
6. E. Peli, L. Arend and A.T. Labianca. Contrast perception across changes in luminance and spatial frequency. J. Opt. Soc. Am. A, **13**, 1953–1959, 1996.
7. R.E. Jacobson. An evaluation of image quality metrics. J. Photogr. Sci., **43**, 7–16, 1995.
8. M.A. MacGregor, P.-Å. Johansson and M.-C. Béland. Measurement of small-scale gloss variation in printed paper. In Proc. 1994 Intl. Printing and Graphic Arts Conf., Tappi Press, Atlanta, pp33–43, 1994.
9. M.-C. Béland, S. Lindberg and P.-Å. Johansson. Optical measurement and perception of gloss quality of printed matte-coated paper. J. Pulp Pap. Sci., **26**(3), 120–123, 2000.
10. F.L. Van Ness and M.A. Bouman. Spatial modulation transfer in the human eye. J. Opt. Soc. Am., **57**, 401–406, 1967.
11. E. Peli. Contrast in complex images. J. Opt. Soc. Am. A, **7**, 2032–2040, 1990.
12. A.A. Michelson, **Studies in Optics**, U. Chicago Press, Chicago, 1927.
13. R.F. Hess, A. Bradley and L. Piotrowski. Contrast coding in amblyopia. I. Differences in the neural basis of amblyopia. Proc. R. Soc. London, **B 217**, 309–330, 1983.
14. J. Gottesman, G.S. Rubin and G.E. Legge. A power law for perceived contrast in human vision. Vision Res., **21**, 791–799, 1981.
15. J.C. Stevens and S.S. Stevens. Brightness functions: effects of adaptation. J. Opt. Soc. Am., **53**, 375–385, 1963.
16. C.R. Carlson and R.W. Cohen. A simple psycho-physical model for predicting the visibility of displayed information. Proc. Soc. Inf. Displ., **21**, 229–246, 1980.
17. P.G.J. Barten. Evaluation of subjective image quality with the square-root integral method. J. Opt. Soc. Am. A, **7**, 2024–2031, 1990.
18. P.G.J. Barten. The square root integral (SQRI): a new metric to describe the effect of various display parameters on image quality. Proc. SPIE, **1077**, 73–82, 1989.
19. P.G.J. Barten, Nonlinear Effect of Modulation on Image Quality. In PICS 2002: IS&T's PICS Conference, An International Technical Conference on Digital Image Capture and Associated System, Reproduction and Image Quality Technologies, pp109–114, Portland, Oregon, 2002.
20. B.D. Jordan, J.S. Aspler, M.A. O'Neill and J. Chasle, Quality of uncoated wood-free papers in a commercial heatset offset printing trial. In Proceedings of the 1998 Pan-Pacific and International Printing and Graphic Arts Conference, pp13–29, Quebec City, Canada, PAPTAC, Montreal, 1998.
21. J.S. Aspler, Print quality test methods for linerboard. In 2004 Proceedings of the Technical Association of the Graphic Arts, Rochester, N.Y., in press.
22. D.C. Donderi and J.S. Aspler. Proscale: A Fast New Way to Measure Subjective Print and Paper Quality. Pulp & Paper Canada, **101**(5), T136–138, 2000.
23. G.W. Snedecor and W.G. Cochran, **Statistical Methods**, 7th edition, The Iowa State University Press, p477, 1980.

24. S.G. De Groot and J.W. Gebhard. Pupil size as determined by adapting luminance. J. Opt. Soc. Am., **42**(7), 492–495, 1952.
25. C.-M. Fahlcrantz. Evaluating systematic print mottle. J. Graphic Technol., **1**(2), 19–28, 2003.

