The Influence of Image Content and Paper Grade on Quality Attributes Computed from Printed Natural Images

Raisa Halonen [1], Tuomas Leisti [2] and Pirkko Oittinen [1]
[1]Dept. of Media Technology, Helsinki Univ. of Technology, Espoo, Finland [2]Dept. of Psychology, Univ. of Helsinki, Helsinki, Finland

Abstract

Computation of quality from digital photographic images has been widely studied whereas research on quality computation from printed natural images has been scarce to date. This study was motivated by needs to develop characterization of the quality potential of paper for digital printing by electrophotography and ink-jet employing subjectively meaningful objective methods. The goal was to find whether commonly used algorithms of blur, noise, contrast and colorfulness are feasible for quality characterization within the range of variation originating from paper and to evaluate whether the performance of paper grades is dependent on image content type. According to the results, image content is highly important and the applicability of the algorithms is complicated by the role of noise in prints.

Introduction

The growth of on-demand and home printing has created new needs for paper producers to convey the quality potential of paper to end-users. In the past, paper was mainly purchased by professionals more concerned about technical issues than subjective quality preferences. The new situation requires that the quality potential is specified using metrics which are relevant to the end-user.

This study is a part of a project [1] which aims to develop a quality model and quality index for the visual quality of digitally printed natural images (photographs) from the paper standpoint. The work has analogy with efforts which are ongoing in the printer systems [2] and mobile camera (I3A) [3] communities from the respective perspectives.

The purpose of this study was to evaluate the feasibility of computing quality attributes from printed digitized images. So far flat test fields or sinusoidal patterns have been used for computation of quality. Flat fields or periodic patterns are not well suited to visual quality assessment and instead images of natural objects and scenes need to be used. As for influences on the syntactic level of image information, color, detail content and lack of artifacts such as noise on smooth image areas are known to be important. Images for quality evaluation are usually selected with these aspects in mind.

The literature about quality metrics determined from digital natural images is abundant. This paper focuses on the feasibility of extending computational quality metrics to the print context.

Methodology

Material

A series of samples was prepared to study the influence of image content and paper grade on the computed quality attributes as well as the subjective evaluations of the respective attributes. The test layout covering two A4 sheets included four natural images, three of which were used in this study (Fig. 1), as well as test fields. The image contents included typical content types such as objects with details (*cactus*), a human portrait (*man*) and a landscape (*lake*).

Variation in paper properties was achieved by selecting 36 different papers for the study. The selection consisted of 15 electrophotographic (EPG, numbered 1-15), 6 multipurpose (MP, 16-21) and 15 ink-jet (IJ, 22-36) papers. EPG papers and IJ papers were printed using their respective printing methods and MP papers with both methods. The variation in paper and print characteristics in the test series is presented in Table 1.

***Figure 1**. The different contents of the natural images used in the study.*

Table 1. The variation in paper and print characteristics in the test series.

Paper		Grammage (g/m^2)	Whiteness (%)	Brightness (%)	Opacity (%)	Fluorescence (%-units)	Permeability Bendtsen (ml/min)
EPG		91 – 274	107 – 161	90 – 101	92 – 100	24 – 73	0 – 213
MP		77 – 84	79 – 157	89 – 100	86 – 94	0 – 68	392 – 706
IJ		98 – 280	91 – 150	86 – 98	89 – 99	7 – 59	0 – 193
Paper / Print		Roughness PPS (µm)	Roughness Bendtsen (ml/min)	Paper Gloss (GU)	Print Gloss (Black, GU)	Print Density (Black, D)	Color Gamut (a*b*)
EPG		0.7 – 4.1	0 – 122	8.2 – 87	13– 53	1.55 – 1.80	7700 – 9000
MP	EPG	4.5 – 7.2	91 – 247	4.0 – 7.4	9.0 – 20	1.59 – 1.65	7500 – 8500
	IJ				0.6 – 0.9	1.09 – 1.18	5600 – 6300
IJ		0.6 – 5.7	0 – 270	2.2 – 96	0.1 – 88	1.32 – 2.11	8700 - 13800

