

Use of System Image Quality Models to Improve Product Design

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Abstract

At Eastman Kodak Company full-system image quality modeling has been regularly used in formulating business strategies, guiding design decisions, establishing product aims, budgeting system tolerances, and benchmarking products. Development of a general image quality model includes the following stages: (1) linking psychophysical responses and objective measurements to create attribute-specific predictive equations; (2) creating a mathematical method for predicting the combined effects of multiple image quality attributes; (3) building a capability model that predicts the output of systems operating under ideal conditions; (4) building a performance model that generates the complete frequency distribution of final image quality, including contributions from manufacturing, environmental, and customer-induced variability sources, and where possible (5) creating automated system design features that optimize the component specifications based on the predicted image quality. This paper will review specific examples where image quality models have been used to improve the design of conventional and digital systems.

Introduction

The paper, "Characterization and Prediction of Image Quality" [1], presented by B. W. Keelan, provides an overview of the research leading to the development of perceptually relevant image quality models. The utility of image quality models for guiding design decisions and budgeting system tolerances is greatly enhanced when a capability model that predicts the output of systems operating under ideal conditions is extended to a performance model that generates the complete frequency distribution of customer-perceived image quality, including contributions from manufacturing, environmental, and customer-induced variability sources.

Capability and Performance

The capability of a system is typically realized when all components in the imaging chain are operating near their design aim-points. To model the perfomance of a system, the process used to model capability is executed repeatedly, while varying the behavior of individual components in response to conditions representing the intended use of the product. The calculated value from each iteration is accumulated to create the complete frequency distribution of quality. In essence, each iteration represents an individual image that has been captured, processed (chemically or digitally), displayed, and rated for quality by a typical end-user.

Changes in imaging system characteristics may affect system capability, performance relative to capability, or both. The performance of a system is conveniently described by a cumulative distribution function (CDF) of quality. Figure 1 shows two such distributions. The x-axis is quality in JND (just noticeable difference) units [1], with higher quality to the right, and the y-axis cumulative frequency, i.e. the fraction of images having quality less than or equal to x. Better systems will plot farther to the right and will be more steeply sloped. The capability in JNDs may be read off as the x-value producing a high y-value (such as 0.99). The median quality in JNDs can be read off as the the x value corresponding to y = 0.5.

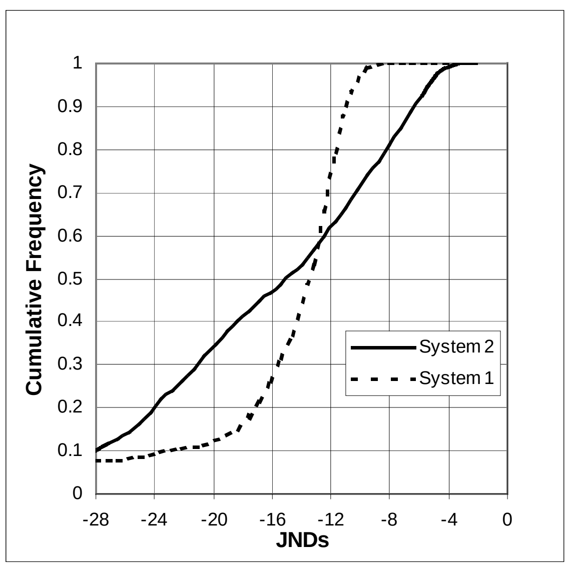

Figure 1: Cumulative image quality distributions

Figure 1 illustrates two systems that vary in both capability, and performance relative to capability, leading to crossing of the cumulative distribution functions. In this example, System 2 has improved lens MTF, but fewer autofocusing zones than System 1. The former leads to improved peak sharpness (higher capability), the latter to an increase in the number of images blurred due to suboptimal lens focus (lower performance). It is the combination of higher capability but lower performance relative to capability (slope) that leads to the curve crossing depicted in Fig. 1.

To the degree practical, all of the variability factors having a large effect on image quality should be included in the performance calculations. These variability factors often arise from sources beyond the control of the product designer that may be difficult to characterize. For example, we have found that a Monte Carlo technique sampling photomotivation space is needed to accurately mimic the results from consumer imaging systems. Photospace refers to the locations, light levels, and distances where photographers attempt to capture images. Because amateur photographers routinely disgregard product-specific guidelines and instructions, situations that challenge imaging systems are often encountered. To create photospace data from which valid performance simulations can be generated, images from specific customer segments must be carefully evaluated and collected over a long enough period to avoid short term and seasonal effects.

