

Digital Image Quality Assessment Based on Standard Normal Deviation

Hyung-Ju Park

Culture Technology Research Institute
Chung-Ang University, Seoul, 156-756, South Korea

Dong-Hwan Har

School of Integrative Engineering
Chung-Ang University, Seoul, 156-756, South Korea

ABSTRACT

We propose a new method that specifies objective image quality factors by evaluating an image quality measurement model using random images. In other words, No-Reference variables are used to evaluate the quality of an original image without using any reference for comparison. 1000 portrait images were collected from a web gallery with votes constituting over 30 recommendation values. The bottom-up data collecting process was used to calculate the following image quality factors: total range, average, standard deviation, normalized distribution, z-score, preference percentage. A final grade is awarded out of 100 points, and this method ranks and grades the final estimated image quality preference in terms of total image quality factors. The results of the proposed image quality evaluation model consist of the specific dynamic range, skin tone R, G, B, L, A, B, and RSC contrast. We can present the total for the expected preference points as the average of the objective image qualities. Our proposed image quality evaluation model can measure the preferences for an actual image using a statistical analysis. The results indicate that this is a practical image quality measurement model that can extract a subject's preferred image quality.

Key words: Image Quality, Preference, Objective, Subjective.

1. INTRODUCTION

Recently, topics related to the evaluation of image aesthetic quality have received considerable attention [1]-[5]. In these existing works, color, composition, and other general features of an image are analyzed to represent the aesthetic quality of the image. Most of the existing works evaluate the overall aesthetic quality of an image, no matter whether it is indoor or outdoor, whether it is a portrait picture or a natural scene, or whether it is taken by a professional or a common consumer [6]. Instead of using global features extracted from the entire image, Luo and Tang evaluate the photo quality by focusing on the main subject [5]. Their subject-based method achieves significantly better performance in quality classification than that of [3]. This result confirms an intuition that different parts of an image have unequal effects on people's perception of the image quality. Psychology research in perception also confirms that certain kinds of content will do more than others to attract the eyes, either because we have learned to expect more information from them or because they appeal to our emotions or desires [6]. Since massive digital

images are produced by diverse media, image consumers are increased radically. In other words, we need to objectively assess image quality in between different mediums. Recently there are tendencies to focus on studies concerned to automatic image quality evaluation in terms of visually higher aesthetic aspect. And also, diverse automatic image quality measurement programs are developed [5]-[12]. These researches in early stage evaluated the overall quality of an image, but current tendency of researches instead of using global features extracted from the entire image, evaluate the photo quality by focusing on the main subject. Their subject-based method achieves significantly better performance in quality classification than that of [13]. This result confirms an intuition that different parts of an image have unequal effects on people's perception of the image quality [3], [5], [14]. Fig. 1 shows the diagram of delivery process on image quality evaluation by consumers.

* Corresponding author, Email: igotitu@cau.ac.kr

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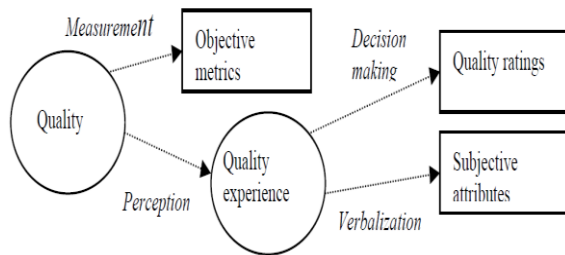


Fig. 1. Simple illustration of the information available about image quality (in rectangles) and the image quality aspects typically studied (in ovals) [5].

Engeldrum introduced The Complete Image Quality Circle and it defined the objective image quality composing factors, physically controlling parameters, and recognition of consumers' image quality. Throughout those factors, consumers can make a decision of the final preference of image quality [15]. In the modeling process, each variable is connected to the final image quality decision and it has the strong correlation between them. Also, Research has shown that images elicit different emotional responses in individuals, often linked to the subject matter, depicted objects or scenes contained within the image [14], [16]. It is also known that aesthetically pleasing images must follow certain design principles, which many artists consider universal. The growing field of computational aesthetics is focusing on revealing or applying these principles toward the analysis of visual and photographic art, music and other media [21]. At the same time, new multidisciplinary scientific fields such as neuro-aesthetics are studying brain mechanisms involved in appreciation and emotional reaction to art. Understanding how aesthetic responses to images can be modeled for use within the field of computational aesthetics [15].

Therefore, the purpose of this research is to empirically examine the factors that affect to digital image quality preference. Moreover, this study specifies the objective image quality factors in a certain image. We gather 1000 images and specify ten groups into figure's ratio of 10% (0~10%, 11~20%, 21~30%, 31~40%, 41~50%, 51~60%, 61~70%, 71~80%, 81~90%, 90~100%). According to the bottom-up method data collection, we extract the data's maximum and minimum values and calculate total range, average, standard deviation, and normal distribution. Based on those results, we convert into a percentage of a certain image's preference measurement from the normal distribution (z-value analysis). Image quality measurement is carried out Image Quality Assessment ver.1.0 program developed by our research. It measures the final estimated image quality preference based on a grade on a scale of one hundred points; dynamic range, color, and contrast. In other words, proposed image quality measurement program in this research can assess and be numbered the real image sample preference. Throughout the result, we can introduce practical research, specify the consumer's preferred image quality range and estimate its preference.

