A Theory of Image Quality: The Image Quality Circle

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A theory of image quality, called the Image Quality Circle, is presented and described in detail. It includes many of the well recognized elements of image quality, but arranges them in a way that makes the subject of image quality both understandable and complete. This tutorial report provides a comprehensive description of the underlying assumptions and rationale of the theory. An organizational view of the Image Quality Circle is also provided to facilitate the establishment of image quality goals and specifications.

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Imaging Technology Perspective

The topic of image quality did not develop overnight. The notion of image quality has its genesis in the field of optics. Optics–as a science and technology–dates back to about 1200 BC with the invention of curved mirrors.[1] The invention of the optical microscope by Zacharis (1580–1638) and Hans Janssen, and telescope by Hans Lippershey (1570–1619) in the late sixteenth and early seventeenth centuries surely established the concept of a visual image.[2] But the images in those days were transient and unrecorded.

Permanent recording of images had to wait for the development of photography in the first half of the nineteenth century. Attempts at making permanent images started with Joseph Nicéphore Niepce in 1822, using a photopolymerization process. The first commercially successful imaging process was developed by Louis Jacques Mandé Daguerre in 1837. Photography, the two step negative–positive process we know today, is credited to William Henry Fox Talbot, who developed it during the period 1835 to 1845.[3]

Photography integrates two image forming processes. The first image forming process is performed by the lens, creating an image of a real world object on the light sensitive film. The second process is performed by the photographic film, recording the quantity of light falling on a particular location. Once these two steps are completed, the image has been formed, and exists as a latent image on the film. Then film developing and print making produce finished images.

The twentieth century brought the development of television and digital imaging. Demonstration of a complete television system by Philo Farnsworth on September 7, 1927 ushered in the age of electronic imaging.[4] Like the images in Lippershey's and Galileo's telescopes centuries earlier, live television images are transient. Photographic film was used to record images in the early days of television, before magnetic tape recording. In its day, the system for recording a television broadcast was perhaps the most complicated imaging system devised, comprising optics, photography and electronics.

The launch of the Sputnik satellite by the Soviet Union on October 4, 1957 lit the fuse on the race into space, and imaging probes have always been a principal component of space exploration. The first probes imaged the moon; later they were sent to outer planets of the solar system. These probes ushered in the age of digital imaging with both terrestrial and space applications.

Today digital imaging has progressed from expensive one-of-a-kind space applications to achieving widespread commercial importance, starting initially in diagnostic medical imaging and the prepress area of commercial printing. Digital imaging has been fully developed in the consumer, office and industrial sectors since the advent of the personal computer a little over 20 years ago.

Looking at the history of imaging technology, we see that image quality has not been at the top of the list of design criteria during the initial phases of technology development. The imaging system first had to "work" and record an image. Only after achieving successful image recording does image quality become a high priority.

The first image quality topic usually addressed by product developers is the rendering of tones that comprise the image, then the spatial structure or the image details. Finally, as an imaging technology develops, attention is focused on the color quality of the image.

Image Quality Today

Market studies consistently show that image quality is one of the top customer considerations in purchasing

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an imaging product, along with such purchase factors as cost. Achieving high image quality still requires substantial effort, even with so-called "mature" technologies. It is not a solved problem. There are several reasons why, after so many years, image quality remains such an elusive target.

The first reason is that the emphasis for the study of image quality, past and present, has been on so-called *objective image evaluation*, which involves physical measurement of images. Years ago this was a difficult task and required substantial investment in instruments called microdensitometers. A major goal of objective image evaluation is to make the connection between image quality and the imaging technology variables, but this has not been universally achieved. Present emphasis is on gathering extensive image measurements, and empirically exploring relationships among the measurements to elucidate predictors of image quality. Collecting vast amounts of image data is feasible today because the costs of instruments, specifically desktop scanners equivalent to the microdensitometers of old, are orders of magnitude less, and the measurement speed is far greater. These efforts have not yielded robust relationships between the physical image parameters and image quality because they generally fail to account for the characteristics of a human observer. Simply making more and more image measurements has not brought us closer to elucidating the underlying relationships.

Secondly, from a historical perspective, image quality has not gotten the attention of academics. The study of image quality today is a multidimensional, multidiscipline topic, driven by equipment and supplies manufacturers' product development efforts. As a scientific pursuit, image quality has few academic adherents. But this is changing with the traditional role of industrial research and development migrating into the universities.

Although the study of image quality is driven by manufacturers, an Image Science or Image Quality function rarely appears on a corporate organization chart, even when the corporation is principally in the imaging business. Making image quality happen is typically left to product development engineers, perhaps in concert with the marketing function. With no top level concern or assigned responsibility, it is no wonder that image quality sometimes falls between the organizational cracks. Worse yet is that, since we are all human observers, the easiest path is to bypass expensive and complicated image quality programs completely: we establish image quality by decree, with a statement such as, "I can tell if the image quality is good enough by looking at it."

Still another reason image quality is elusive is that a set of myths and mysteries surrounds collecting image quality and other attribute judgments from human customers. This process of collecting and analyzing judgments has been termed subjective image evaluation in the photographic industry, and is treated as a poor second cousin to objective image evaluation.

The prevailing myth is that, "humans can't be meters, so why should we even ask them?" This view is both unjustified and illogical. The science of psychometrics and psychometric scaling provide methods to make humans be reliable meters. In a very real sense, the customer is the ultimate "meter" when making the final purchase decision. (Of course, the buying decision is complicated by many non-image-related factors.)

A corollary to the myth about the inability of humans to perform as meters is the mystery of psychometric scaling itself. Since the origins of psychometrics are not in the physical sciences, they are categorized by some as "soft science," with the implication being that psychometrics are not "good enough" to be called real science. In fact, there is nothing "soft" about the science of psychometric scaling. Indeed, some of the greatest contributors to psychometric scaling started their careers as physical scientists. The reason for this "soft science" myth probably lies with the fact that the appropriate methods are not well known within the imaging community.

Finally, the lack of a unifying view of image quality has kept people from taking an organized and comprehensive approach to the discipline. Image quality was, and still is, a difficult topic to understand. For more than a half a century a plethora of terms described various components of image quality, but there was no theory or structured way to get a view of the "big picture."