APPENDIX A

MOTTLE INDEX DEFINITION FOR DIGITIZED IMAGES OF SOLID BLACK PRINTS

The mottle index proposed uses the square root integral (SQRI) metric from Barten [17–19] as the basic form of the relationship between perceived mottle and measured contrast. Before introducing the definition of the mottle index, the concept of the SQRI will be briefly reviewed. This metric was derived for self-luminous images (video display). The empirical performance of the SQRI as a measure of perceived image quality is excellent [17–19].

Barten's SQRI has the form:

$$J = \frac{1}{\ln 2} \int_0^{u_{\max}} \left[\frac{M(u)}{M_t(u)} \right]^{1/2} d(\ln u) \tag{1}$$

- u_{max} is the maximum angular spatial frequency. For television, it is determined by the luminance bandwidth of the television signal, and for data display, it is delimited by the number of addressed pixels.
- M(u) is the modulation transfer function (MTF) of the display. The modulation transfer function is defined as the ratio of the contrast of the output image over the contrast of the source image. This ratio is determined for a range of spatial frequencies.
- $M_t(u)$ is the modulation threshold function of the eye. It gives the minimum discernible contrast for a given spatial frequency. It can be understood as the MTF of the human visual system (HVS). This function is the inverse of the Contrast Sensitivity Function.

The superiority of the SQRI over other forms of perceived contrast functions is discussed in details in reference [17]. In summary, the logarithmic integration allows a better balance between the effects of low and high spatial frequencies as compared to linear integration. Table 2 compares the R^2 for the correlation between the objective ratings and the mottle indices obtained by the two integration methods. Since the power spectra of intensities of

Table 2 R^2 values for the correlation between the subjective ratings and the mottle indices calculated using linear and logarithmic integrations of the weighted contrast terms in the mottle index calculation.

Sample Set	R^2 linear integration	R^2 log integration
Set A	0.46	0.70
Set B	0.88	0.92
Set C	0.83	0.84
Set D-Coated	0.75	0.78
Set D-Surface Sized	0.81	0.84

images often show that the amplitudes of the wave components are inversely proportional to the spatial frequency, Barten found appropriate to use an integration scheme to reflect this. The square root of the ratio of the MTFs of the image takes into account the non-linear behaviour of the eye response.

The SQRI expresses the display quality in units of just noticeable differences (JND) where 1 JND is defined as giving a 75% correct response in a two alternative forced choice experiment. This corresponds to a detection probability of 50%. Using a similar method, Carlson and Cohen [16] have determined that a difference of 1 JND is insignificant, a difference of 3 JNDs is significant, and a difference of 10 JNDs is substantial. For print quality, the hypothesis is that a print containing a higher number of JNDs (high SQRI) would rate worse in terms of quality than another one containing fewer JNDs. However, in some cases, the end user may still prefer a print with high SQRI if it presents another desirable property such as a very high print density for example.

Barten introduced the factor 1/ln2 in front of the integral expression using the assumption that the value of J would increase by 1 JND when the square root of $M(u)/M_t(u)$ would increase by 1 unit in a single spatial frequency channel with a width of a factor of 2 [17].

To obtain the mottle index, the SQRI was adapted for implementation for digitized images of prints. The proposed mottle index (MI) for a greyscale image measured at a resolution corresponding to pixel size Δx is:

$$MI = \frac{1}{\ln 2} \sum \frac{\sqrt{M^*(u) \cdot S(u)}}{u} \tag{2}$$

- $M^*(u)$ is the detected contrast of the image.

- S(u) is the contrast sensitivity function (CSF) of the human eye. S(u) is the inverse of the modulation threshold. See Equation (4)
- u is the spatial frequency in cycles/degree. It is a function of the viewing distance, vd and the image pixel size, Δx.

Using a detected modulation term M* instead of the raw modulation M differs from Barten's approach. The detailed expressions for each component of the index will be given below. In this method, only the suprathreshold contrasts are kept for each spatial frequency and then they are weighted by the CSF. S(u) is equivalent to $1/M_t(u)$, but was preferred because it conveys more the idea of the image contrast being filtered by the human visual system.