2. PROPOSED APPROACH

Recently diverse media produce fast-growing digital images; therefore image consumers are increased rapidly. Related researches are based on the objective quality and subjective contents of image quality. In this research, in order to specify the objective image quality factors of an actually preferred image, we propose a new method to evaluate image quality measurement model with using random images. In other words, as using No-Reference (NR) variables, we evaluate the original image quality without any comparison reference. We choose dynamic range, color, and contrast which can be related to physical image quality factor and cognitive image quality measurement. For image data collecting, we selected 1000 portrait images from the web gallery voted over 30 recommendation numbers. With the bottom-up data collecting process, we calculated the image quality factors total range, average, standard deviation, normalized distribution, z-score, preference percentage, and making a grade out of 100 points. It ranks and grades the final estimated image quality preference in terms of total image quality factors. We referred the previous researches in the introduction which cannot deal with the synthesized automatic program based on consumer's image quality preference as the objective image quality factors or the subjective image quality evaluation. Also, current researches show the independent aspect to measure image quality in terms of the objective and the subjective evaluation. For example, standardized test environment and target are used in the objective image quality measurement test; otherwise real images are used for measuring preference in the subjective image quality evaluation. Therefore, it is hard to analyze correlation between the objective and subjective image quality assessment. In this research, we specify the objective evaluation factor range of consumer's preferred image quality and measure the real image evaluation, not a target measurement. With the real image as variables, image quality measurement methods are divided into three ways in Table 1.

Table 1. Method of image quality assessment [10]

Items	Contents
Full-Reference (FR)	FR image quality measures based on the difference between original and distorted image.
Reduced-Reference (RR)	RR image quality measures quality of distorted image evaluated based on information extracted from original image.
No-Reference (NR)	NR image quality measures based on the measurement of image distortion at the place of receipt without any knowledge about the original.

We select No-Reference (NR) image quality measurement method which is based on the assessment of no image information. Also, we assume that consumer's preferred image shows the similar range of image quality parameters. And we

select dynamic range, color, noise, and contrast, which are related to each other in terms of between image's physical measurement factor and cognitive evaluation factor.

Table 2. Connection between previous physical image quality factors and cognitive image quality factors [11]

Physical image quality factors	Cognitive image quality factors
1. Luminance	1. Brightness
2. Contrast	2. Contrast
3. Color reproduction range	3. Colorfulness

Table 2 shows that connection between physical image quality factors and cognitive image quality factors. In the process of subjective evaluation, the test subjects make a decision of total image's content impression(negative, neutral, and positive) and skin color tone impression(cool, neutral, and warm). Images are gathered on the web gallery (<http://www.dpchallenge.com>) that whose audiences can evaluate their preference of a certain image within a range of 0 to 10 points.

3. EXPERIMENTAL METHODOLOGY

In this research, we measure and database dynamic range, color, contrast, and noise of high preference images. Those four items are connected to between physical image quality factors and cognitive image quality factors. For the specific image information, we extract metadata. Those image quality evaluation factors are provided by International Organization for Standardization (ISO) as measuring a digital camera image quality evaluation factors. For the subjective image quality evaluation factors, we select impression of contents, color tone, and preference of contents.

3.1 Dynamic Range Measurement

It is a dynamic range or tonal range that the ability of human eye vision can distinguish a tone. A tone means brightness of a certain part and dynamic range is used for relative measurement between one image system and another [17]. Digital camera's dynamic range is the stable signal ranges from the brightest part to the darkest part. It is measured by capturing a standard target and used F-stop unit or EV(Exposure Value). ISO 14524 defines it Opto - Electronic Conversion Function which means the relation between the input signal value and the output level value [18]. But in the real random images, we cannot measure the actual dynamic range, therefore we apply histogram equalized method. It redistributes level values from the white to the black points to make the enhanced image quality. Also, it automatically adjusts brightness contrast, but it does not change brightness frequency. It shows the next three.

1 step: calculate $hist[j]$ which means brightness value of j , and then make the input image's histogram.

2 step: calculate accumulated frequency from 0 to i on each brightness value, i , accumulated frequency formula (1).

$$sum[i] = \sum_{j=0}^i Hist[j] \quad (1)$$

3 step: normalization accumulated frequency from the second step (normalization accumulation sum). Normalization of accumulated frequency formula(2).

$$n[i] = \sum [i] \times \frac{1}{N} \times I_{MAX} \quad (2)$$

N means total pixels; I_{max} is the maximum brightness value. In 3 steps, it converts input image pixel value, I , to normalization value, $n[i]$. And then, we get the equalized result image. We assume that the actual scene histogram level value means the real dynamic range. In other words, to measure the real scene dynamic range is calculating the difference between the original image histogram and the equalized histogram value.

Our Proposed Dynamic Range = The Equalized Histogram Value - The Original Image Histogram

From the result of histogram equalization, the difference between the image levels on accumulated distribution function and the original histogram level values, if the differences are big, it means the dynamic range is narrow, and otherwise, dynamic range is wide. We develop DR histogram ver.1.0 based on MATLAB and measure the difference between histogram levels.

3.2 Color Measurement

In 1976, CIE(International Commission on Illumination) announced the representative of even color space, CIE LAB, which is digitalized the observed colors under the standard illumination by the standard observer. It standardized the information of illumination and the observer. CIE LAB is based on Hering's Opponent-color's Theory that human recognize colors in terms of yellow-blue and red-green color theory. It represents the errors and differences between colors and approaches to human emotional responses. In CIE LAB, color coordinate shows L^* , a^* , and b^* . L^* means the brightness range of lightness and darkness. A^* is to some degree between red and green. B^* is to some degree between yellow and blue. If the distance between a^* and b^* is narrower, it moves to the central which is colorlessness. For the measurement of the real image color, we developed Lab color info ver.1.0 by MATLAB. It uses the image's RGB data to XYZ, and then, converts to LAB. XYZ color space is obtained by linear conversion from RGB color space (3).

$$\begin{bmatrix} R_{lab} \\ G_{lab} \\ B_{lab} \end{bmatrix} = \begin{bmatrix} 3.2406 & -1.5372 & -0.4986 \\ -0.9689 & 1.8758 & 0.0415 \\ 0.0557 & -0.2040 & 1.0570 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \quad (3)$$