An Image Quality Theory: The Image Quality Circle

This lack of a unified view of image quality has lead to confusion and chaos, which adds significant cost to the development of imaging products. In an attempt to bring some order to the existing chaos, an image quality theory was developed and first presented in 1988.[5] Initially it was described as the Four Way Approach, but it is now called The Image Quality Circle.

A theory is "a formulation of apparent relationships or underlying principles of certain observed phenomena which has been verified to some degree."[6] It is within this definition that the Image Quality Circle is put forth as a theory of image quality.

The Image Quality Circle (IQC) is a robust framework, or formulation, which organizes the multiplicity of ideas that constitute image quality. It also serves as a process model that can simplify and focus research, product development, marketing, and technology activities.

What's New?

The original comprehensive description of the Image Quality Circle was published in Ref. 11 in 2000. Since then, the IQC has undergone revision, clarification and expansion. This paper describes the updates to the original description, particularly in the areas of:

- image quality value
- image quality definition
- preference versus judgment
- image quality requirements and the image quality value
- common image quality practice and IQC diameters
- image quality models
- multidimensional aspects of attributes
- approach to image quality specification setting

The Image Quality Circle

Before describing the details of the Image Quality Circle, a few definitions are needed to establish a frame of reference for the terms *image* and *quality*. Not all of the definitions presented here are recognized by international standards bodies.

Image

In this article, the term image is used to mean a colorant arranged in a manner to convey "information" to a human observer. Colorant is used in its most general sense. It can be ink, plastic (toner), wax, dye, silver, phosphors, light emitters, and so on. The function of the image is to visually communicate information, which can be in the form of text, graphs, graphics, pictorial imagery, or even fine art. The idea of an image is very broad, and need not be a "hard copy" on a physical substrate. It can be a "soft copy" image on some form of electronic display, or any other appropriate medium.

Image Quality

So far as is known, there is no formal or *de facto* definition of image quality. Lacking an alternative, the following is proposed[7]: *Image Quality is the Integrated Perception of the Overall Degree of Excellence of an Image.* Image quality, as defined here, is not intended to describe the "fitness for purpose," or utility, the application of the image, the observers who view the image, the context of the image making process, or the component attributes that comprise image quality. Its thrust is how good does the image look in the sense of a "beauty contest," as the quality judgment has often been described.

The major, though not exclusive, focus of this image quality definition is commercial imaging systems or devices. There are other areas of imaging such as security, reconnaissance, and medical imaging, where the image quality focus is on detection and recognition. Detection and recognition typically require a different approach to image quality. Medical image quality, for example, is often evaluated with a different set of tools, such as signal detection theory.[8] Users of these systems nonetheless express their personal preferences, so "beauty contests" still come into play in the design and use of these systems.

There have been other proposed definitions for image quality. Janssen and Blommaert[9] have suggested "the quality of an image to be the degree to which the image is both useful and natural. The usefulness of an image [is defined] to be the precision of the visual representation of the image, and the naturalness of an image [is defined] as the degree of correspondence between the visual representation of the image and knowledge of reality as stored in memory."[9] This concept assigns to image quality two perceptual attributes: usefulness and naturalness. To use such a definition unnecessarily restricts the concept of image quality to two perceptual attributes or dimensions that may, in fact, be functions of other perceptual dimensions. With the Janssen and Blommaert definition, it is unclear where synthetic or abstract images fit in. For example, how does one characterize the quality of a synthetic image that is not at all "natural," but useful?

Keelan takes a different tack and proposes a definition that considers the image making context:[10] "The quality of an image is defined to be an impression of its merit or excellence, as perceived by an observer neither associated with the act of photography, nor closely involved with the subject matter depicted." According to this definition, image quality is not, apparently, in the eye of the photographer, the art director, the advertising executive, the producer, director, or a "soccer mom," to name just a few. Although Keelan makes an interesting case for his definition, the requirements that the observer be distant from the imaging or image making industry and not be involved with the subject of the image are needless and unrealistic complications.

Although the factors mentioned in some of the above definitions do indeed affect the judgment and preferences of image quality on an individual basis, the view taken with the Image Quality Circle is that these are factors to be controlled or understood in any image quality judgment situation. The variation in preferences or judgments according to observers groups is not unlike the concept of "market segmentation" that is used to group customers in market research studies. (More on this later.)

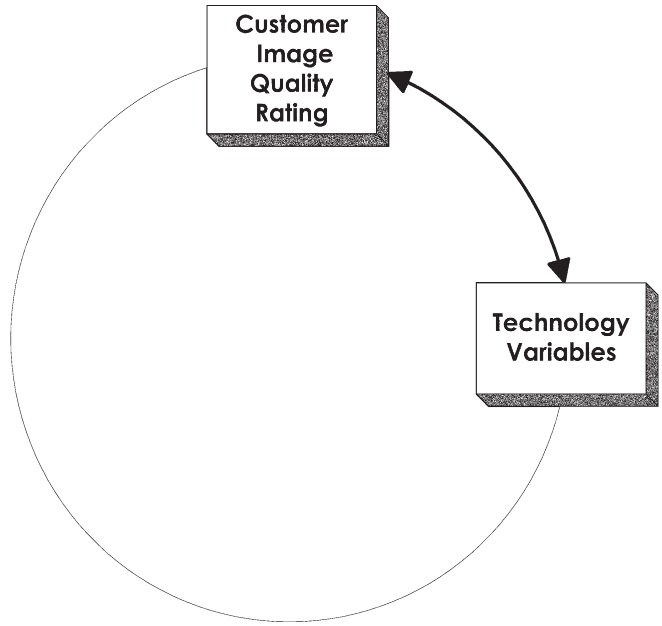

Figure 1. First two elements of the Image Quality Circle; Customer Image Quality Rating and Technology Variables.

Image Quality Circle Elements

The Image Quality Circle, then, is a process that connects the Customer Image Quality Rating, shown in the top box in Fig. 1, to the Technology Variables of the specific imaging system or technology, shown in the right hand box. In practice, the Image Quality Circle provides a structure for putting image quality into products.