Raw modulation (contrast) of the image M

The data used to calculate the modulation term of Equation (2), comes from a digital image of the mottled print, and can be obtained using a camera, a scanner or a photo-sensor device. The reflected light intensity is measured and converted to a integer greyscale value that depends on the bit depth of the imaging device. For an 8-bit device, the greyscale ranges from 0–255. Depending on the configuration, the point to point intensities are obtained by rastering the sensor on the surface or if using a sensor array such as in a camera, all the intensities are collected at once for the surface of interest.

The greyscale image is then converted to physical reflectance values using a formula established by digitizing a series of uniform prints of known reflectance and calculating the best fit relation between the greyscale and reflectance. The reflectance of the calibration prints were measured independently using a reflectometer. The greyscale to reflectance conversion function is specific to each measurement device. The reflectance values are converted to luminance values assuming typical office lighting conditions.

The modulation of the image means the contrast of the image. As is discussed in the introduction, there is no definite expression for the contrast of an image containing randomly distributed grey levels. The contrast calculation in this study was adapted from Hess et al. [13].

$$M\,(m,n) = \frac{|FFT\,(L(i,j) - L_{avg})|}{L_{avg}} \tag{3}$$

$$L_{avg} = \frac{1}{XY}\sum_i \sum_j L(i,j) \tag{3–1}$$

- $L(i,j)$ is the luminance of pixel located at coordinates (i,j) on the image.
- m and n are matrix coordinates in Fourier space.
- L_{avg} is the average luminance of the image.

The Fourier approach to the calculation allows to obtain contrast values over the range of spatial frequencies contained in the image in one operation. This facilitates the required convolution operation with the contrast sensitivity function also defined in Fourier space.

Contrast sensitivity function (CSF)

The contrast sensitivity function S(u) is directly adapted from a physical model of the spatial contrast response of the human eye proposed by Barten [3].

$$S(u) = \frac{M_{opt}(u)}{k \cdot A \cdot (u) B(u)} \tag{4}$$

- $M_{opt}(u)$ is the optical modulation transfer function of the eye. It includes the behaviour of the eye lens, stray light from the optical media, diffusion in the retina, and the discrete structure of the receptor elements. See Equation (5)
- k is a dimensionless constant selected from fitted empirical results [3].
- A(u) is the spatial and temporal integration limit of the eye factor. See Equation (6)
- B(u) is the photon and neural noise factor. See Equation (7)

$$M_{opt}(u) = \exp(-\pi^2 \sigma^2 u^2) \tag{5}$$

$$\sigma = \sqrt{\sigma^2{}_0 + (C_{sph} \cdot d^3)^2} \tag{5–1}$$

$$d = 4.6 - 2.8 \tanh(0.2 \log(0.625 L_{agv})) \tag{5–2}$$

- σ is the radial standard deviation of the optical point-spread function.
- u is the spatial frequency. It is a function of the viewing distance, vd and the image pixel size, Δx.
- σ_0 is the value of σ at small pupil sizes and is derived from published empirical results [3].
- C_{sph} is a constant describing the spherical aberration effect [3].
- d is the pupil diameter from de Groot and Gebhard [24].
- L_{avg} is the average luminance of the image.

$$A(u) = \sqrt{\frac{2}{T}\left\{\left(\frac{1}{X_o}\right)^2 + \left(\frac{1}{X_e}\right)^2 + \left(\frac{u}{N_e}\right)^2\right\}^{½} \left\{\left(\frac{1}{Y_o}\right)^2 + \left(\frac{1}{X_e}\right)^2 + \left(\frac{u}{N_e}\right)^2\right\}^{½}} \tag{6}$$

- T is the integration time of the eye [3].
- (X_0, Y_0) is the angular size of the observed image.
- X_e is the maximum size over which the eye can integrate the information [3].
- N_e is the maximum number of cycles over which the eye can integrate the information [3].

