Device-independent Graininess Reproduction

Junki Yoshii*, **Shoji Yamamoto**[1], **Yuto Hirasawa, Norimichi Tsumura**

Graduate School of Advanced Integration Science, Chiba University, 1-21-11 Kurosunadai, Inage-ku, Chiba 263-0041, Japan

[1]Tokyo Metropolitan College of Industrial Technology, 8-17-1 Minamisenju, Arakawa-ku, Tokyo 116-0003, Japan

Abstract. We evaluated a method for building a psychophysically based model of graininess perception for a device-independent graininess-reproduction system. The model was developed through experiments that explored the relationship between physical parameters of graininess objects, subjective rating, and the maximum luminance of the displays used to present the objects. The graininess model was generated via multiple regression analysis of the parameters and was used to calculate curved surfaces for which graininess perception was equalized. Even if the values of maximum luminance on the display is changed in the model, the value of graininess under the changed luminance is hold by changing the physical parameters of graininess generation in the model. We found that the proposed model and process for device independent graininess reproduction were effective for our adopted displays with various maximum luminance.

Keywords: magnitude estimation, subjective rating, graininess, roughness, multiple regression analysis, revision

A part of this paper was presented at CIC25, held in Lillehammer, Norway

* E-mail address: yoshii@chiba-u.jp

1. Introduction

Recently, electronic commerce (e-commerce) such as online shopping has become commonplace with improvements in high-speed networks and computer science. In particular, e-commerce has benefitted from the development of computer graphics (CG) techniques and rendering engines. Excellent representation of commercial products excites consumer interest, and a high-quality accurate representation makes real transactions possible in a virtual world. In this system shown in Figure 1, an image of a product is taken with a digital camera and is then displayed on a distant device through a network. Recently, displaying a rendered CG image of a product instead of a single digital photograph has become widespread in e-commerce trading. This is accomplished by uploading information such as the shape of the product to a server. With the proper design, consumers can browse product images interactively by controlling the viewpoints and lighting conditions as they wish. The CG image data are recorded and stored by the input system and distributed throughout the network. Because consumers browse product images in this way before purchasing the product, faithfully reproducing the product through CG is extremely important. However, the appearance of the product might differ depending on the environment in which the product image is viewed. For example, differences in appearance can be caused by varying characteristics in the consumer's display, such as maximum luminance and color reproduction range. When this happens, it can lead to customer dissatisfaction and an increase in returned goods, which are negative outcomes for both corporations and customers. This problem is outlined in Figure 2. Differences in appearance are a serious problem for items such as clothes and art objects because how they look is a major factor in their purchase.

Accurate color reproduction is the most important factor affecting the commercial value of products and is a point of quality control for e-commerce. The color-matching technique is a useful method for fitting the diffuse color and texture of commercial products. This technique uses numerical calculations to calibrate color between the input device and the display. The appearance of surface graininess is also an important factor for product images. Fine-grained surfaces that appear coated and polished are the best for giving the impression of “premium” quality. Moreover, this characteristic of surface graininess involves the sense of touch and hold. Because the shape and function of a product are important to us as consumers, we must be sensitive and pay attention to the appearance of surface graininess, even in images designed for representations in e-commerce. Although an appearance-matching method similar to color matching should be developed to further e-commerce growth, the numerous parameters and complicated handling make managing surface graininess difficult. In this paper, we address this issue by proposing a device-independent graininess-reproduction method that matches the appearance of graininess by the control of CG images (Fig. 3). We derive the perceptual space for surface graininess via an experiment that determines the magnitude of subjective rating. Some factors that change the appearance of surface graininess are resolution, maximum luminance, and color reproduction range. In this preliminary study, we controlled the height and distribution of the CG image bump profile according to the maximum luminance. The proposed method can be used for a device-independent graininess-reproduction process that manipulates the physical parameters mentioned above to match the graininess on the display with different maximum luminances.