Each sample was printed and digitized according to a distinct process, for details see [1]. The electrophotographic samples were printed with Xerox DC6060 (CMYK) and the ink-jet samples with Epson Stylus Pro 3800 (CMY, light C, light M, light K, light light K and photo K or matte K). On both devices, optimal print settings were chosen for each paper by identifying the print media type. Printer-specific algorithms were used for halftoning. DC6060 enabled also paper-specific calibrations, for which an X-Rite QuickCal densitometer was used. Paper-specific ICC profiles were determined for both devices in Profilemaker Pro 5.0.8. The profiling targets used were IT8.7-3 CMYK for DC6060 and TC9.18 RGB for Stylus Pro 3800. The targets were printed with i1_iO layout as the measurements were carried out with an Eye-One Pro spectrophotometer attached to an Eye-One iO table. With DC6060, ten copies were made to control the print-to-print variation. The ninth was chosen for further study. With Stylus Pro 3800, three copies were made and the one with the best overall quality was chosen.

The printed samples were digitized at 150 dpi and 48 bits with an Epson Perfection V750 Pro scanner, using the professional mode of Epson Scan software. Paper-type-specific ICC profiles were used following a clustering based on their optical properties. Six profiles were used for the electrophotographic samples and seven for the ink-jet samples. Profilemaker 5.0.8 and Scan Target 1.4 RGB were used for the profiling. The target for each paper type was printed on a chosen representative paper grade. Photoshop 7.0.1 or newer was used for printing, scanner profile assigning and CIELAB conversions. Fig. 2 presents magnified examples of typical digitized samples.

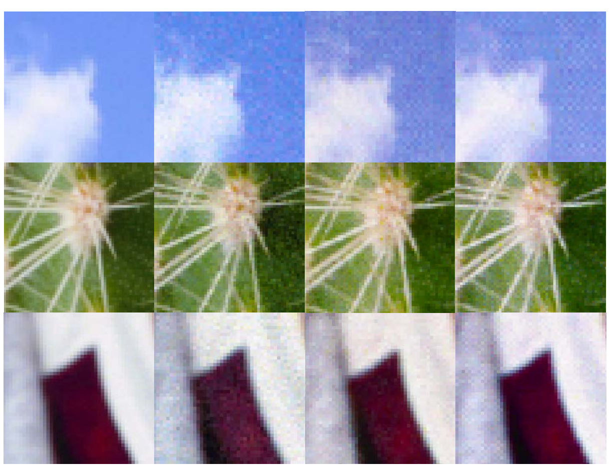

Figure 2*. Five-time magnifications of typical digitized images. Papers from left to right: 26 (IJ), 20 (MP, printed with IJ), 20 (printed with EPG) and 8 (EPG).*

Computation of Quality Attributes

The following algorithms were used in the study: Marziliano et al. [4] for blur, Immerkaer for noise [5], rms for contrast [6], and Hasler and Süsstrunk [7] for colorfulness. Blur, noise and contrast were computed from the L* channel of the CIELAB color space. Some observations of the special features of the print context were made during computation, especially concerning the blur and noise algorithms. These were related to the halftoning and paper structures.

The blur algorithm of Marziliano et al. detects the edges in an image by filtering (e.g. a vertical Sobel filter) and applying a given threshold. Edge maps (Fig. 3) reveal how the choice of the edge threshold is critical.

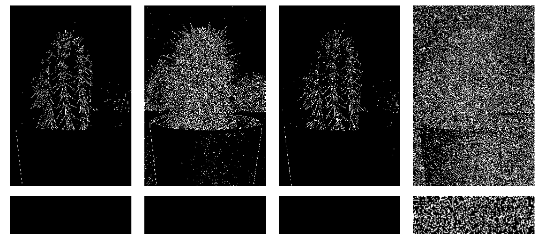

Figure 3*. Edge maps of digitized cactus images produced in the process of Sobel filtering the image. Papers and thresholds from left to right: 26 (IJ) with threshold 0.06 (L* channel scaled from 0 to 1 for computation), 26 with 0.006, 20 (EPG) with 0.06 and 20 with 0.006. Below each cactus edge map is an edge map of a digitized 50% gray test field from the same sample.*

Although a threshold of 0.06 has been successfully used with digital images [8], in this context it did not distinguish all relevant edges in the image. With 0.06 the cactus edge maps of paper 26 (IJ) and 20 (EPG) appeared rather similar and on neither paper the edge map of the 50% gray showed any edges. However, with 0.006, the algorithm produced a reasonable cactus edge map on 26 (IJ), but on 20 (EPG) it seemed to find nothing but noise as edges from both the cactus image and the 50% gray field. This problem has previously been pointed out i.e. in [9].