$$B(u) = \sqrt{\left\{\frac{1}{\eta p Il} + \frac{\Phi_0}{(1 - F(u))^2}\right\}} \tag{7}$$

$$Il = \frac{\pi}{4} d^2 L_{avg} \tag{7–1}$$

$$F(u) = 1 - \sqrt{1 - \exp(-\frac{u^2}{u_0^2})} \tag{7–2}$$

- η is the total quantum efficiency of the eye photoreceptors derived from published empirical results [3].
- p is a constant derived from the spectral energy distribution of the light source [3].
- Il is the illuminance of the eye.
- d is the pupil diameter. See Equation (6–2).
- L_{avg} is the average luminance of the image. See Equation (4–1).
- Φ_0 is the neural noise density at high spatial frequencies [3].
- 1–F(u(m,n)) is the MTF of the lateral inhibition in the eye.
- u_0 is the spatial frequency below which attenuation of the contrast sensitivity takes place [3].

Since the CSF takes into account the luminance of the sample, the viewing distance, and the size and resolution of the image and weights the image contrast distribution for each spatial frequency of features of the image, it removes the need for the operator to make subjective choices of parameters for the mottle index calculation. Apart from the assumptions of Barten's model and that only low level vision phenomena are being modelled, the main operational assumptions of the proposed mottle index are the viewing distance and the luminance value for a perfectly white sample (R = 1). These two parameters can be easily varied in the software to look at their effect on specific results.

The approach proposed here is similar in concept to the one reported recently by Fahlcrantz [25], but differs in its implementation. Both approaches advocate the use of the contrast sensitivity function (CSF) of the HVS to weight the different spatial components of the variance of the reflectance of the print. The expression for CSF(u) used here is based on a physical model of the HVS that accounts for the effect of noise rather than a fit of experimental data which was also proposed by Barten [17] prior to the elaboration of his physical model. Fahlcrantz's approach is aimed at quantifying systematic mottle, and he includes several $f(\xi)$ fitting functions which were not required in this case because no digital prints were examined. Another difference is that Fahlcrantz's mottle estimate includes a texture parameter whereas the performance of the mottle index proposed here did not seem to be improved by the inclusion of a texture descriptor in its expression. As discussed in the text, the possibility of including a texture descriptor is not excluded if it would improve the performance of the mottle index. The main conceptual difference between the two models is that Fahlcrantz does the integration of the CSF-weighted variances before the square root, i.e. he considers that our non linear perception is to the global variance of the reflectance, whereas here the square root is applied before the integration, implying that the contrast at each spatial frequency is perceived differently. Both approaches outperformed "traditional" models, showing the pertinence of including some model of the human visual system, albeit simplified, into the quantification of print uniformity.

APPENDIX B

RESULTS AND OPTICAL PROPERTIES OF TESTED SAMPLES

Table 3 Uncoated woodfree fine papers – Set A

Sample	Proscale rating	% Accepted	Printed Gloss Avg. (%)	Printed Gloss S.D. (%)	Optical Density Avg.	Optical Density COV (%)	Mottle Index	Mottle Index S.E.
1T	10.1	100	9.5	0.7	1.30	0.98	286	19
3T	12.6	100	7.2	0.5	1.26	0.55	89	5
4T	5.5	40	10.4	1.0	1.32	1.07	467	25
6T	2.5	0	10.3	1.6	1.34	2.69	467	24
7T	6.6	65	7.6	0.9	1.31	1.01	375	22
8T	8.2	80	9.5	0.7	1.34	1.50	325	24
10T	10.6	85	5.8	0.4	1.24	1.10	197	15
11T	9.2	100	10.7	0.8	1.36	1.97	416	8
13T	8.2	70	8.1	0.5	1.32	1.68	219	20
14T	9.4	90	9.4	0.9	1.30	1.49	313	22
17T	5.4	35	8.5	0.8	1.31	1.39	479	42
18T	4.7	20	8.3	1.1	1.27	0.97	428	50
19T	10.4	90	6.1	0.4	1.23	0.97	205	13
21T	11.5	100	8.5	0.7	1.29	0.82	230	26
23T	11.6	100	7.3	0.8	1.28	1.07	170	12
24T	9.8	100	10.6	0.6	1.31	0.96	439	24
25T	2.7	0	11.3	2.0	1.32	2.47	458	36
26T	6.0	50	9.4	1.0	1.33	1.19	329	23
29T	13.2	100	7.0	0.3	1.29	0.97	102	14
30T	7.4	95	8.5	0.5	1.29	1.52	345	19