Figure 1. The e-commerce process

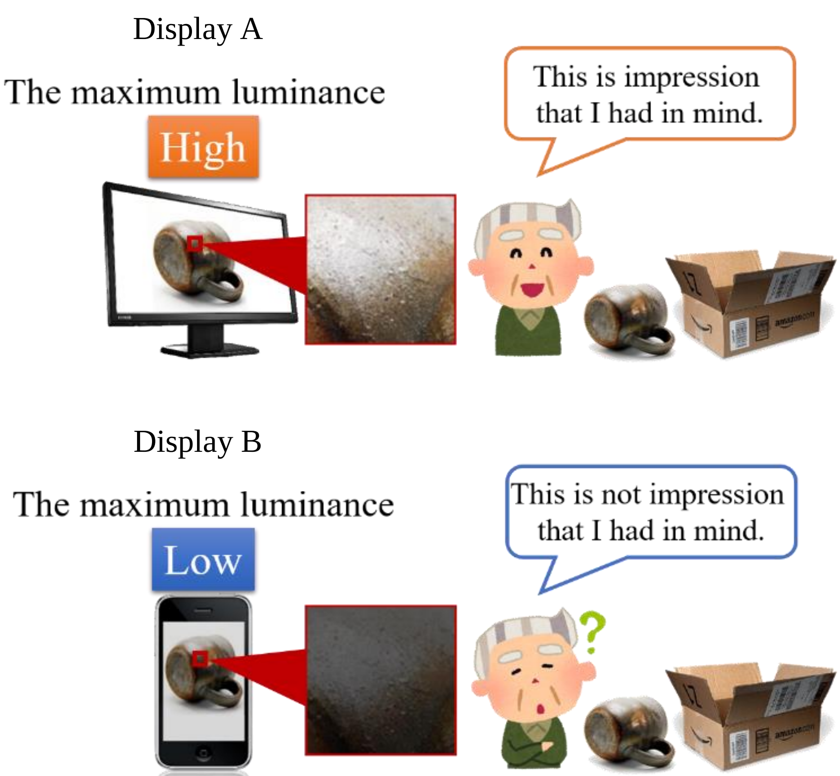


Figure 2. Differences in appearance caused by varying display characteristics

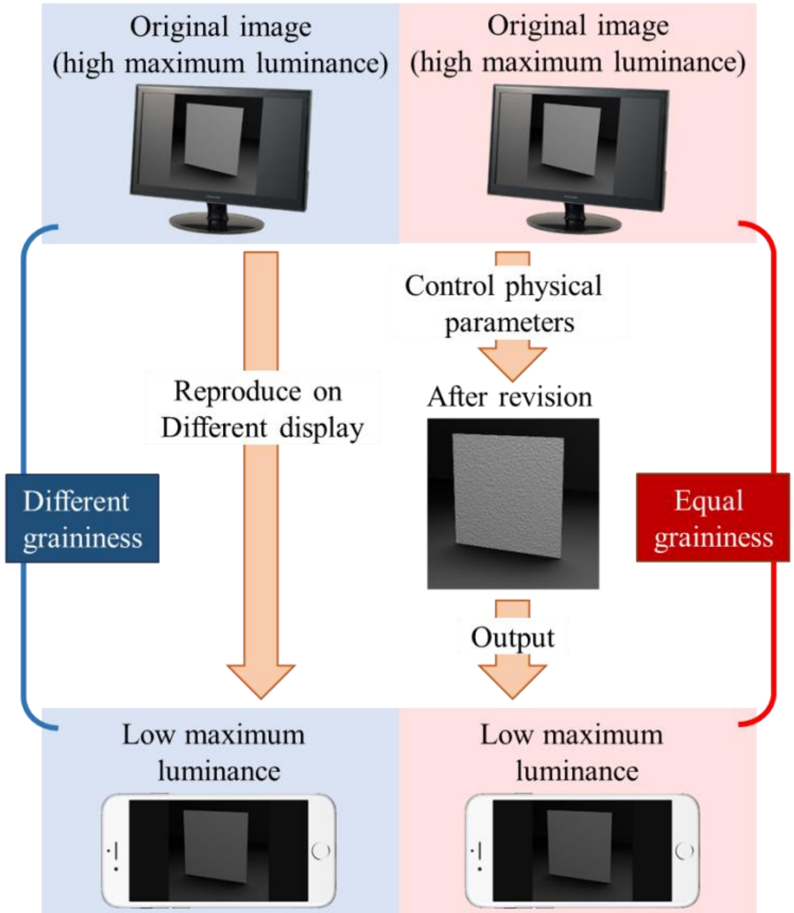


Figure 3. Outline of the graininess-matching procedure

2. Related Work

The surface shape an object is important for understanding and interpreting the object's appearance and other characteristics. Several studies[1-3] have investigated the appearance of graininess using CG objects. Glossiness is another characteristic that changes how objects are perceived and which can be altered by manipulating physical parameters. The current study was inspired by several studies that focused on glossiness. Some[1)] have studied gloss in which graininess is perceived as a result of light scattering. Like graininess, the glossiness of an object depends on the change in maximum luminance of the device used to display it. Therefore, we must distribute images to consumers that do not change in glossiness depending on the device or display environment, especially when the items for which appearance such as color or gloss is emphasized.

Pellacini et al.[4] have developed a new model to quantify the perception of gloss on an object's surface. They conducted two experiments that explored the relationship between physical parameters and the perceptual dimensions of a glossy appearance. The parameters of an object's geometry that are related to the perception of glossiness are not well known and the number of factors is likely quite large. However, narrowing the number down to a few parameters that contribute the majority of the perception might be possible. In the first experiment, they used a pair-comparison method to reveal the dimension of gloss perception for simulated painted surfaces. They visualized the data using multidimensional scaling techniques[5] and found perceptual dimensions that express two important features related to glossiness. These features are denoted by Eq. 1.

$$d = 1 - \alpha$$
$$c = \sqrt[3]{\rho_s + \rho_d/2} - \sqrt[3]{\rho_s/2} \qquad (1)$$

where d and c are perceptual dimensions, ρ_d is the object's diffuse reflectance, ρ_s is the specular reflectance, and α is the spread of the specular lobe, all of which are introduced by Ward's anisotropic BRDF model[6,7] The dimensions d and c are qualitatively similar to the contrast gloss and distinctness-of-image (DOI) gloss observed by Hunter[8].