Similarly, as open systems consisting of components from many manufacturers are assembled by system integrators and customers, and the variety of rendering and output options increases, variability data from additional sources must be included in the performance modeling and design optimization process.

Product Design Examples

In the previous paper by B. W. Keelan [1], Fig. 6 illustrates the excellent agreement between image quality distributions predicted by models and measured from customer intercept data. Image quality models were used throughout the development of the Advanced Photo System [2] to ensure that component designs were capable of meeting the overall image quality goals, which were to produce print quality that was within one JND of 35-mm format at equal angular magnification (same subject size on print) and equal photospace coverage. With similar image quality and photospace coverage, the Advanced Photo System could then be distinguished based on its new features, which include drop-in loading, three print formats, smaller camera size, information exchange, negative return in film cassette, and mid-roll film change.

During the initial design stages, parametric equations and measured data from previous products and processes were used as inputs to the models. These initial analyses allowed designers to quickly evaluate competing design proposals. As test coatings and hardware prototypes became available, predictions were updated and design specifications were refined to ensure conformance with system quality goals. Image quality modeling played a key role in selecting the new film and print format sizes and evaluating proposed features such as pseudo zoom. Specifications for film design attributes, camera autofocusing and exposure control systems, camera and printer lens MTFs, and component positioning tolerances, were developed with the aid of system performance models.

The rest of this paper outlines cases where full-system capability and performance models have been used to evaluate and improve the design of conventional and digital imaging components and systems.

Figure 2 illustrates the use of photospace data to tailor camera designs for specific applications. In this example, the baseline camera design (Cam 1) is a compact 3X zoom model with automatic focusing and exposure control. The curve labeled “Cam 1: Normal” depicts the image quality distribution for this camera when capturing images at ISO 400 over standard customer photospace, which includes outdoor, indoor home, and indoor public building locations. The “Cam 1: Stadium” curve shows the quality distribution for the same system capturing images with the camera-to-subject distances and artificial lighting found in sports

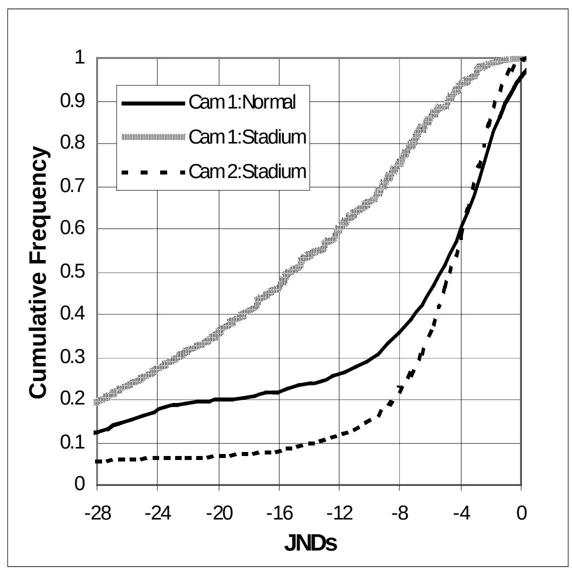

Figure 2: Optimization of camera design based on photospace

stadiums. The substantial drop in performance clearly demonstrates the inability of the baseline camera design to provide adequate photospace coverage in the more demanding stadium applications. The “Cam 2: Stadium” curve shows the image distribution for an improved design that features a 1.5 stop faster lens aperture and an improved camera shape that reduces camera motion during exposure, thereby permitting a 1-stop longer hand-held shutter time. The combination of these design changes provides significantly improved performance in sports stadiums and in areas of normal photospace (e.g., long distance flash shots) where the baseline camera produces low quality images. Figure 2 also shows systems with similar capability (peak quality) delivering very different performance levels.

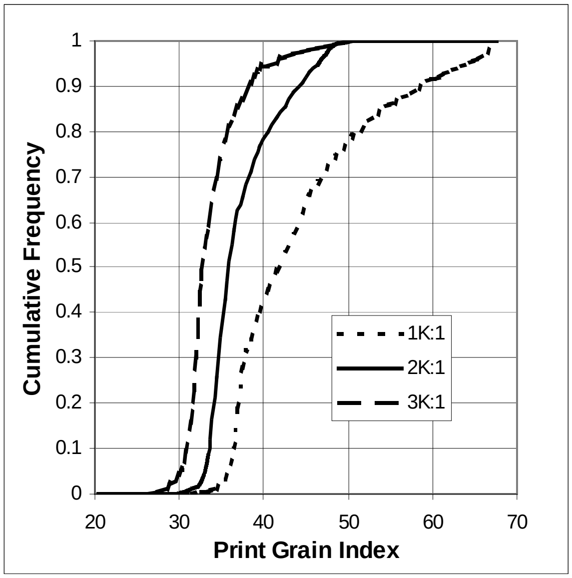

Figure 3: Assessment of scanner dynamic range: fixed exposure camera

Figures 3 and 4 demonstrate the importance of including appropriate customer exposure distributions, generated from representative photospace, when setting dynamic range aims for film scanners. In these examples, the x-axis is Print Grain Index [3], with higher quality to the left, and the y-axis is cumulative frequency.