Noise maps are produced as the algorithm [5] filters off the real structure of the image. Reviewing the noise maps reflects the different types of noise produced by electrophotography and ink-jet. Whereas the noise in the ink-jet samples was point-form, the noise in the electrophotographic samples appeared as banding. The algorithm also seemed to have difficulties in distinguishing the image structure from the noise; in most cases image structure was seen in the noise maps.

Subjective Tests

The sharpness, graininess, colorfulness and contrast of the electrophotographic samples were evaluated in subjective tests. Observers (n = 29) were university students and naïve as regards to print and image quality. The tests were carried out in a laboratory covered with mid-gray curtains and tablecloths. The illumination on the evaluation table was 2200 lux and color temperature 6500 K. For easier handling, the randomly numbered images were attached to mid-gray frames.

The four attributes were evaluated as semantic differentials (e.g. blurry–sharp) on a questionnaire on a 5-point category scale (e.g. 1: clearly blurrier than sample set average, 2: slightly blurrier, 3: about the average, 4: slightly sharper, 5: clearly sharper). The samples of one image content at a time were placed on the table in a random order. The observer was asked to evaluate each sample on all attribute scales. Order of the contents was randomized and three versions of the questionnaire were used with different attribute orders.

Results and Discussion

The computational quality data is illustrated in Fig. 4 showing the attributes as a function of paper roughness. It is evident that the differences arising from the image content are prominent compared to the differences arising from the paper. The original images were characterized by different blur, noise, contrast and colorfulness values (computed at the same resolution as from the prints) and although printing on paper may lead to a considerable change in this, the plots remained distinct for the three images. Moreover, it can be observed that compared to the original images, the prints were more blurred and contrast was lower.

With increasing roughness, blur of the ink-jet prints decreased whereas blur computed from the electrophotographic prints remained almost unchanged. Noise of the electrophotographic prints had an unexpected trend of decreasing as roughness increased, whereas noise of the ink-jet prints showed an opposite trend. For both printing methods, contrast decreased expectedly as roughness increased. Colorfulness did not show any distinct trend on either of the printing methods.

One-way ANOVAs were performed to analyze the effect of image content and paper grade on the computed quality attributes. As expected based on Fig. 4, image content had a significant effect on all the four attributes (p being < 0.001 for all attributes) for both printing methods. Within the electrophotographic samples, paper grade had no effect on any of the attributes (p being 0.17 for noise and 1.00 for others). Within the ink-jet samples, paper grade had a significant effect on noise ($p = 0.05$), but again no effect on the other three attributes ($p = 1.00$ for all). These results underline the challenges raised by noise both within and between the two printing methods.