In the second experiment, Pellacini et al.[3] determined the relationship between the perceptual dimensions for glossy appearance and the physical parameters used to describe the reflectance properties of glossy surfaces. They evaluated two kinds of objects described by c and d which were related to physical dimensions such as ρ_d, ρ_s, and α, and they used subjective ratings to estimate the relationship between the physical qualities of the stimuli and human perception. The experiment was useful because it quantified glossiness by asking observers to provide numerical answers regarding the CG image of the glossy object. From this experiment, they were able to compare the objects described with the physical parameters to the perceptual dimensions. This property of the model might make it easier to create objects that are perceived to have the same glossy appearance.

Gloss perception was also quantified by Ikeda et al.[9] who used an experimental approach to reproduce equally glossy objects with CG even if the objects were presented on displays with different maximum luminances. They prepared images with differing intensity (A_1) and spread of the specular reflectance (A_2) (from Phong's model[10]). Then, they varied the maximum luminance $V_{\max}$ of the display and used a magnitude-estimation method to evaluate how glossy the items in the images were. The multiple regression analysis produced the model denoted by Eq. 2

$$G = 54.7\sqrt{A_1} + 4.1\times10^2\sqrt{A_2} + 5.4\sqrt{V_{\max}} - 76.3\,, \tag{2}$$

where the coefficient of determination (R^2) was 0.803. Thus, this model accounted for a good proportion of the variance in the dependent variable. The model indicates that the perceptual gloss G can be expressed with the physical gloss parameters A_1, A_2, and $V_{\max}$. Therefore, an equal sense of gloss can be achieved by adjusting A_1 and A_2 depending on the maximum luminance of the display. However, the model is greatly affected by the radiance of the display. This factor can be pre-defined in a color management system such as sRGB or ICC.