Figure 3 shows the print grain resulting from both film granularity and scanner-induced noise for scanners with 1000:1, 2000:1, and 3000:1 dynamic ranges, when presented with the film exposure distribution from a fixed exposure point camera (same shutter time and f-number used for all scene light levels) exposing high speed film. These cameras are prone to overexposure when images of high illuminance scenes are captured. The film latitude is typically sufficient to produce good renditions of these scenes in traditional (optical) photofinishing channels. However, in digital printing systems, as film exposure level (dye density) increases, the scanner signal-to-noise ratio becomes less favorable for a larger portion of the original scene tones. The point where scanner noise begins to significantly degrade the image quality is reached sooner (at lower film exposure levels) with scanners having less dynamic range. In essence, film overexposure latitude increases with increasing scanner dynamic range.

Figure 4 includes results from the same film and scanners; however, in this example, a camera with automatic exposure control (shutter speed and f-number adjusted in response to scene light level) was employed. The camera exposure control system successfully eliminates the extremely high density (overexposed) images, thereby permitting all of the scanners to operate in a favorable signal-to-noise regime.

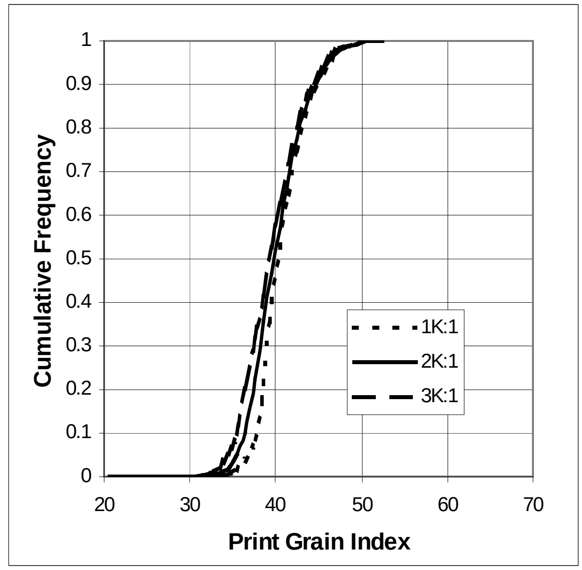

Figure 4: Assessment of scanner dynamic range: auto exposure camera

Figure 5 illustrates the number of digital still camera (DSC) pixels needed to produce high quality (capability) images for several print formats. The x-axis is CCD pixel count (millions) and the y-axis is quality due to image

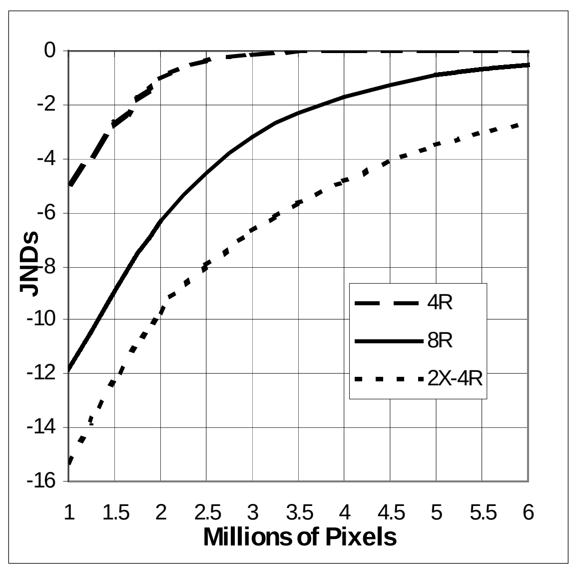

Figure 5: Determination of digital still camera pixel number requirements for various print sizes

sharpness in JND units, with higher quality at the top. The system includes a high-quality taking lens, DSC pixel fill-ratio of 0.7, birefringent blur filter, Bayer CFA (color filter array) with adaptive interpolation, spatial filtering, cubic convolution to achieve the number or pixels required for rendering, and a 300 DPI (dot-per-inch) printer. The three print formats are: 4 by 6 inch full-frame (4R curve), 8 by 10 inch full-frame (8R curve), and 4 by 6 inch crop from a 2X digital zoom (2X-4R curve). The results demonstrate the need for capturing more pixels when enlargements and prints from electronic zoom are generated. The 2X-4R case, although equal to the 8R case in pixels per-unit-area on the print, is more demanding, because the smaller (2X-4R) print is viewed at a shorter distance.