Now, in CIE xyY, x and y are color coordination and Y is brightness. It should convert to CIE XYZ and go through the next step.

$$\begin{aligned} X &= Y x/y \\ Z &= Y(1 - x - y)/y \end{aligned} \quad (4)$$

And, R/ar, G/ar, and B/ar Have the range [0,1] within the color space range. The white is (1,1,1). CIE 1931 2° standard observer's D65 white is (X,Y,Z=0.9505, 1.0000, 1.0890). From (4), in order to make the independent-equipment even color space, XYZ values is adjusted to (5).

$$\begin{aligned} L^* &= 116 f(Y/Y_n) - 16 \\ a^* &= 500 [f(X/X_n) - f(Y/Y_n)] \\ b^* &= 200 [f(Y/Y_n) - f(Z/Z_n)] \end{aligned} \quad (5)$$

where,

$$f(t) = \begin{cases} 1 & t > 6/29 \\ \frac{1}{3} \left(\frac{29}{6}\right)^2 t + \frac{4}{29} & t \leq 6/29 \end{cases}$$

Here, Xn, Yn, and Zn are the trichromatic colorimeter values from the normalized white point standard in CIE XYZ. ROI(region-of-interest) can be selected, and it graphed to the three-dimensional from the Lab data. Also, it shows the same scene Lab color space comparison and a random scene color space. The next Fig. 2 is a sample of color measurement in our research.

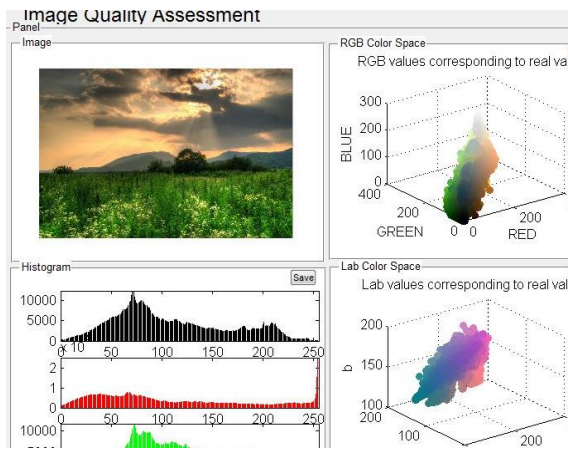


Fig.2. Sample of Lab color info ver.1.0 by MATLAB

3.3 Noise Measurement

In ISO 15739, noise is the original signals or besides component from the imaging system [19]. In other words, in digital image, noise means the unwanted signals by the non-linearity of image sensor or the external influence. In ISO's noise measurement method is to measure the standard target under the test condition, but it cannot be adjusted in a random images. Therefore, in order to measure in a random image's noise, we apply the medium filter which reduces noises in an image and measure the amount of deleted noises. For the noise measurement, we developed Pixel profile ver.1.0 based on MATLAB. In other words, after adjustment of medium filter to

the original scene, A, the difference between the original and the application of medium filter means the relative noise between them. The main idea of the median filter is to run through the signal entry by entry, replacing each entry with the median of neighboring entries. The pattern of neighbors is called the "window", which slides, entry by entry, over the entire signal. For 1D signals, the most obvious window is just the first few preceding and following entries, whereas for 2D (or higher-dimensional) signals such as images, more complex window patterns are possible (such as "box" or "cross" patterns). Note that if the window has an odd number of entries, then the median is simple to define: it is just the middle value after all the entries in the window are sorted numerically [20].

Worked 1D example

To demonstrate, using a window size of three with one entry immediately preceding and following each entry, a median filter will be applied to the following simple 1D signal:

$$X = [2 \ 80 \ 6 \ 3]$$

So, the median filtered output signal y will be:

$$Y[1] = \text{Median}[2 \ 2 \ 80] = 2$$

$$Y[2] = \text{Median}[2 \ 80 \ 6] = \text{Median}[2 \ 6 \ 80] = 6$$

$$Y[3] = \text{Median}[80 \ 6 \ 3] = \text{Median}[3 \ 6 \ 80] = 6$$

$$Y[4] = \text{Median}[6 \ 3 \ 3] = \text{Median}[3 \ 3 \ 6] = 3$$

$$\text{I.e. } Y = [2 \ 6 \ 6 \ 3].$$

3.4. Contrast Measurement

Contrast in a digital image is the main factor to decide image quality along with colors. Contrast is influenced by resolution, viewing distance, content of image, and memory color; therefore, to measure brightness of an image without considering other contents, it is not based on the total impression of audience's image quality. In this research, we adopt perceptual contrast method based on audience recognition which is called RSC (Retinal-like Subsampling Contrast) [21]. In order to verify RSC contrast algorithm, there is a test to analyze correlation on the subjective image quality evaluation between the professionals and the RSC algorithm values. It shows its result as correlation coefficient 0.84 which means the higher correlations between the professional subjects and the accurate method to measure perceptual contrast [22]. Also, RSC contrast method is based on Human Visual System algorithm which is referred to Local Information and the Global Impression of a certain scene. RSC contrast measurement algorithm takes into account the brightness and color of an image based on CIE LAB. In other words (6), it applies color coordinate value, a* and b* on CIE LAB. It shows the RSC contrast measurement algorithm.

$$\begin{aligned} RSC_c &= \frac{1}{\#liv} \sum_l \left[\frac{1}{m^{(l)} n^{(l)}} \sum_l DOG^{(l)}(i) \right] \\ DOG &= C_3 = \frac{R_c(x, y) - R_s(x, y)}{R_c(x, y) + R_s(x, y)} \\ RSC &= \alpha \cdot RSC_L + \beta \cdot RSC_a + \gamma \cdot RSC_b \end{aligned} \quad (6)$$

C means each R,G,B channel. DOG is Difference Of Gaussian. l is level values. m(l) and n(l) are length and width level values. Rs is width of Gaussian center factor. X and y means coordinate of pixel. L*a*b* is coordinate of CIE L*a*b*.