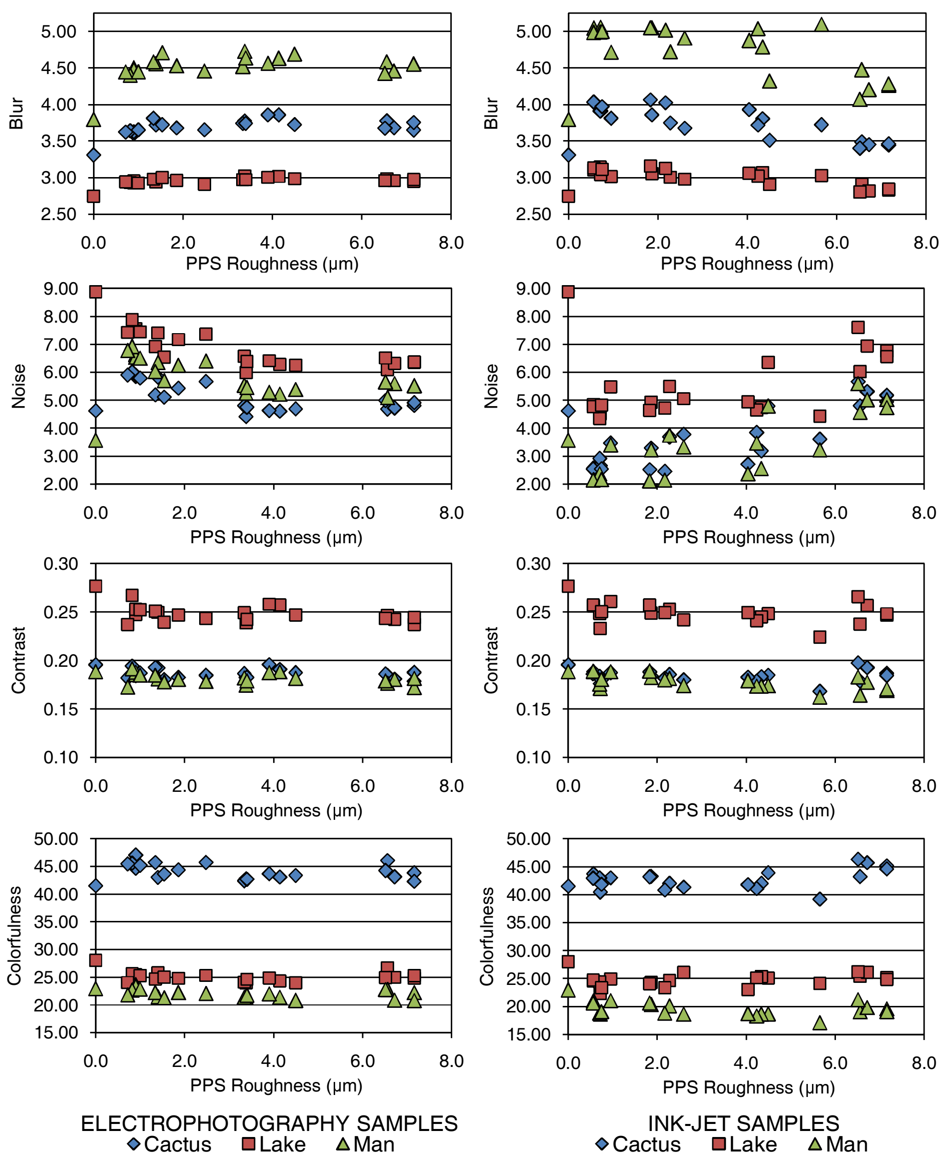

***Figure 4**. Computed quality attribute values as a function of PPS roughness: electrophotography samples on the left, ink-jet samples on the right. A roughness of 0.0 µm denotes the original digital image.*