Table 4 Coated board samples – Set B

Sample	Description	Proscale Rating	% Accepted	Printed Gloss Avg. (%)	Printed Gloss S.D. (%)	Optical Density Avg.	Optical Density COV (%)	Mottle Index
19	Cover, 216 g/m^2	8.0	81	43.5	2.3	1.69	1.6	227
20	Cover, 216 g/m^2	7.6	94	48.8	2.0	1.68	0.6	276
21	Text, 88 g/m^2	5.2	25	19.3	1.5	1.50	2.0	357
22	Reply card, 159 g/m^2	2.2	6	15.3	1.4	1.57	1.4	687
23	Reply card, 159 g/m^2	2.9	6	16.8	0.9	1.65	0.9	580
24	Text, 88 g/m^2	5.7	69	38.5	2.4	1.51	1.1	258
25	Text, 148 g/m^2	7.3	81	43.2	2.4	1.63	0.6	259
26	Text, 88 g/m^2	6.1	63	35.2	2.5	1.52	0.9	331
27	Text, 148 g/m^2	5.2	38	23.8	2.0	1.57	1.1	393
28	Cover, 216 g/m^2	8.5	94	25.1	1.6	1.57	1.2	184
29	Cover, 270 g/m^2	8.7	94	39.0	2.5	1.60	0.7	139
30	Cover, 270 g/m^2	8.0	88	26.8	1.6	1.58	0.9	167
31	Text, 88 g/m^2	4.6	13	18.3	1.0	1.46	2.4	433

Table 5 Surface sized and dry finish (not surface sized) board samples – Set C

Sample	Description	Proscale Rating	% Accepted	Printed Gloss (%)	Optical Density	Optical Density COV (%)	Mottle Index	Mottle Index S.E.
1	White-top – uncoated	17.9	11	3.8	0.95	5.0	382	35
5	Solid – surface sized	50.6	100	7.0	1.15	7.0	125	23
6	Solid – surface sized	40.2	100	5.2	0.93	1.3	85	20
7	White-top – uncoated	11.8	0	3.9	0.90	1.9	613	38
8	Solid – uncoated	11.8	11	4.4	0.89	3.6	651	34
9	Solid – surface sized	3.4	0	3.8	0.79	5.8	809	34
10	White-top – uncoated	8.7	0	3.9	0.87	5.3	520	59
11	White-top – surf. sized	2.3	0	3.5	0.88	5.1	905	33
12	White-top – uncoated	2.4	0	3.6	0.90	8.6	900	72
17	White-top – surf. sized	17.4	11	3.1	0.95	3.0	513	100
18	White-top – surf. sized	26.9	22	5.5	0.98	2.5	357	85
19	White-top – surf. sized	19.6	11	5.0	0.97	2.9	519	62
20	White-top – surf. sized	18.8	11	4.4	0.94	3.7	582	39
21	White-top – surf. sized	16.1	11	4.2	0.94	3.5	639	98
22	White-top – surf. sized	11.8	11	3.9	0.90	4.2	777	64
23	White-top – surf. sized	11.9	11	3.2	0.85	3.3	776	56
24	White-top – surf. sized	22.2	22	3.5	0.92	2.9	452	8
25	White-top – surf. sized	20.6	11	3.4	0.91	4.1	480	69
26	White-top – surf. sized	15.1	11	3.1	0.90	1.5	730	34
27	White-top – surf. sized	40.2	89	8.0	1.00	1.5	169	15
28	White-top – surf. sized	38.8	89	10.2	1.02	1.9	339	53
29	White-top – surf. sized	12.8	11	3.1	0.90	3.1	810	36
30	White-top – uncoated	11.9	11	3.4	0.87	2.9	625	27
31	White-top – uncoated	14.7	11	3.0	0.91	2.9	572	37
32	White-top – uncoated	20.9	11	4.7	0.96	2.8	309	59
33	Solid – surface sized	44.8	100	6.4	0.97	1.6	97	18
35	White-top – surf. sized	29.8	33	4.7	0.97	3.2	321	47
37	White-top – surf. sized	25.3	22	4.6	0.98	2.2	295	59
38	Solid – surface sized	29.3	33	4.8	0.92	2.2	328	34
39	White-top – surf. sized	43.2	100	5.2	1.01	1.0	86	15
40	White-top – uncoated	17.5	11	3.5	0.96	2.1	479	42