α , β , γ is a constant on each channel. In this test, if RSC contrast value is high, its contrast is high. Therefore, neutral grey without contrast has the 1 of RSC value.

3.5. Metadata Extraction

While taking a photo in a digital camera, metadata is automatically creating with shooting information. In photography, metadata is not a new concept. Photojournalists are already using it constituted by IPTC (International Press Telecommunications Committee). IPTC requests photojournalist to use the exact metadata and assures their copyright. Since November 1995, most digital cameras produced in Japan contain EXIF metadata constituted by Japan Electronics and Information Technology Industries Association. EXIF (exchangeable image file format) is automatically saved with image data while shooting and records data as text format easy to manage. EXIF metadata is constituted of camera brand, model, firmware version, shooting time, saving time, location of latitude and longitude(available with GPS), shooter information, shutter speed, focal length, aperture, exposure compensations, shooting program, photometric method mode, white balance, file compression, file name, copyrighter, and etc.

3.6. Contents Factors Selection

As subjective evaluation factors, image contents' impression (negative, neutral, positive) by audiences is decided mainly color tone and main figure. The next Table 3 shows the results of audiences feeling factors of artistic judgment.

Table 3. Artistic characteristics [23]

Artistic characteristics	Percentage (n=30)
Good color	56.7%
Subject matter	46.7%
Sharpness	43.3%
Composition	36.7%
Lighting/shadows	33.3%
Simplicity	13.3%

To better understand these characteristics, principal component and cluster analysis were used to reduce the full dimensionality into meaningful groups with similar characteristics. For this analysis, scenes were grouped according to patterns of artistic ratings of images by observers. For both people and non-people images, principal component explained the largest amount of the total variability non-people = 42.0%, people = 55.8%) [23]. In this research, in order to analyze affective factors by image contents, we made options to select audiences' impression of contents(negative, neutral, positive) and contents' color impression(cool, neutral, warm).

4. MAIN TEST

4.1. Automatic Image Quality Evaluation Program Development

4.1.1. Main test design

We design the main test to increase efficiency of research in Table 4. Throughout the main test, we draw the advanced method which can be adjusted to the objective image quality evaluation model.

Table 4. Main test design for each step

Test design	
Step 1	Collecting high preference 1000 images from the web gallery(according to face ratio of 10%, total stages are 10 and each stage got 100 images) using no-reference(NR) to increase samples
Step 2	Specifying and measuring collected image's preference, dynamic range, RGB, contrast, LAB, EXIF, noise, feeling of contents(negative, neutral, positive), color tone(cool, neutral, warm)
Step 3	The result of each measured factor is databased by using the standard normalization statistics.
Step 4	In the result of the standard normalization, deducting image quality measurement model and measuring the estimated image quality values.

4.1.2. Selection of test images

We collected the preference of image observer on the web gallery (<http://www.dpchallenge.com>). This web gallery provided recommendation frequency which can analyze the audience preference of a certain image. The reason is that we selected the web gallery for generalization and diversity of main test image samples to apply the random image quality evaluation. The preference range is from 1 to 10 on the unit of one. 1000 preferred portrait images are selected and divided into 10% ratio(0~10%, 11~20%, 21~30%, 31~40%, 41~50%, 51~60%, 61~70%, 71~80%, 81~90%, 90~100%). Based on the bottom-up data collecting method, we calculated the total range, average, standard deviation, standard normalization, z-score and etc. Throughout the result, we deducted preference as percentage and developed Image Quality Assessment ver.1.0 program to measure image quality.

The current study investigated the image attributes of people vs. No people, main subject size, and perspective cues as mediators of aesthetic quality as well as contexts in which to identify other important aesthetic features. Observational studies have indicated that images with people encompass a large proportion of consumer images. In addition, images with people may have a different image structure than images without people [24]. Main subject size is an important attribute because it also dictates the structure of the image [25]. As an example, a close-up image of a child has very different characteristics than a wide angle scenic image. Perspective cues enable visual attention to important parts of the image through drawing the eye to a vanishing point [26], [27].

4.1.3. Image quality measurement program

Based on the previous research, we selected dynamic range, color, noise and contrast which are related to between

physical and cognitive image quality measurement factor. We developed image quality program, Image Quality Assessment ver.1.0, via MATLAB. It uses level values in image histogram, R, G, B, and CIE LAB information to measure dynamic range, color, noise, and RSC contrast. We set the premise that preference can be affected by image contents, therefore, there is an option to select the feeling of contents (positive, neutral, negative) and color tone(warm, neutral, cool). The reason to specification of contents is that it provides the clues to analyze how contents effect the image quality evaluation. Also, we added image metadata extraction tool. Those factors are measured in Image Quality Assessment ver.1.0 which is applied to the difference of level values in histogram equalization, RGB average values, and RSC contrast [refer Fig. 3].