Figure 6 shows the effect of DSC sensor-to-lens positioning variablitiy (x-axis in mm units) on image quality (y-axis in JNDs). The modeled system features a DSC with a 3 million pixel CCD generating 8 by 10 inch prints, and includes components similar to those of Fig. 5. If the product image quality goal and the maximum aperture size have been specified (e.g., with an f/2.8 lens, all units will have imager positioning errors producing less than 2 JNDs of quality loss), the positioning error representing the limit is found by dropping a vertical line to the x-axis where the –2 JND line intersects the curve representing the specified f-number. Similarly, if the manufacturing process variability is known and not subject to modification, the fastest lens f-number meeting the quality goal, in the presence of the current positioning variablity, can be extracted from the plot.

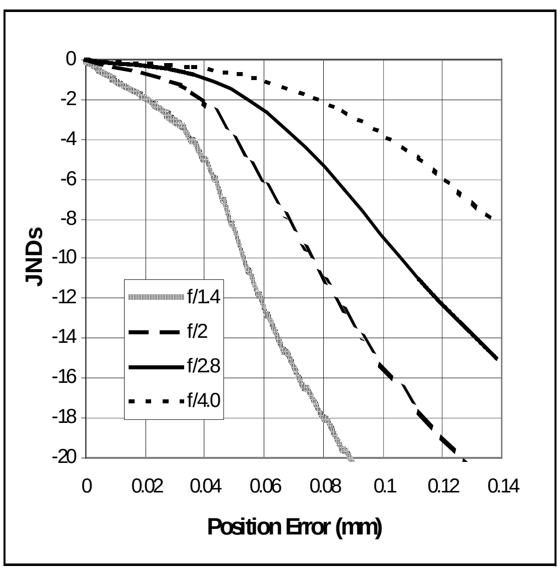

Figure 6: Determination of digital still camera optical positioning tolerances

Figure 7 illustrates the trade-off between sharpness and CFA artifacts when optimizing the spot spacing for a DSC anti-aliasing filter. The modeled system features a DSC with a 2 million pixel CCD, and includes features similar to those of Fig. 5. The "Sharpness:1" and the "Artifacts:1" curves

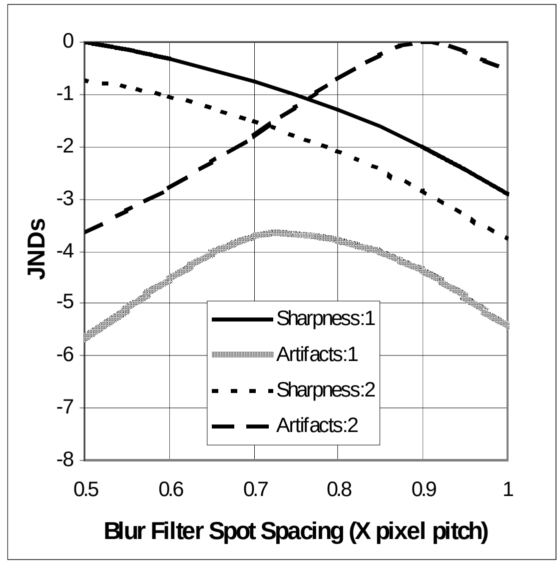

Figure 7: Selection of blur filter spot separation

show the JNDs of quality loss associated with blur filter spot separations from 0.5 to 1.0 times the CCD pixel pitch, when the CCD pixel fill-ratio is 0.5. The "Sharpness:2 and "Artifacts:2" curves show the same relationship for a CCD with a pixel fill-ratio of 1.0. In both cases, the CCD pixel pitch is the same; however, the DSC with a pixel fill-ratio of 0.5 exhibits better sharpness, but a greater propensity towards aliasing because of a smaller sampling window coupled with more inactive area between pixels. As blur filter spot separation increases, sharpness decreases (quality loss) and artifacts are reduced (quality gain). In the 0.5 fill-ratio case, a smaller spot separation provides optimal artifact control.