3. Development of Graininess Space

3.1 Generation of graininess stimuli

Our experiment was designed to determine the relationship between perception and physical elements than comprise graininess. Therefore, we reproduced various graininess patterns on objects using a CG renderer. For the first challenge, we specified that the material object be made by mat. In order to produce the graininess, we used a bump-mapping technique. This technique can render ruggedness on a flat object by changing the pixel value according to a normal map. In this process, the direction of reflected light is changed falsely according to the change in the texture's pixel value. Although the surface of the actual object is flat, it is possible to make it appear rugged by changing the appearance of the object with shading and shadow. Figure 4 depicts a rendering result produced by bump mapping. On our first attempt, some observers pointed out that the graininess values differed depending on the region within the image. This difference is assumed to have occurred because of binary noise in the generation algorithm. Therefore, we added Gaussian noise so that perception of graininess in the image would follow a normal distribution.

We anticipated that the depth of ruggedness and the size of the grains would have a large effect on the perceived graininess of the rendered image. In our reproduction method, the change of depth for ruggedness is generated by changing the pixel value of the normal map with Gaussian noise. Additionally, the size of the grains was varied through dilation in the morphological processing. Dilation is an image processing technique used to expand an element of a digital image. By expanding the element in the normal map during bump mapping, the size of the grains are larger after processing. However, a rapid change of ruggedness as shown in Figure 5(a) appears if dilation produces grain that are too large.

Therefore, we applied a Gaussian filter to the normal map after the dilation to smoothen the rapid change. Figure 5(b) shows the result after smoothing. In our experiment, the standard deviation used for the Gaussian filter was empirically decided to be 0.3 times the size of a grain. Moreover, we found that perceiving graininess was difficult for objects such as those shown in Figure 5(b) because of the hollowed-out appearance. By inverting the luminance value of the texture, we were able to generate the graininess objects shown in Figure 5(c). We show an enlarged view of the graininess object in Figure 5 because the grain can be easily perceived.

In addition the degree of ruggedness and the size of the grain, we incorporated a parameter for the maximum luminance of a display. This parameter is dependent on the maximum pixel values of the displayed image. For the implementation of this parameter, the relationship between pixel values and the luminance of the display must be checked. We used an EIZO FlexScan S2001W monitor, and measured luminance with a chromameter (CS-100A, KONICA MINOLTA, Japan). As the result of the measurement, we obtained the characteristic curve denoted by Eq. 3.

$$L = 0.001P^2 - 0.003P - 0.257 \, , \tag{3}$$

where the coefficient of determination (R^2) was 1.00, L is the luminance, and P is the pixel value of the display. Eq. 3 assumes that changes in the maximum pixel values are variations in the maximum luminance of the displays. Therefore, we can adjust the graininess image according to the maximum pixel value in the display.

Because graininess varies according to the pixel value of the texture image used for bump mapping, the depth of ruggedness and the size of the grain can be manipulated by applying image processing to the texture. As shown in Figure 6(a), the depth of ruggedness can be increased by widening the scale of the pixel values. Further, the size of the grains can be increased by applying a dilation process to the texture as shown in Figure 6(b). Depending on the display, different maximum luminance values can be assumed by lowering the pixel value of the whole stimulus. The change in the maximum luminance value is shown in Figure 6(c).

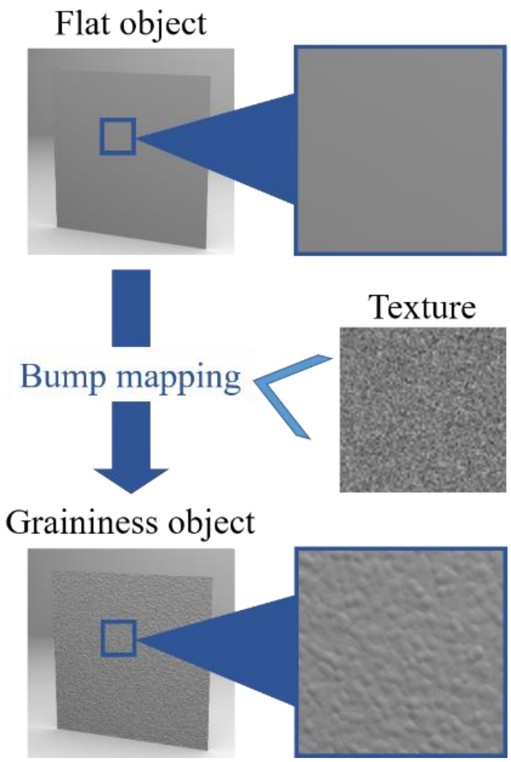
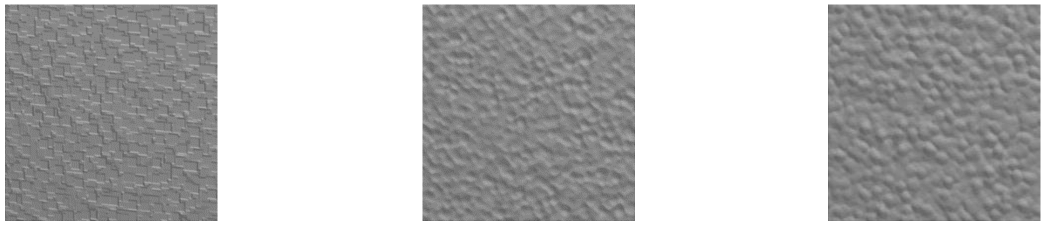