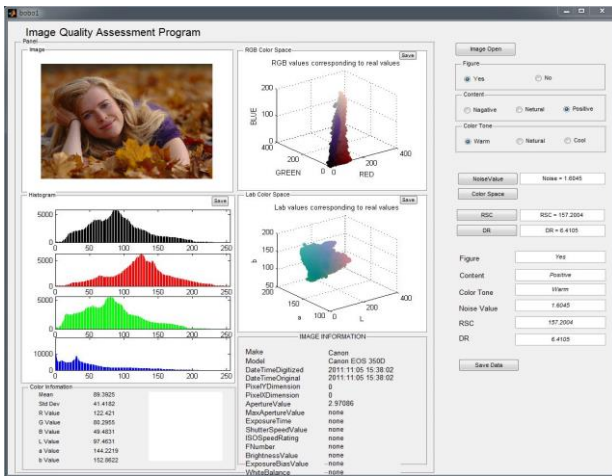


Fig. 3. Sample of Image Quality Assessment ver.1.0

4.1.4. Statistical analysis results

We used PASW Statistic 18 to analyze measured test results. Using descriptive statistics, we calculated total range, average, standard deviation, and normal distribution. Normal distribution is the distribution of continuous random variable between minus and plus. It is characterized by μ and σ . Probability density function shows (7).

$$f(x : \mu, \sigma) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{(x - \mu)^2}{2\sigma^2}\right], \quad (7)$$

$$-\infty < \mu < \infty, \sigma > 0$$

It is normal distribution which has average, μ and distribution, (or standard distribution, σ) like function 7, probability distribution. In this research, preference, x can be calculated by how far away from the average, μ with multiplying standard deviation, σ . If z is 3, x is away from μ As far as function (8). It can be calculated the probability about 0.13% of normalized distribution by assuming the provability is the general audience's preference.

$$Z = \frac{x - \mu}{\sigma} \quad (8)$$

4.2. Image Quality Test Results

4.2.1. Portrait image result analysis

We collected image preference evaluated by audience on the web gallery. Based on perfect 10 points, audience can evaluate preference by 1 unit. Portrait images are selected by the bottom-up data collection. There are total range, average, and standard deviation without the maximum and minimum value because of its possibility of distraction in total results. Image Quality Assessment ver.1.0 is used for measurement. The next table 5 is the results of the main test measurement.

Table 5. The results of scenes ratio parameter analysis

Ratio %	Preference	Noise	RSC	DR	R	G	B	L	A	B	
0~10	A	6.02	2.62	286.20	6.16	95.57	84.38	77.36	91.11	132.34	134.10
	SD	0.49	1.07	133.58	3.86	50.90	46.38	45.43	48.94	6.25	9.53
11~20	A	6.12	2.43	327.51	7.57	103.83	93.69	88.33	100.27	132.27	132.77
	SD	0.54	0.96	156.85	5.73	48.22	47.09	49.47	47.85	5.43	9.30
21~30	A	5.90	2.26	333.59	6.69	106.70	95.57	87.97	102.43	132.37	134.42
	SD	0.42	0.87	154.58	5.25	49.57	46.11	47.27	47.58	6.63	10.06
31~40	A	5.97	2.29	130.72	6.95	107.63	91.06	82.90	99.76	134.21	135.70
	SD	0.52	0.90	147.37	6.64	42.31	37.08	35.91	39.02	7.58	8.02
41~50	A	5.89	2.32	329.58	6.80	120.59	104.72	96.25	112.66	133.85	135.30
	SD	0.50	0.91	142.59	6.09	46.27	43.07	43.21	44.37	5.76	8.07
51~60	A	5.89	2.42	347.23	6.77	108.97	94.89	86.13	102.65	133.17	135.33
	SD	0.47	0.85	126.31	4.46	43.69	37.47	37.27	39.23	7.62	9.80
61~70	A	5.71	2.29	324.04	6.99	124.75	107.55	98.48	116.26	134.28	135.96
	SD	0.41	0.98	118.89	6.30	42.97	39.74	40.62	40.30	7.04	9.18
71~80	A	5.84	2.47	263.56	9.23	117.68	102.02	94.13	110.38	133.82	135.05
	SD	0.50	1.08	103.18	6.92	46.37	43.84	44.15	45.03	5.90	7.97
81~90	A	5.82	2.56	268.14	8.08	124.85	109.87	102.38	117.97	133.37	134.66
	SD	0.49	1.08	117.43	9.90	47.29	42.92	43.61	44.53	6.21	7.48
91~100	A	5.73	5.73	216.70	8.95	122.39	107.60	100.85	116.21	133.55	134.28
	SD	0.51	1.53	74.33	8.10	47.05	40.98	40.48	43.38	6.30	7.25

Table 6. The results of total scenes parameter analysis

Item	Mean	SD	Total range
DR	7.42	6.32	1.1~13.74
Preference	5.89	0.48	5.41~6.37
RGB	R	113.23	R 66.77~159.69
	G	99.13	G 56.66~141.6
	B	91.48	B 48.74~134.22
LAB	L	106.97	L 62.95~150.99
	A	133.32	A 126.85~139.79
	B	134.76	B 126.09~143.43
RSC	282.73	127.51	155.22~410.24
NOISE	2.74	1.02	1.72~3.76

In Table 6, the feeling of contents is divided into 26 negative, 61 neutral, and 913 positive opinions. Portrait color tone, especially for face area, is shown as 25 cool tone, 935

neutral tone, and 40 warm tone opinions. Audience's preference average is 5.89(perfect 10 points) and standard deviation 0.48. Dynamic range average is 7.42 and standard deviation 6.32(from the minimum 1.1 to the maximum 13.74). In RGB values, R average is 113.23(SD 46.46), G average is 99.13(SD 42.47), and B average is 99.13(SD 42.47). In LAB values, L average is 105.97(SD 44.02), A average is 133.32(SD 6.47), and B is 134.76(SD 8.67). RSC contrast has the average of 282.73 and the standard deviation is 127.51. Noise average is 2.74 and SD is 1.02. In other words, the audience preferred images have a tendency to wide dynamic range standard deviation, wider contrast range, and low level of noise. These results present the possibility of image grading and ranking with standard normal distribution of 1000 images. The next Fig. 4, 5, 6, 7, 8, 9, 10, 11, and 12 shows the normal distribution of preference, dynamic range, RSC contrast, skin tone R,G,B,L,A,B.