Table 6 Coated and surface sized board samples – Set D

Sample	Description	Proscale Rating	% Accepted	Printed Gloss (%)	Optical Density	Optical Density, COV (%)	Mottle Index	Mottle Index S.E.
2	Solid – coated	47.7	100	43.1	1.40	1.3	667	113
3	Solid – coated	50.5	100	10.8	1.23	1.0	159	31
4	Solid – coated	47.2	100	49.4	1.39	1.8	578	79
5	Solid – surface sized	48.4	100	7.0	1.15	0.7	125	23
6	Solid – surface sized	30.5	44	5.2	0.93	1.2	85	20
9	Solid – surface sized	2.8	0	3.8	0.79	5.8	809	34
11	White-top – surf. sized	2.4	0	3.5	0.88	5.1	905	33
13	White-top – coated	45.5	100	33.6	1.37	1.3	544	91
14	White-top – coated	47.0	100	32.3	1.38	1.8	577	91
15	White-top – coated	38.3	78	38.4	1.35	2.1	950	65
16	White-top – coated	38.1	78	39.6	1.37	1.8	834	67
17	White-top – surf. sized	9.9	0	3.1	0.95	3.0	513	100
18	White-top – surf. sized	21.8	11	5.5	0.98	2.5	357	85
19	White-top – surf. sized	15.4	0	5.0	0.97	2.9	519	62
20	White-top – surf. sized	11.3	0	4.4	0.94	3.7	582	39
21	White-top – surf. sized	9.7	0	4.2	0.94	3.5	639	98
22	White-top – surf. sized	8.4	0	3.9	0.90	4.2	777	64
23	White-top – surf. sized	8.3	0	3.2	0.85	3.3	776	56
24	White-top – surf. sized	15.8	0	3.5	0.92	2.9	452	8
25	White-top – surf. sized	13.8	0	3.4	0.91	4.1	480	69
26	White-top – surf. sized	9.8	0	3.1	0.90	1.5	730	34
27	White-top – surf. sized	33.0	44	8.0	0.99	1.5	169	15
28	White-top – surf. sized	32.8	44	10.2	1.02	1.9	339	53
29	White-top – surf. sized	9.4	0	3.1	0.90	3.1	810	36
33	Solid – surface sized	36.9	78	6.4	0.97	1.6	97	18
34	Solid – coated	45.7	89	40.6	1.36	1.2	573	107
35	White-top – surf. sized	23.6	22	4.7	0.97	3.2	321	47
36	White-top – coated	40.9	89	19.9	1.33	1.8	818	132
37	White-top – surf. sized	21.0	0	4.6	0.98	2.2	295	59
38	Solid – surface sized	22.9	11	4.8	0.92	2.2	328	34
39	White-top – surf. sized	34.5	56	5.2	1.01	1.0	86	15