Customer Image Quality Rating—The Image Quality Value

The Image Quality process begins with determining Customer Image Quality Rating. The Image Quality Circle element labeled Customer Image Quality Rating (Fig. 1) represents the judgment a customer renders for a sample image. In a typical judgment situation, a set of image samples is given to a human observer, usually a customer or customer surrogate, and the observer makes a judgment about image quality for each sample presented. This judgment process is repeated by a number of observers. Using appropriate psychometric methods, these judgments are used to construct a numerical scale of image quality.[11] This value represents the customer's judgment of image quality for the sample, and in the Image Quality Circle framework is independent of context, application and fitness for purpose. The underlying assumption is that the customers know image quality as a whole and, under appropriate conditions, they can express a judgment about it.

During the measurement of the Customer Image Quality Rating, it is essential to avoid tying explicit or implicit image applications to the image quality judgment, for a very good reason. A frame of reference or context constrains the image quality scale values to being valid only for that context or frame of reference. For example, suppose the market application of a product is for casual snapshots of the family. The usual approach is to ask customers for a response in context of the application; e.g., "Please express an image quality rating for these samples to be used as family snapshots." This context results in values on a scale of image quality for "use as family snapshots." A scale constrained in such a way would not be valid or useful for any other imaging application because the observers were instructed to consider only the stated application when the judgment was made.

Viewing image quality in an abstract or context-independent way is a departure from conventional wisdom. The main argument for this treatment is based upon the repeated empirical observation that experts and non-experts judge image quality similarly when the task is application-independent.[12] Performing the judgments in an application-independent environment lowers the confusion in understanding, interpreting, and using Image Quality Rating values. Put another way, this approach results in an image quality scale that is more "absolute."

The original embodiment of the Image Quality Circle used the phrase "Customer Quality Preference" for what is now called "Customer Image Quality Rating". The term "preference" caused confusion because it was an incorrect statement of what was intended. It is important for understanding the IQC concept to distinguish between a *judgment* (rating) of image quality, where we assume the observer is acting "objectively," and a *preference* for an image. These are two entirely different concepts that are often confused. Observers have opinions, preferences, about such things as acceptability, satisfaction, utility, and value. This theory focuses image quality judgments, rather than image quality preferences. When a researcher asks, "Which one do you prefer?" versus, "Which one has the higher image quality?" one would expect to get different values for the same set of samples. The first question asks the observer to express a preference, or opinion, while the second specifically asks for a judgment about the image quality. The concept of the IQC is based on a judgment, not on an opinion or preference. It is confusion between these two concepts that is at the root of the idea that different classes or groups of observers "see" image quality or the perceptual attributes differently.

There is general agreement that image quality requirements are contingent on the application or use of the image. However, if image quality scales are not designed to be context-independent, then a plethora of potentially confusing application-dependent scales will evolve. In such an environment, Customer Image Quality Ratings can never be stated emphatically, and decisions resulting from the use of the Image Quality Circle will always have application caveats associated with them. At first glance, the construct of a single judgment scale for image quality may seem too restricting and wholly impractical because it does not include the well known image quality dependencies. However, there is at least one method, the "overlay" method, that can be used to bring together both the important image quality application/opinion and the judgment (rating) parts. To generate the overlay, the customer/observer is asked to express application-specific preferences or opinions *after* making a judgment about image quality, or a "ness." Asking preference questions to a group of observers allows one to construct a cumulative histogram with the independent variable being the image quality rating and the dependant variable being the number of observers preferring a specific level of image quality.[13] This has an advantage of enabling an empirical probability statement about the preference of image quality scale values. As an example, suppose after asking an observer to make a judgment of image quality, say using the graphical rating scale method,[11] the observer is asked an opinion question. Such a question might be, "Indicate on the scale before you the minimum image quality level you would accept for family snapshots." From the observer responses one can construct an empirical curve of the fraction (%) of observers accepting at least the abscissa value of image quality versus image quality level. The x axis of this empirical curve is the image quality, or "ness" values determined from a suitable psychometric scaling study. The acceptable image quality value is on the same scale, and one can choose a criterion based on the percentage of customers who find the image quality of the samples "acceptable".

The point of the overlay is to enable one consistent image quality scale, which significantly reduces organizational confusion about image quality numbers. Since it is unlikely that the perception of images by humans will change in the short term, such an image quality scale should be reasonably stable if properly constructed. As the marketplace is dynamic and product improvements come at a rapid pace, the image quality scale may have to be extended into the high quality region. When that happens, one does not have to throw out the existing scale, one merely adds a portion at the higher quality end using suitable psychometric techniques.[11] The more dynamic parts of image quality, such as acceptance levels, applications, user segments, and all the other aspects that are driven by market conditions, can be relegated to a series of frequently changing overlays. As opposed to changing the scale itself, the overlay approach utilizes a stable image quality scale while relegating marketplace dynamics to ever changing points on the scale.

Technology Variables—The Things We Control

These are the items that are used to describe an imaging product, such as dots per inch or pixels per inch, image sensor megapixels, paper thickness, or the waterfastness of the image materials. The list of Technology Variables is almost endless. Imaging system technologists are in control of the Technology Variable list. Their primary function is to choose the set or sets of Technology Variables or parameters from the list that yields the required image quality. This is easier said than done.

The Simple Process

Especially in a field with some degree of complexity, newness or unfamiliarity, we tend to latch onto those aspects that are concrete. Technology Variables are very concrete. So are Physical Image Parameters (to be introduced below). We measure them because they are measurable. We change technology variables because we can. The process implied by Fig. 1 is never-ending. Change Technology Variables. Make samples. Have customers give image quality judgments. Manipulate Technology Variables. Make new samples. Get more customer judgments. There must be a better way!

Among the obvious advantages of using the "make changes–make samples–collect judgments" workflow implied in Fig. 1, are that the process is intuitive and simple. It can be quickly implemented, and customer feedback is direct.