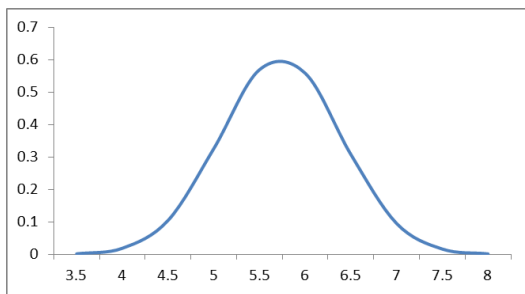


Fig. 4. The normal distribution graph of portrait preference

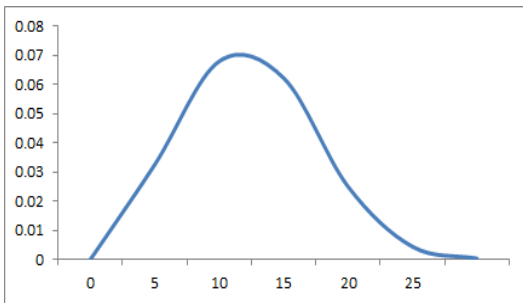


Fig. 5. The normal distribution graph of portrait dynamic range

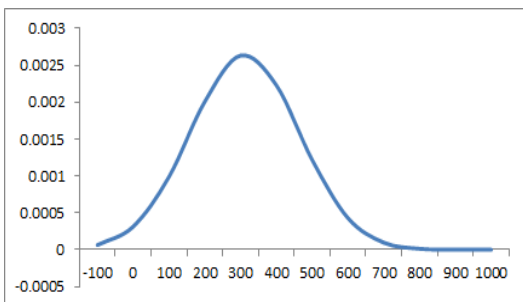


Fig. 6. The normal distribution graph of portrait contrast

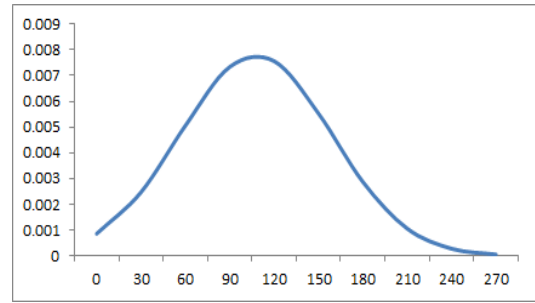


Fig. 7. The normal distribution graph of portrait skin tone R

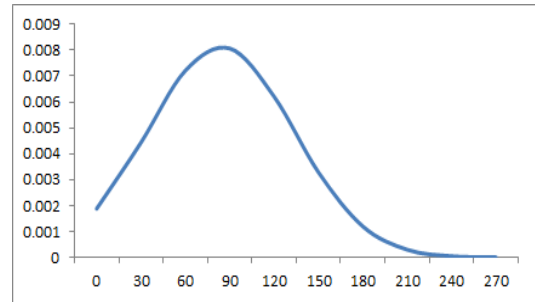


Fig. 8. The normal distribution graph of portrait skin tone B

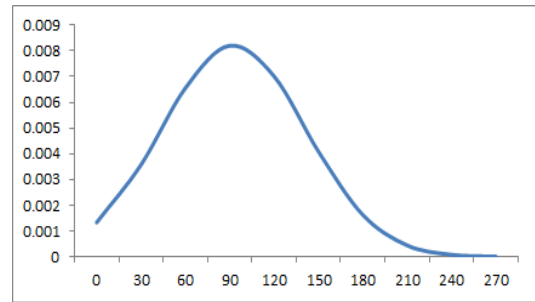


Fig. 9. The normal distribution graph of portrait skin tone G

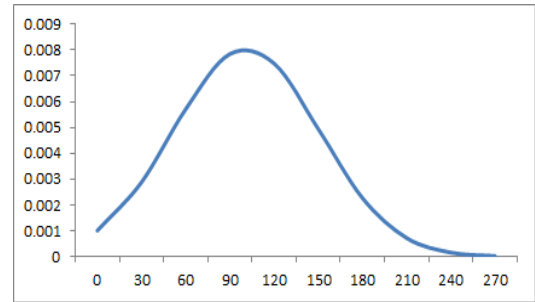


Fig. 10. The normal distribution graph of portrait skin tone L

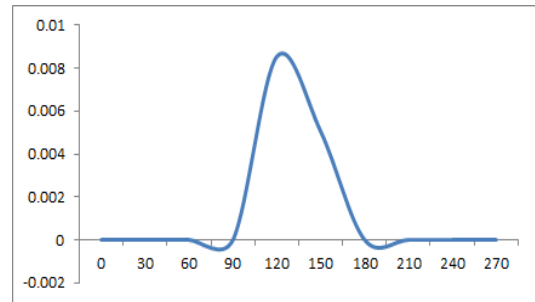


Fig. 11. The normal distribution graph of portrait skin tone A

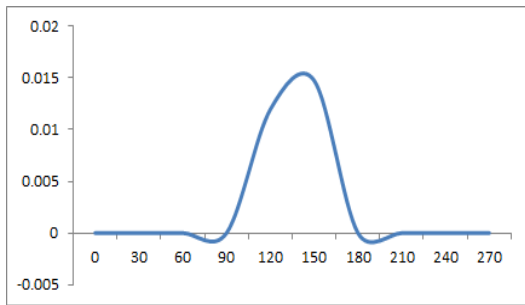


Fig. 12 The normal distribution graph of portrait skin tone B

Fig. 4 shows the normal distribution graph of portrait preference. It has preference average 5.89(SD, 0.48). Dynamic range in portrait has the normal distribution graph in Fig. 5 which shows the average 7.42 and SD 6.32. Fig. 6 is the normal distribution graph of portrait RSC contrast (average 282.73(SD 127.510)). In Fig. 7, 8, 9, 10, 11, and 12 we present the normal distribution of skin tone results in RGB; R is the average of 113.23(SD 46.46), G is the average of 99.13(SD 42.47), and B is the average of 91.48(SD 42.74). LAB results also show the normal distribution; L is the average of 105.97(SD 44.02), A is 133.32(SD 6.47), and B is 134.76(SD 8.67). Therefore, we draw a conclusion that those factors (preference, dynamic range, contrast, skintone RGB, LAB of 1000 portrait images) are able to make the standard normal distribution. It means that a random image can be ranked and graded in the standard normal distribution results.