Transcription of Discussion

QUANTITATIVE MOTTLE MEASUREMENT BASED ON A PHYSICAL MODEL OF THE SPATIAL CONTRAST SENSITIVITY OF THE HUMAN VISUAL SYSTEM

Lyne M. Cormier

Pulp and Paper Research Institute of Canada (PAPRICAN), 570 Boulevard St-Jean, Pointe-Claire, Quebec, H9R 3J9, Canada

Peter Herdman Arjo Wiggins Ltd

I would like to ask two questions if I may, Mr Chairman. First of all, in Figure 3 page 1164 of the proceedings, there is a very interesting observation. It seems that in some papers the error bars for the human perception are very small, yet the instrumentation has got lot of spread and in other cases, you have got exactly the converse. Do you have any comment on that? For example, can we discuss point 430, 4.5 first?

Lyne Cormier

There is an easy explanation for this one. Remember that we measured four areas and took the average and standard deviation of these four ~2 *cm* x 2 *cm* areas. Now, I hope you agree that its position on the graph places it with the very mottled samples. Since the print is severely mottled, the people who ranked it could not but agree that it was mottled (hence the small error bar), okay and well, if the sample is very mottled you would expect a lot of variation within each 4 cm^2 area (high mottle index), and if some scales of mottle are very large, you can also expect variation of the mottle index of these areas (large error bar). So, this makes sense.

Discussion

Peter Herdman

Now for point 420, 9.5, you have got exactly the converse.

Lyne Cormier

Yes, and they (points 420, 9.5 and 440, 9.8) also do not fit on the regression line. Obviously, there is something going on there and I do not know what it is yet. The large error bars on the visual rating indicate that there are some mottle features that were not found disturbing by the judges who assigned the print a good rating whereas other judges noticed them and assigned a much lower rating. The small error bars on the mottle index indicate that the mottle texture is probably relatively uniform from one area to another even though the mottle index is high. We could refer to this as "uniform non-uniformity". This could explain why some judges liked this print even if there were different contrasts in it.

Patrice Mangin

What you are mentioning, Peter, is obviously something related to human perception of these phenomena.

Peter Herdman

Yes. The other thing that I would like to ask is in a completely separate area. I do not know how much of your supporting funding comes from people that make wallpaper or posters or something like this, but characteristically, these materials are viewed from much greater distances than 30 *cm*. Have you thought about the possibility of just having a 12 degree camera as the capture mechanism with standard illumination? Then you would have a sort of scale distance independence and could carry the test out at whatever viewing distance the end paper is going to be used.

Lyne Cormier

In the presentation I have only shown examples for 30 *cm*, but the model does allow you to input any viewing distance you want into the model; this is one of its distinguishing features. It will recalculate the spatial frequency of the mottle features in cycles per degree according to the viewing distance that is inputted. Of course, you have to select your acquisition size in relation to the end-use viewing distance if you want meaningful results. From an experimental point of view your suggestion is an interesting way of looking at it. Thank you.

Wolfgang Bauer Graz University of Technology

I think this graph (Figure 3 on page 1164) also illustrates very well the problem that industry people have with instrumentally measured mottle indices, because it shows on the one hand that visual evaluation of mottling is rather easy and when the mottling is poor and that everyone agrees in their visual judgment on that. On the other hand most industrial papers, especially the ones coming from one mill are in a rather narrow range regarding mottling-let us say somewhere between the range of 10 and 14 in the graph. Then it becomes difficult to differentiate only in this narrow range. Another issue is, of course, that the printing machine is not perfect and that you will get some variations in density and colour when printing the same paper at different printers and that will also give variations in the instrumental results. In visual judgement the human eye will just ignore those minor variations and will rate them rather similar regarding mottling.

I personally believe that what we can do with computer methods just does not really imitate the resolution of the human eye and the human perception of mottling or a poor printing result, since there are just too many variables influencing human perception.