On the other hand, there are several disadvantages. It is an expensive process that, in principle, never stops. Conducting studies of this kind often requires the services of a market research firm to organize the study, recruit (sometimes for a fee) study participants, and write or present the results. It is rare today that prod-

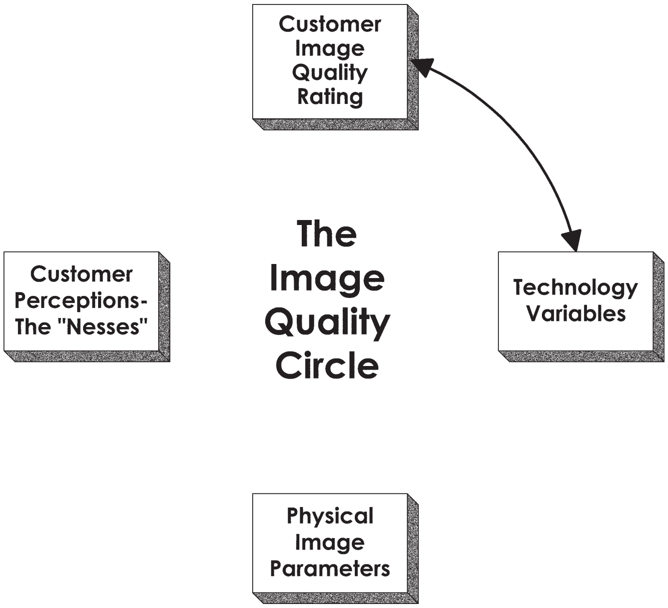

Figure 2. The four basic elements of the Image Quality Circle: Customer Image Quality Rating, Technology Variables, Physical Image Parameters, and Customer Perceptions–The "Nesses".

uct design cycle times permit even one of these types of studies. In short, the simple process is expensive in both time and resources, and never-ending.

The "make changes–make samples–collect judgments" process is only useful for the technology variables that are changed to produce the samples. Of course, technology variables have their highest uncertainty during the early stages of imaging product development. At best, studies conducted during this phase of the development process are snapshots of limited longevity. Tomorrow's new technology advance will almost certainly raise questions on the usefulness and validity of today's image quality study.

Results from the simple process apply only to the imaging technology tested. The customer quality judgment is explicitly tied to the samples that were judged by the customer. Many technology variables contribute to image quality in complex, little-understood ways. Only at some very global level is it reasonable to develop generalizations about technology variables. As we develop the Image Quality Circle, it should become clear that customers do not judge image quality on technology variables at all.

Although the simple process is quick and it gives fast results, it does not contribute in an organized way to understanding the overall image quality issues of the product or technology over the long run. To be sure, conducting repeated customer studies on image quality will increase overall knowledge about both technology variables and customer preferences. However, it is highly unlikely that these studies by themselves help one understand the components of image quality or help one proceed on a path to the robust image quality prediction and specification.

To address the longer term, both in terms of understanding and prediction, and to provide a comprehensive framework for image quality, two additional elements need to be added to the Image Quality Circle. These additional elements are Customer Perceptions and Physical Image Parameters (Fig. 2).

Customer Perceptions—The "Nesses"

Customer Perceptions are the perceptual attributes, mostly visual, that form the basis of the quality preference or judgment by the customer. A *percept* is a sensation or impression received by the mind through our senses.[6] An *attribute* is a characteristic of the image.[6] So a *perceptual attribute*, or "ness," is a characteristic of an image that we sense (see). Most visual perceptual attributes associated with imaging end with the suffix "ness," so this is the telltale clue. Some examples are sharpness, graininess, colorfulness, lightness, and brightness. Although visual percepts will often be used as examples, the Image Quality Circle is not restricted in this way. There are other important imaging-system-related perceptual attributes that are not visual. One common example related to tactile perceptual attributes, "nesses," is the "quality" of the substrate upon which image are printed. A higher thickness substrate is often judged to have higher quality than a lower thickness substrate.

In this article, "ness" is used as a shorthand notation to mean some perceptual attribute, to emphasize the connection to human perception, and to distinguish a Customer Perception from a Physical Image Parameter.

Understanding Customer Perceptions is a key to understanding the Image Quality Circle. Customers or observers do not make image quality judgments on Technology Variables or Physical Image Parameters per se, as many technologists believe. Instead, observers make a quality judgment, or express a preference for a particular image, based on what they see–the "nesses." This idea is a major departure from the conventional wisdom in many areas of imaging. By constructing a theory of image quality in this way, one can start to understand why many traditional physical measures of image quality often lack robustness. Specifically, if the physical measure captures the "ness" adequately in most situations, i.e. it is robust, then it will be a good predictor of a component of image quality. But few popular Physical Image Parameters adequately measure a "ness," and therefore few are acceptable predictors of image quality.

Although we use the shorthand term "ness" to characterize the Customer Perceptions, not all Customer Perceptions end in "ness." There are some perceptual attributes in imaging that are more complex, such as "tone reproduction." Also, in color imaging, we have the percepts of "hue" and "chroma." For clarity in identifying Customer Perceptions, the suffix "ness" will sometimes be attached to such traditional terms. In all likelihood, nowhere but in this paper will the reader encounter "hue-ness," which we use to describe the perceptual attribute of color, denoted by words such as blue, green, red, and yellow.

No single "ness" completely encompasses the idea of image quality, since we define image quality as the *integrated* perception of image excellence. However, it may happen that a given set of images may have only one "ness" that varies, so when customers are asked to judge the quality of such a set, they will typically respond on the basis of that "ness" varying in the image set. In such cases, one must not be drawn to the erroneous conclusion that a specific "ness" constitutes image quality. A large number of "nesses" are generally possible in any image set. Fortunately, only a small number of them vary in typical images, and it is this small set of Customer Perceptions that drives the judgment of image quality.[14–17]

Again we see that establishing a scale, or "ruler," for the "nesses" requires human judgments and thus the application of psychometric scaling. When the objective is to generate a scale of a specific "ness," it is absolutely imperative to ask the observer to make a judgment of the "ness." This is no place for the question "Which do you prefer?" and calling the resulting scale a "ness" scale. Although this may seem obvious, it is an all too common occurrence in the imaging literature.

Physical Image Parameters

Physical Image Parameters (PIPs) are quantitative and usually obtained by physically measuring the image with instruments or computations on an image file. These are the most widely recognized and used "image quality measures." Physical image parameters have historically been called *objective* measures of image quality. Typical of such measures, or parameters, are optical density or spectral reflectance factor. More complex, both in terms of description and measurement, are functions of spatial frequency such as modulation transfer, Wiener spectra, or amplitude spectra.

Physical Image Parameters can be any measurable aspect of an image or even an image file. They can be single values, functions of spatial position x, y, or functions of wavelength, or even functions of functions. There is no limit except that they be physical and measurable. Imaging scientists do not want for PIPs. There is a plethora of them in the scientific literature, and specific embodiments can be found in international standards, so further elaboration is unnecessary.