4.2.2. Correlation analysis between contents and color tone in portrait

In total 1000 images, the feeling of contents can be divided into 26 positive, 61 neutral, and 913 positive opinions. Cool tone is 25, neutral tone is 935, and warm tone is 40 in total color tones results. Portrait images are 10 steps in total range according to 10% ratio. The results of color tone analysis in Fig. 13.

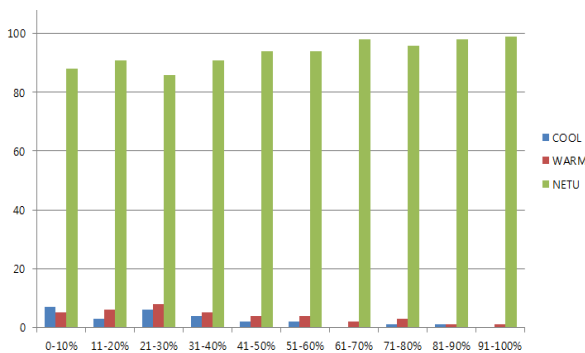


Fig. 13. Distribution of color tone by 10% ratio

According to analysis of face ratio distribution, we cannot present easily the meaningful results because of many neutral contents and color tone. Therefore, we analyze the correlation between the feeling of contents and color tone in statistics. In table 7, it shows meaningful correlation between the feeling of contents and color tone.

In other words, it has the highest relationship warm tone, neutral, and cool tone, respectively. But in the feeling of

negative contents, it shows the normal correlation (correlation coefficient 0.44) with cool tone. Also, positive contents have the correlation with warm tone (cc 0.59) and cool tone (0.47) which are the medium correlation, but in the neutral tone shows the negative correlation of cc. -0.56. If the contents are more positive contents, warm tone is preferred to cool tone. Neutral contents has the relation in cool tone (-0.57) and warm tone (-0.41). If the contents is neutral, color tone has a tendency to being neutral tone. If the contents are negative, cool tone is more generally preferred (cc. 0.44). It has weak relation when the color tone is neutral (cc. -0.19) or warm tone (cc. -0.08).

Table 7. The results of the feeling of contents and color tone

Content	Color tone	Correlation coefficient
Positive	Cool	0.47
	Neutral	-0.56
	Warm	0.59
Neutral	Cool	-0.57
	Neutral	0.52
	Warm	-0.41
Negative	Cool	0.44
	Neutral	-0.19
	Warm	-0.08

4.2.3. Correlation between preference and contents, preference and color tone in portrait

In table 8, preference and positive contents have the positive correlation (cc 0.79) and it means that positive contents show the good preference. On the contrary to this, negative contents has the 0.27 correlation coefficient which means weak relation, but neutral contents shows the strong negative correlation with the neutral contents(cc -0.73). Correlation between preference and color tone has a tendency to higher preference if it is related to warm tone (cc 0.72). Also, cool tone shows the positive correlation (cc 0.69) with preference, therefore, warm and cool tone have close relation in statistics. On the other hands, neutral color tone has the correlation with preference of -0.74 as negative relation which means preference shows close relation with colors. According to correlation analysis, we conclude that in portrait if the feeling of contents is positive or the contents is warm or cool tone, the final preference will be high.

Table 8. The results of correlation between preference and contents

	Content correlation	Correlation coefficient
Preference	Negative	0.27
	Neutral	-0.73
	Positive	0.79
Color tone correlation	Cool	0.69
	Neutral	-0.74
	Warm	0.72

4.3. Proposed image quality evaluation model

In this research, we try to measure a random image preference and propose image quality evaluation model below Fig. 14. With the proposed image quality evaluation model, we collect 1000 images which had more 30 recommendation reviews on the web gallery. The many number of recommendations shows the general audience preference. Also, according to the contents, it will affect to audience's preference; therefore, we divide the feeling of contents as negative, neutral, and positive. The subjects should decide their opinion of contents when they evaluate an image. With the average of dynamic range, RGB, LAB, and RSC contrast in total 1000 images, we analyze the total range of results, standard deviation, normal distribution, z-score, and percentage of preference.