Figure 8 shows the multivariate relationship among sharpness, oversharpening artifacts, noise, and overall image quality, expressed as JNDs on the y-axis, in response to changes in unsharp masking response, expressed as spatial filter gain on the x-axis. In this example, the spatial filter gain was optimized for a 512 DPI output device producing 4 by 6 inch prints from high resolution input sources with low levels (-2 JNDs) of image noise present. As spatial filter gain is increased, sharpness increases; however, for this system, filter gains greater than about 2 begin to add undesireable oversharpening artifacts (e.g., harsh edges) to the image. In addition, noise is also amplified as spatial filter gain increases. Consequently, for this modeled system, the optimum balance between the attributes, as represented by the peak on the "Total Quality" curve, is achieved with a spatial filter gain of about 2.

Figure 9 illustrates another output device design consideration: the evaluation of scene rendering algorithms. Once again, the x-axis is quality in JND units, with higher quality to the right, and the y-axis is cumulative frequency; therefore, better systems will plot farther to the right and will be more steeply sloped. The "LAD" (large area density) curve depicts the image quality arising from typical printer setup and calibration in the trade combined with a simple automatic printer algorithm (no operator intervention) that classifies images and adjusts output color based on the average (full-field) color characteristics of each input image. The "SBA" (scene balance algorithm) curve shows the image quality distribution for an automatic rendering technique that analyzes the characteristics of individual image pixels and uses a series of predictors to classify the images and select appropriate printing conditions. The "Custom" curve illustrates the image quality that would be obtained for this population of images if an expert evaluated each image and implemented optimal printing conditions, thereby eliminating errors caused by calibration and scene classification. The fact that the "Custom" curve fails to produce an ideal image quality distribution simply reflects the fact that the modeled system exhibited problems in capture (e.g. misfocus, bad exposure) that are not fully correctable in the printing process.

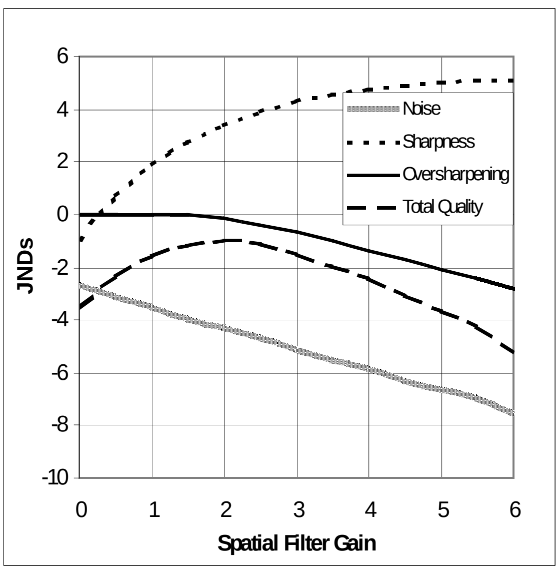

Figure 8: Selection of spatial filter gain

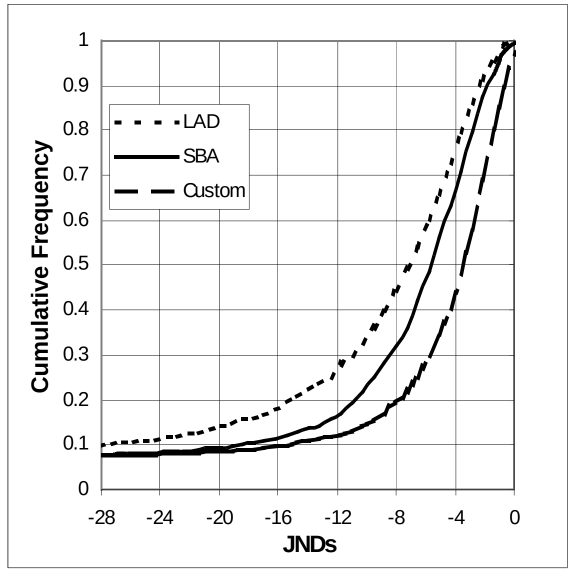

Figure 9: Evaluation of rendering algorithms

Conclusion

At Eastman Kodak Company, image quality modeling has proven to be of great value in formulating business strategies, guiding system design decisions, establishing product aims, budgeting system tolerances, and benchmarking competitive products.

References

1. B.W. Keelan, "Characterization and Prediction of Image Quality", this volume.
2. R.B. Wheeler, "Advanced Photo System: Integrated System Design Methodologies", Proceedings of the IS&T 49th Annual Conference, Minnesota, 1996.
3. Kodak Publication E-58, "Print Grain Index – Assessment of Print Graininess from Color Negative Films".