In the IQC concept, the PIPs are not direct measures of image quality, but just stepping-stones on the way. Again, this is a departure from the conventional view of the role of PIPs in image quality measurement and prediction. In Fig. 2 we note that Physical Image Parameters are diametrically opposite Customer Image Quality Ratings. The very configuration of the Image Quality Circle implies that Physical Image Parameters are not "close" measures of image quality, and in fact, they are not.

Image Quality Circle Connecting Links

To complete the Image Quality Circle we need the connecting links, (see Fig. 3) which allow us to move back and forth between elements of the circle, and allow movement around the circle. Moving around the circle is exactly analogous to performing a system design or trade-off analysis. Generally, the question is something like, "What set of Technology Variables do we need to yield X image quality in our product?" To answer the question one would proceed counterclockwise around the Image Quality Circle starting with the Customer Image Quality Rating. On the other hand what if the question was something like, "How does increasing the Z Technology Variable by 100% affect our image quality?" The approach then would be to start at the Technology Variables element and go clockwise around the Image Quality Circle. Using the Image Quality Circle in these two directions is illustrated by the use of two-headed arrows in Fig. 3.

The three connecting links are represented in Fig. 3 as ellipses, and are as important as the other elements of the IQC depicted by the boxes. We shall start the connecting link descriptions, commencing at the System/Image Models and going clockwise around the Image Quality Circle.

System/Image Models

System/Image Models, sometimes referred to as image models, are formulas, physical models, algorithms, or computer code that connect the Physical Image Parameters and the Technology Variables. The System/Image Model that connects Technology Variables and Physical Image Parameters is a computation or prediction. In one sense, the input is a Technology Variable and the output is a Physical Image Parameter. The double arrow indicates that these models can be used in both directions. Conceptually, inputs to and outputs from the System/Image Models depend on which way one is traveling around the circle. Traveling in a clockwise direction, the Technology Variables are the inputs and the Physical Image Parameters are the outputs. Traversing in a counterclockwise direction exchanges the inputs and outputs. In practice, these directional variations would almost always require at least pairs of system or image models each having inputs and outputs dependent on the direction of travel around the IQC. This general pairs requirement will be true for all the connecting links of the Image Quality Circle.

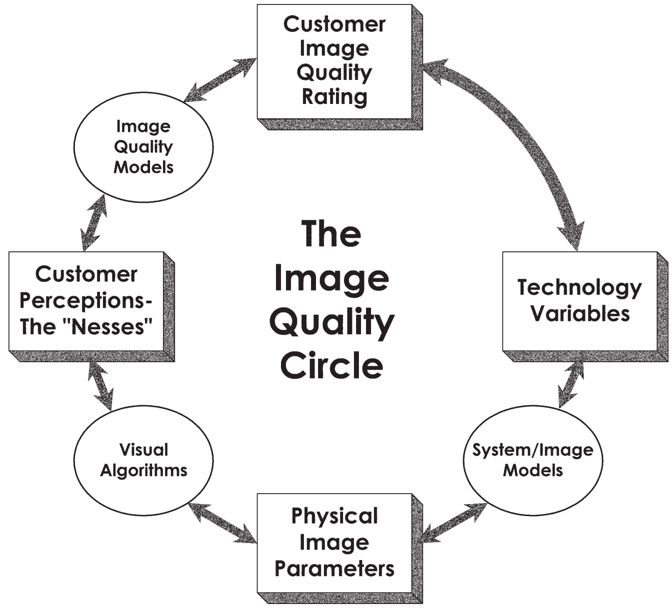

Figure 3. The complete Image Quality Circle with the three connecting links: System/Image Models, Visual Algorithms, and Image Quality Models.

No constraints are put on System/Image Models other than that they provide the linkage between the Physical Image Parameters and the Technology Variables. In some cases, a System/Image Model is simply a measurement. Pragmatic engineers and scientists often use models that relate just a few critical Technical Variables to a few critical Physical Image Parameters. The relationships can be purely empirical, like a multivariate equation developed via regression analysis, or one based on fundamental detailed image physics.[18]

Typically, in the early stages of an imaging technology development, there are no models at all. Rather, they tend to evolve over time, which makes building System/Image Models a long term process. An example of a simple long term objective of the System/Image Model connecting link might be the capability of predicting or computing the measured spectral radiance factor (color) of an arbitrary image point.

Placing the System/Image Models in this part of the image quality process is a break with past conceptualizations. Previous arrangements have used system or image models to directly predict "nesses" or image quality, a difficult and all-encompassing requirement. The underlying motive for this new construct is to avoid placing such restrictions on the model. Requiring these System/Image Models to predict or compute only Physical Image Parameters instead of image quality or "nesses" simplifies the System/Image Models, increases their modularity and portability, and increases the success rate.

Visual Algorithms

Visual Algorithms connect Physical Image Parameters to Customer Perceptions. Like System/Image Models, these algorithms can be formulas, models, or computer code, recipes that are used to compute a value of a "ness", e.g., sharpness, from a physical image measurement. An example might be computing sharpness from the gradient of an edge image. Visually based algorithms have an extensive history in photographic image quality, and in recent years, their use has been extended to digital imaging.

Robust Visual Algorithms must include at least two fundamental properties of the human visual system: the nonlinear response to light (luminance), and bandpass-like spatial frequency properties. See Wandell[19] for a modern view of visual science that relates directly to visual algorithms.

There are a few internationally standardized visual algorithms. In the field of color science, the definition of CIE lightness is a visual algorithm in the context of the Image Quality Circle. The CIE[20] definition of lightness is, for $Y/Y_n < 0.008856$, given by: $L^* = 116(Y/Y_n)^{1/3} - 16$, where Y is the CIE luminance or Y tristimulus value and Y_n is the Y value of the reference white. In this example, the Visual Algorithm connects Physical Image Parameters to Customer Perceptions in two steps. First comes the calculation of Y from the spectral radiance, transmittance or reflectance properties of the image, which would include the light source of the viewing illuminant for reflectance or transmittance images (Physical Image Parameters). Then, lightness (L^*) is calculated from Y and Y_n, using the CIE defining equation.[20]

In the CIE L*a*b* system of color coordinates, there are other visual algorithms for "chroma-ness" (chroma, C^*) and "hue-ness angle" (hue angle, h_{ab}).[20] The Physical Image Parameter—the spectral reflectance, transmittance or radiance property of the colored object/image—is the same for these "nesses."