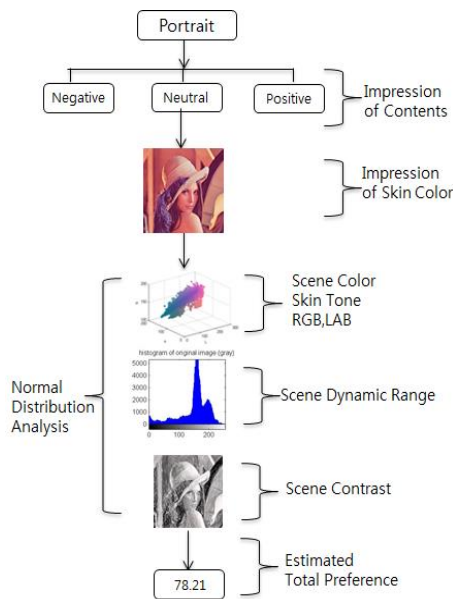


Fig. 14. The whole process of image preference assessment

In table 9, we present the results of a random image's statistic parameters. There are average, standard deviation, the image's real parameter measurement, standard normal distribution z-score, and one-sided test probability. The actual measurement of a random sample image has that dynamic range is 6.4stop, preference is 5.25(SD 0.48), in skin tone RGB, R is the average of 122.42(SD 46.46), G is 80.3(SD 42.47), B is 49.48(SD 42.47), in LAB values, L is the average of 97.46(SD 44.02), A is 144.22(SD 6.47), B is 152.86(SD 8.67), and RSC contrast is 157.2(SD 127.51). Normalized distribution is measured by Function 8 and 9. The z-score of dynamic range is 0.16, preference is 1.33, R is 0.2, G is 0.44, B is 0.98, L is 0.22, A is 1.69, B is 2.09, and RSC contrast is 0.98. In the standard normal distribution table, we can find out z-score as dynamic range is 0.06356, preference is 0.40824, R is 0.07926, G is 0.17003, B is 0.33646, L is 0.08317, A is 0.45449, B is 0.48169, and RSC contrast is 0.33646. The chance of showing the probability of measured z-score is 6.36% for dynamic range, 40.82% for preference, 7.93% for R, 17% for G, 33.65% for B, 8.32% for L, 45.45% for A, 48.17% for B, and 33.65% for RSC contrast. In terms of converting the percentage to 100 points, dynamic range is 93.64 points, preference is 59.18 points, R is 92.07 points, G is 83 points, B is 66.35 points, L is 92.86 points, A is 91.68 points, B is 51.83 points, and RSC contrast is 66.35 points. Finally, we can present the total expected preference 72.36 points as the average of dynamic

A is 91.68 points, B is 51.83 points, and RSC contrast is 66.35 points. Therefore, total 9 factors of the objective image quality evaluation items show the total average is 72.36 points. In other words, we can expect the estimated final image quality of a certain image via our proposed normalized distribution measurement model.

Table 9. The results of parameters in portraits

Item	Mean	SD	Measurement	ND	SND	One-sided test	
DR	7.42	6.32	6.4	0.16	0.06356	6.36%	
P	5.89	0.48	5.25	1.33	0.40824	40.82%	
RGB	R	113.2	46.46	122.42	0.20	0.07926	7.93%
	G	99.1	42.47	80.3	0.44	0.17003	17%
	B	91.5	42.74	49.48	0.98	0.33646	33.65%
LAB	L	107	44.02	97.46	0.22	0.08317	8.32%
	A	133.3	6.47	144.22	1.69	0.45449	45.45%
	B	134.8	8.67	152.86	2.09	0.48169	48.17%
C	282.7	127.51	157.2	0.98	0.33646	33.65%	
N	2.74	1.02	1.68	1.04	0.35083	35.1%	

5. CONCLUSION

The results of proposed image quality evaluation model are that dynamic range is 6.4 stop, preference is 5.25(SD 0.48), skin tone R is the average of 122.42(SD 46.46), G is 80.3(SD 42.47), B is 49.48(SD 42.47), L is 97.46(SD 44.02), A is 144.22(SD 6.47), B is 152.86(SD 8.67), and RSC contrast is 157.2(SD 127.51). Normalized distribution z-score is that dynamic range is 0.16, preference is 1.33, R is 0.2, G is 0.44, B is 0.98, L is 0.22, A is 1.69, B is 2.09, and RSC contrast is 0.98. With the z-score, it is converted to standard normal distribution table z-value; dynamic range is 0.06356, preference is 0.40824, R is 0.07926, G is 0.17003, B is 0.33646, L is 0.08317, A is 0.45449, B is 0.48169, and RSC contrast is 0.33646. With the chance of probability of z-value, it shows that dynamic range is 6.36%, preference is 40.82%, R is 7.93%, G is 17%, B is 33.65%, L is 8.32%, A is 45.45%, B is 48.17%, and RSC contrast is 33.65%. These percentage values are converted to 100 points perfect; dynamic range is 93.64 points, preference is 59.18 points, R is 92.07 points, G is 83 points, B is 66.35 points, L is 92.86 points, A is 91.68 points, B is 51.83 points, and RSC contrast is 66.35 points. Finally, we can present the total expected preference 72.36 points as the average of dynamic

range, preference, R, G, B, L, A, B, and RSC contrast. It shows that our proposed image quality evaluation model can measure the actual image's preference as statistical analysis method.

6. DISCUSSION

This research results can be shown diverse results in different environment, region, races, ages, education, background knowledge, and etc. Also, it means that preferred image does not always have the average range of parameters. Vice versa, the higher preferred image does not mean the optimum parameter range. Moreover, there needs to be a weighted grade program on the objective image quality factors, because each factor definitely effects differently in evaluating image preference. The weighted grade program on each factor can attribute understanding contents, contexts, or preference which is decided by the subjects. For the matter, in order to minimize the defects and specifications, we divide into the feeling of contents as positive, neutral, and negative. Skin tone also divides into cool, neutral, and warm tone which can be felt by the test subjects. With the results, we can propose the practical image quality measurement model which can specify the subject's preferred image quality. And also, we expect the follow-up study which can integrate the whole factors and estimate the credible data.

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Hyung-Ju Park

She received Ph.D in imaging quality evaluation from Chung-Ang University, S.Korea. She has been working as a research professor at Culture Technology Research Institute at the same University. Her major areas include photography, digital imaging,

image quality and standardization, and academic Industrial cooperation. Also, she has been devoting herself as a lecturer in diverse academies.



Dong-Hwan Har

He received the B.S., M.A., in industrial photography from Brooks Institute of Photography, and Ohio University, U.S.A., respectively and also, received Ph.D in educational technology from Han-Yang University, Korea. He is a professor in digital scientific imaging lab,

Graduate school of advanced imaging and multimedia, at Chung-Ang University. His main research interests include forensic, scientific, forgery, medical, and digital photography