Lyne Cormier

Yes, the thing with existing instruments is that they do the measurement, and some even allow the calculation for several mottle scales, but then they turn around and do a visual ranking and depending on what agrees better with the visual ranking for a specific sample set they use that number, *e.g.* the mottle in this case is pertinent between 1 and 3 *mm*. It works probably a lot of times when the mottle features happen to be in the same range but we wanted it to be as user-independent as possible.

When you look at the contrast sensitivity curve, we do detect a wide range of scales but our visual system does not assign the same weight to each, so I would be cautious with methods that totally exclude certain wavelengths. One thing that our method does not account for, since it is Fourier-based, is that sometimes you have one flagrant defect that just throws the whole rating off. I am working on a texture parameter to describe the spatial organisation of the mottle features which could be an aspect of a visual “disturbance factor”.

Discussion

The results reported for set B in the paper illustrate that with our method we can get very good discrimination of high quality prints. If set B samples were compared to the first sample set (set A in the paper) shown in the presentation, except for 2 samples maybe, they would probably all fit between 15 and 16 rating, but we can still differentiate them with the mottle index. I do not think the problem with instrumental mottle measurement today is a resolution problem as image capture systems can have sufficient resolution and MTF. I think it is more a question of integration of the captured information. The image processing performed by our visual system is a lot more complex than the simple image statistics that are usually performed by instruments and I am not even considering the other brain functions which make us decide if a particular bit of information is important to us or not.

Joseph Aspler PAPRICAN

Just a comment on that last question. The papers on that slide are all commercial, off the shelf papers. None were experimental. We had solicited them from a large number of North American Mills. They were printed at the Rochester Institute of Technology, which has a commercial press, but it is as controlled as any commercial press could possibly be.

Lyne Cormier

This was actually the first sample set we used when we started this mottling index work. The reason why we started this one was because the existing methods were not giving any valid results, and we were quite happy when we started obtaining regressions that made some sense.

Wolfgang Bauer Graz University of Technology

In response to Dr. Aspler's remark, I think that this is part of the problem because, in day-to-day printing practice, the printing machine is not controlled and therefore causes variations in density and color that will influence instrumental mottling values but not necessarily human perception. Of course I think that an instrumental judgment of mottle is needed for the industry, but there are a lot of further variables we have to consider when trying to imitate human perception. I wish you the very best for your further work and I hope that you will succeed.

Lyne Cormier

To address your comment that the printing machine is not perfect, I agree with you, but this is where a dependable instrumental mottle measurement would prove useful as you can do a lot more measurements and have some statistics to help you assess if the observed mottle is paper-related or press-related.

Patrice Mangin

Let us go back on the basics for a while. You used terminology which I liked very much. To carefully differentiate human perception or avoid controversy, you talk of "visually equivalent". Is it because the Contrast Sensitivity Function (CSF) does not allow for human perception or does CSF have some human perception component in the Barten approach?

Lyne Cormier

All the CSF does is tells you if you have 50% probability of detecting a feature of certain size and certain contrast. But what it does not tell you is, after you have detected it, will it visually "annoy" you?

Patrice Mangin

What about the high print density situation? The eye is linked to the brain and signal saturation might happen at high density and signal saturation might be a factor in explaining the two lines at low and high density. The eye may not be sensitive to the mottle at a high density. How do you account for that in your index?

Lyne Cormier

No, the CSF should account for that because it does account for the average print density, so sensitivity to mottle at higher print densities should be scaled. At the luminance levels corresponding to high print densities, there is no indication from the CSF that there would be signal saturation.

Patrice Mangin

However when you have two lines, it simply means that you have one print quality dimension that a judge sees but that is not considered in your print mottle index.

Lyne Cormier

I have to agree, and I think that the reason why I get these two lines (aside from the fact that they have different print densities) is that, visually, they have different textures and this is what the mottle index, as presented here, is not capturing.