Color "nesses" are practical examples of the many-to-one mapping characteristic of the clockwise rotation around the Image Quality Circle. (More on this later.) When moving clockwise from Physical Image Parameters to Customer Perceptions, the "many" are the spectral properties at thirty or more wavelengths (reflectance factor, for example), and the "one" (three really) are the lightness, "hue-ness" and "chroma-ness" perceptual attributes. The complete CIE colorimetric system has its roots in psychophysical scaling to specify the color stimulus that is not unlike the "nesses." See Fairchild[21] for a comprehensive view of color and color appearance.

Some "nesses" have to do with the spatial structure of images, e.g., the variation in nominally uniform areas called "uniformity-ness." A well known subset of "uniformity-ness" is graininess. Developing a successful visual algorithm for graininess would require the incorporation of the spatial frequency, the nonlinearity, and color vision properties of the human visual system.[22]

Visual Algorithms are not unique to the Image Quality Circle concept. Examples of visual algorithms can be found in the areas of computational vision, visual processing, and human visual models. See Watson[23] and Landy and Movshon[24] for surveys on computational vision and visual information processing.

Image Quality Models

Image Quality Models link Customer Perceptions, the "nesses," with Customer Image Quality Ratings. The image quality model inputs are values of "nesses," and the output is the Customer Image Quality Value. This is the ultimate destination in the many-to-one mapping process of the Image Quality Circle: a one-number summary description of image quality.

The purpose and function of an image quality model (IQM) is to predict the image quality judgment (rating) from the value of the "nesses" in the image. At a very basic level, we are all familiar with this process. We take in "information" from the world around us via our senses, and make decisions based on that information. This is an active research topic in psychology and psychophysics, and is termed information integration[25,26] or multidimensional psychophysics.[27]

The multidimensional aspect of image quality is, in our context, the "nesses" or dimensions that drive the image quality judgment. In the psychology literature, models like the Image Quality Model describe here are termed, variously, composition rule,[27] combination rule,[26] and integration model[25] for multidimensional stimuli. Some authors have identified two different types of combination rules.[26] They distinguish between a stimulus rule and a perceptual rule. The image quality model, which is a combination of "nesses" or percepts, constitutes a perceptual model (rule). More traditional model-building attempts using Physical Image Parameters to predict image quality would be categorized as a stimulus models (rules).

Attributes of image quality, the "nesses," are either integral or separable. Integral dimensions, or "nesses," occur when two dimensions together are perceived as new dimension or percept.[26] Separable dimensions are perceived the same when in combination with other dimensions. Image quality, *per se*, is probably an integral dimension, like color. However, the "nesses" used in successful image quality models are more than likely separable.

There is little in the psychological literature to provide a theoretical substrate from which to formalize an approach to image quality models. The most useful approaches have been developed by the imaging community itself.

A taxonomy of image quality models has been proposed by Engeldrum.[7] Image quality judgments can be made with respect to a reference, which may be explicit, such as a reference image, or implicit, such as a standardized image system. Image processing schemes typically use as a reference the image before processing. Examples of non-reference processes include photography and electrophotography.

Many physically based image quality models have been developed using linear and polynomial regression models on linear or logarithmically transformed variables. The independent variables used in these models have often been the Physical Image Parameters (stimulus models or rules). These have been reported to be useful to various degrees.[28–31]

The impairment method, proposed and developed by Allnatt[32] and colleagues, is an image quality model widely used in the television, digital image compression and encoding arenas. This model is embodied in ITU

Recommendation BT.500.[33] The starting point is a reference image where the observer rates the impairment to the image due to various factors. These impairments are additive (or subtractive) in their effect on overall picture quality.[34]

A variation on the impairment theme, developed by Miyahara, Kotani and colleagues,[35,36] uses distortion factors and principal component and multiple regression analyses to construct a picture quality scale. The distortion factors, which incorporate some characteristics of the human visual system, are developed from the difference image, representing before-and-after processing.

By far the most successful "ness"-based image quality models used in photography, printing, and CRT displays are power models that use Minkowski-like distance metrics. The use of Minkowski metrics has its roots in multidimensional scaling,[37,38] where it is used as a distance measure. As far as can be determined, the first successful application of the Minkowski-like metric, or power model, to multi-attribute image quality model building was by Bartleson in 1982.[16]

A distance interpretation of the Minkowski-like model is widely promoted. However, under many practical conditions, the exponent in the IQM is negative, which violates the positivity requirement for a distance metric.[16,17] In these situations, which depend on whether the "ness" scales are positive ("goodness") attribute scales or negative ("badness") attribute scales, the distance interpretation is not strictly correct. A reciprocal transformation of the independent "nesses," which makes the exponent positive, can restore the distance metric. This model formalism can be generalized and cast as a generalized weighted mean hypothesis (GWMH),[17] suggesting that observers take some form of "ness" average when evaluating image quality.

The application of the "ness"-based power model has been successful in both image impairment modeling and image quality modeling. Some "nesses" incorporated into successful image quality models include graininess and sharpness,[16,39] defect-ness, sharpness, and color accuracy-ness,[17] blurriness and raster ripple in image coding impairment.[40–43]

There are several reasons for the success of the power model form. First, two "nesses" of fundamental importance in photographic and other imaging technologies are graininess (uniformity-ness) and sharpness. It appears that these two "nesses" or dimensions are separable and are represented in "ness space" as two orthogonal axes. Separability of "nesses" increases the prospects of "finding" a useful power model form. The success of Bartleson[16] using the power model form may have been serendipitous. Although it appears that many of the ubiquitous "nesses" found in imaging are separable, no specific experiments in support of this assumption can be found in the literature.

The second reason for the success of the power model form is that the form tends to mimic the tendency of observers to "peak pick;" i.e., they focus on the worst (or best) "ness" to support their image quality judgment. The magnitude of the exponent in these models tends to capture this aspect of human image quality judgments. In the psychology literature, considerable effort has been focused on two different power metrics, the "city block metric," or linear model, and the Euclidean metric. The only difference between these two, from the view of the mathematical formalism, is the value of the exponent. The exponent is unity for the city block and two for the Euclidean. In fact, one can make an argument that if the range of "nesses" in the sample set is small, then a linear model will result.[17] Thus it is quite possible that the exponent value in these power models is some function of the range of "nesses" in the sample set. An example of such a case is described by Keelan.[10b] He proposed that the exponent, power, be a logistic function of the most extreme attribute value. Using this approach, and a common psychometric scale for all attributes, he was able to account for image quality values across four different experiments.