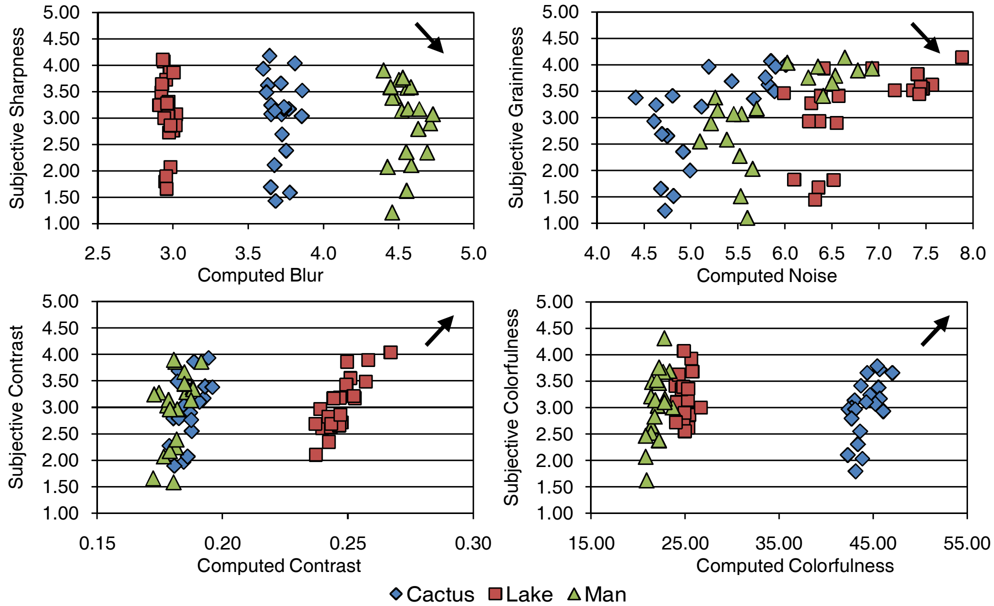

Figure 5*. Subjective quality attribute values of electrophotographic prints as a function of the corresponding computed values. On the subjective graininess scale 1 denotes grainy and 5 non-grainy. The arrow points to the expected direction of the trend.*

Fig. 5 illustrates the subjective quality attribute values against the corresponding computed values. Only the data on contrast and in part colorfulness follow the expected trend. No clear trends can be discerned in the cases of sharpness and graininess. As already noted above, for electrophotographic prints computed noise was lower on rougher papers. Subjectively, prints on these papers were considered to be grainier. Clearly the situation is rather complex.

A two-way repeated measures ANOVA was performed to analyze the effect of image content and paper grade on the subjective quality attribute values. Paper grade had a significant effect on each attribute ($p < 0.001$ for all attributes), whereas image content had statistically no effect on any of the attributes (p ranging from 0.18 to 0.92). This can be understood by the fact that the image contents were evaluated separately and the means and standard deviations were very similar for all three content types.

The interactions between image content and paper grade for each attribute were also analyzed. For contrast ($p = 0.001$) and colorfulness ($p < 0.001$), a significant interaction was found, whereas for sharpness ($p = 0.09$) and graininess ($p = 0.06$) the interaction was almost significant. This strongly implies that the performance of the papers varied depending on the image content.

Conclusions

The study was motivated by the need to develop measurement of four-color digital print quality from the standpoint of paper and end-user. The focus was on computation of quality from digitized photographic images printed on different kinds of paper by both electrophotography and ink-jet.

The results confirmed the high importance of the image content. Current practice is to use several images in the tests whereas the challenge for the future is to combine the relevant features in a single image. It was also found that as far as computational quality is concerned, the print context brings about many new, especially noise-related issues. These complicate the application of quality algorithms which have been developed for digital images. Finding optimal algorithms and tuning them for use on printed images requires further study.

References

[1] P. Oittinen, R. Halonen, A. Kokkonen, et al., Framework for modeling visual printed image quality from the paper perspective. Proc. SPIE 6808, 11 p. (2008).

[2] E.K. Zeise, D.R. Rasmussen, Y.S. Ng, et al., INCITS W1.1 development update: Appearance-based image quality standards for printers. Proc. SPIE 6808, 10 p. (2008).

[3] I3A, CPIQ Initiative Phase 1 White Paper, http://www.i3a.org/wp-content/uploads/2008/03/cpiq_white_paper.pdf

[4] P. Marziliano, F. Dufaux, S. Winkler, et al., A no-reference blur metric, Proc. ICIP, pg. 57-60. (2002).

[5] J. Immerkaer, "Fast noise variance estimation", Computer Vision and Understanding, 64, 2, pg. 300-302. (1996).

[6] E. Peli, "Contrast in complex images," Jour. Optical Society of America, 7, 10, pg. 2032-2040. (1990).

[7] D. Hasler & S. Süsstrunk, Measuring colourfulness in natural images, Proc. SPIE 5007, pg. 87-95. (2003).

[8] M. Malanin, The quality evaluation of digital images and an image agent -based approach to the selection of print images. M. Sc. Thesis. Helsinki University of Technology. Espoo, Finland. 77 p. (2006).

[9] F. Crete, T. Dolmiere, P. Ladret, et al., The blur effect: perception and estimation with a new no-reference perceptual blur metric. Proc. SPIE 6492, 11 p. (2007).

Main Author Biography

Raisa Halonen is completing her M.Sc. in Graphic Arts Technology at Helsinki University of Technology (TKK), Finland. Since 2006 she has worked as a research assistant in the Department of Media Technology at TKK in the research project DigiQ – Fusion of Digital and Visual Print Quality. Her work focuses on the determination of quality from printed natural images.