Another reason for the success of power models is that in the studies reported to date, the "nesses" or range of "nesses" have tended to be monotonic with image quality. "Nesses" are not always monotonic, and it was fortunate that these early studies conformed to this condition. Engeldrum[12a] has extended these functional forms to include such "nesses" where more of the "ness" does not always mean more judged image quality.

Building image quality models is an empirical endeavor that combines scales, or rulers, of both image quality and the "nesses." The models are statistically derived, but the mathematical formalism underlying successful image quality models attempts to capture characteristics of human judgments, so image quality models need not be blind exercises in regression analysis.[17]

What can be particularly valuable and efficient about image quality models, in the Image Quality Circle framework, is that most of the model construction relies entirely on psychometric scaling studies. Thus, investments in infrastructure are minimal, compared to the considerable resources required for the measurement of Physical Image Parameters and Technology Variables.

The details of image quality modeling are complex and beyond the scope of this paper. But for some starting points, see Sawyer,[15] Bartleson,[16] Engeldrum,[17] Higgins,[28] and Hunt.[29] For a more general view on how humans perform when asked to make integrated judgments like image quality judgments, see Massaro and Friedman[25] and Baird.[27]

Image Quality Circle Shortcuts

Two Image Quality Circle shortcuts can be constructed by following a diameter instead of the circumference. One short cut connects Customer Image Quality Rating to Physical Image Parameters, while the other connects the Technology Variables to the Customer Perceptions. Neither of these two popular diameter paths is generally recommended.

The image science and image processing/compression literature describes many attempts to develop measures of image quality by taking these shortcuts. The popularity of the shortcuts rests on the widely held idea that some general mean-squared-difference measure between the reference image or system and the processed image is adequate to describe the Customer Image Quality Rating or "ness." In some cases shortcuts that have "worked" are often found to be feeble when either the Physical Image Parameters or Technology Variables associated with the imaging technology change. In the workable shortcuts, the image quality measure probably included a suitable Visual Algorithm that has captured the relevant "ness." Often, the use of these shortcuts will be unsuccessful because the fundamental attributes and properties of the human visual system have not been taken into account—via Visual Algorithms, or via the "nesses" that are the components of image quality.

There are some exceptions to this no-shortcuts rule—

in the quality assurance function of a manufacturing environment, for example. If all the components and the connecting links of the Image Quality Circle are known, then the set and values of Physical Image Parameters yielding the desired value of image quality are also known. With all the factors known, the quality assurance function can be performed at the Physical Image Parameter level, say, instead of the Customer Perception level. Thus the evaluation of image quality components, the Physical Image Parameters, can be highly automated. Other possibilities, no doubt, exist.

The Many-to-One and One-to-Many Problem

At a global level, starting at Technology Variables and going around the Image Quality Circle clockwise, there are many variables to choose from that will result in one image quality rating–many-to-one. Starting at Customer Image Quality Rating and going counterclockwise around the IQC is a one-to-many process. For any given imaging technology, the product development process is a constant winnowing of the number of parameters, when traversing the IQC clockwise. This process of continuous reduction has not been as clear in previous conceptions of image quality. A conventional view is that image quality is specified by a fixed set of parameters, functions, and technology variables. The set depends on where you are on the IQC, and where you are going. Here we have a significant clue as to why image quality has been a very difficult problem; it is neither linear, nor simple, nor one-to-one.

At the philosophical, practical, and organizational levels, one needs to come to grips with all the implications of managing a many-to-one and a one-to-many process. Of course, we are in a much better position now than a decade ago to deal with many-to-one and one-to-many problems computationally, but the foundation upon which to build the "house of image quality" is not at all complete.

Psychometric Scaling and the Image Quality Circle

If one accepts that humans participating in psychometric scaling studies *become* measuring tools, then a much more thorough understanding about how to use technology to satisfy customer needs will develop, if for no other reason than the discipline of having to think of products in human terms. But the principal benefit of integrating psychometric scaling into a product development process is not derived from generating an array of "ness" or image quality scales. Rather, one develops command over image quality underpinnings and develops the ability to *predict* image quality.

Roughly one-half of the Image Quality Circle, from Visual Algorithms to the Customer Image Quality Rating, require human judgments. Without some means for obtaining measurements from actual customers or customer surrogates, we cannot determine numerically the Customer Image Quality Rating, the Customer Perceptions, or develop Image Quality Models or Visual Algorithms. In short, we have an incomplete Image Quality Circle unless human observers are involved. Thus, psychometric scaling is an absolutely essential tool for implementing the Image Quality Circle.

Many of the key "nesses" associated with imaging have been with us for almost a century. These have been largely viewed as unidimensional "nesses." But there seem to be no studies confirming their perceptual or psychological dimensionality. They have served us well, but it is becoming increasingly clear that there is more to the story of these "nesses."

The most useful tool set for determining dimensions is Multidimensional Scaling (MDS). This is both a curse and an opportunity. The curse is to choose an appropriate technique from the plethora of available and ever-increasing MDS methods.[38,44–46] The opportunity, of course, is to acquire a more complete understanding of imaging "nesses," of which we know very little. Market researchers have been the pioneers in the MDS area, and there are a great number of tools (computer programs, models, etc.) from which to choose. There are very few reports of using MDS to probe image quality and its component "nesses." By and large, when MDS has been used in an image quality context, researchers have explored image quality dimensions for a specific set of samples, but have not addressed such basic questions as the dimensionality of the "nesses." As an example, the "save" command for JPEG, the most widely used image compression method, offers the user a single image quality value from which to choose. However, JPEG is recognized to generate more than one "ness" as the compression parameters are varied. Some researchers have show that there are two perceptual dimensions, but they have not been identified or named.[23] This is but one example, and clearly more work needs to be done to enhance our understanding of the multidimensional nature of both image quality and its components, particularly in the area of image processing.

Image Quality Goals and Specifications

Designing and building an imaging product without image quality goals and specifications is both time consuming and costly. The process of specification development needs to be *managed*. The Image Quality Circle can serve as a tool to help clarify the organizational efforts needed to identify and understand the key items supporting the development of an image quality specification. The complete IQC needs to be in constant view, of course, but the overall goal- and specification-setting task can be broken into smaller pieces associated with the four elements of the Circle.

Who is responsible for establishing image quality goals and specifications? There is often tension between the part of the organization that interacts with customers and the part that has the primary responsibility for making the product. The Image Quality Circle provides an opportunity to make clear boundaries regarding image quality goals and specifications.

One approach to using the IQC to organize the goal- and specification-setting process places responsibility for image quality and "nesses" with market research function, and assigns technology variables to the system architects.

The customer interface to the organization is represented by market research and sometimes the marketing function. Their role is to set an image quality specification in terms of the Customer Image Quality Rating, and the Customer Perceptions. This is Image Quality Specification Level 1, as shown in Fig. 4. Market researchers determine and specify the value of image quality–the Customer Image Quality Rating. Market researchers also decide which Customer Perceptions or "nesses" are important, and level of "nesses" to target.

From this Level 1 Image Quality Specification, other groups of the organization develop the set of Technology Variables that become the Image Quality Specifica-

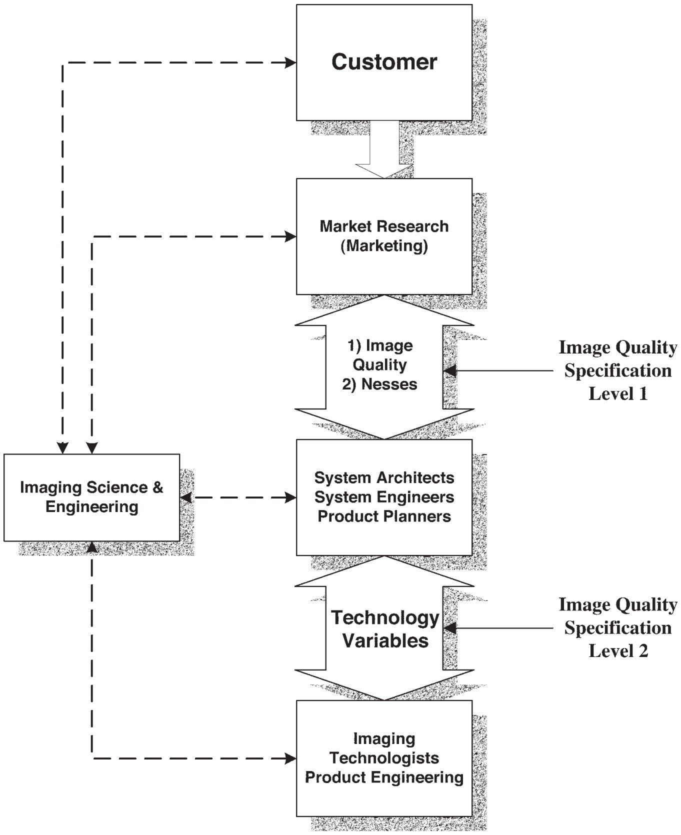

Figure 4. Image quality goal and specification process flow diagram.

tion Level 2. As indicated in Fig. 4, these groups are variously called system architects, system engineers, and product planners. System architects determine the values of Technology Variables needed to deliver both the overall image quality and "ness" levels. In terms of the IQC, the organizational interface between the two specification levels is the Customer Perceptions. Figure 4 illustrates, in an organizational context, how this might be done. The double-headed arrows in Fig. 4 indicate that there is a two-way information flow, or negotiation, between the relevant responsible groups.

The organizational box labeled "Imaging Science and Engineering" is set outside the main goal and specification process path for one simple reason. The function and skill set of Imaging Science and Engineering enables it to span all elements of the Image Quality Circle as it interacts with various groups addressing the specification-setting task. It works with market research in Image Quality Model building, identifying "nesses," and developing psychometric scales. It helps develop Visual Algorithms, provides tools for Physical Image Parameters, and builds System/Image Models in concert with imaging technologists and product engineering.

In the approach presented here, the Imaging Science and Engineering organization "owns" the Image Quality Circle. Where such Imaging Science and Engineering organizations exist, the group has traditionally been relegated to the role of "image quality cop." A big disadvantage of such an assignment is that the group is put in a somewhat negative role, which can create needless tension and decrease the overall productivity of the product development team. Long experience recommends that the Imaging Science and Engineering organization take an active leadership role in the product development process. Since its inherent span of skills connects most of the key components of the IQC, it is an obvious choice to provide the image quality process "glue." Success can be achieved by contributing expertise and guidance at many points along the path, rather than merely making image quality proclamations after all is said and done.

This description of an organizational structure for image quality goal- and specification-setting is necessarily brief, but it is provided as an example of applying the Image Quality Circle to this ever-challenging problem. There are, no doubt, other processes and organizational configurations that will achieve the same objective.

Summary

The theory of image quality called the Image Quality Circle provides an arrangement of many well known elements of image quality into a useful configuration.

Both in its configuration and in underlying assumptions, the Image Quality Circle deviates from conventional views of image quality. Two key concepts underlying the Image Quality Circle are: 1) customer image quality ratings are independent of application, and, 2) image quality is a function of the perceptual attributes, the "nesses," and not the Physical Image Parameters. Applications and other preference questions are treated as overlays to the basic image quality scale.

The Image Quality Circle adds new insights into existing image quality practices, via diametrical IQC paths and the arrangement of its major elements, and offers new approaches to achieving cost effective image quality in products.

An organizational view of the Image Quality Circle is also provided to facilitate the establishment of image quality goals and specifications, and promote the long term understanding of image quality.

Acknowledgment. One does not sit down one day and immediately write down a theory of image quality. It was a problem of extreme interest from my earliest professional days. As a design engineer for many years, image quality was a daily practical problem that was, to me at least, virtually intractable. Some ideas for the Image Quality Circle took root early, but it was not at all a complete picture. Things started to come more clearly into focus during my tenure at a major imaging company. At that time, I had the good fortune to work with a group of colleagues who provided an intellectually stimulating environment. For this, I am greatly indebted to the main cast of characters including: Ron Antos, Peter Burns, Roger Dooley, Bruce Martin Levine, Roland Porth, and Rodney Shaw.

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