Figure 4. The bump-mapping process



(a) (b) (c)

Figure 5. A graininess object before processing (a), after smoothing (b), and after inversing the luminance (c).

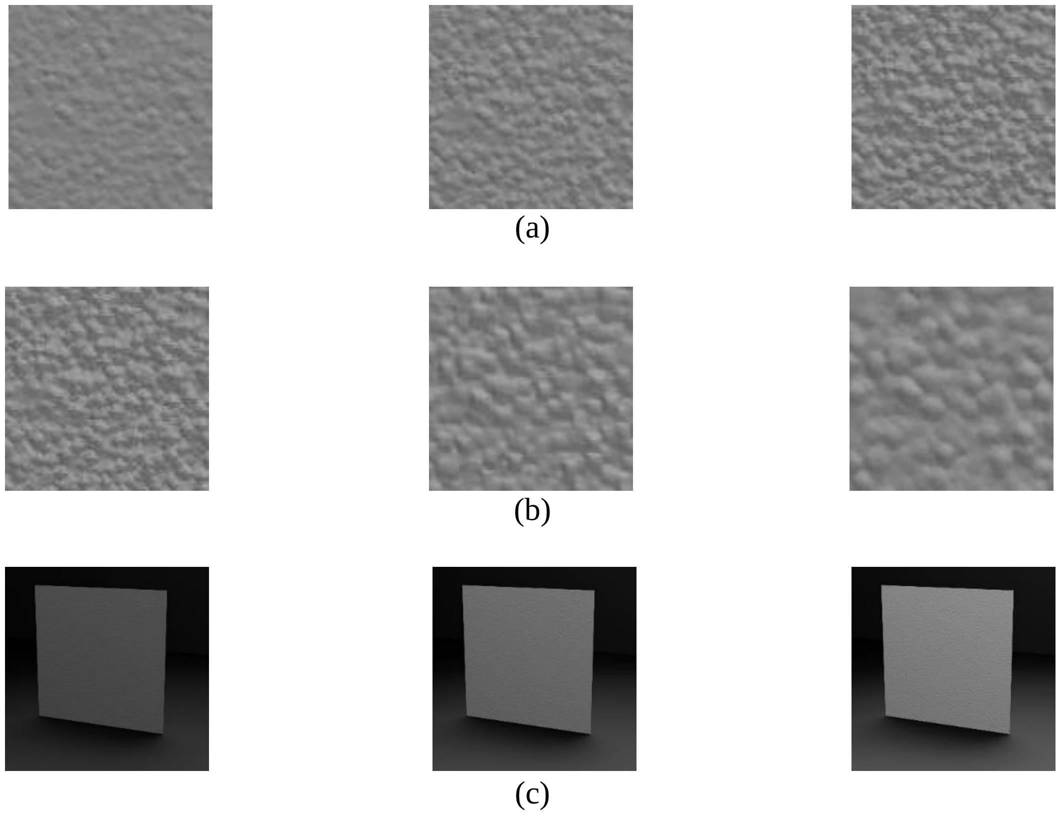


Figure 6. Change in the depth of ruggedness (a), size of the grains (b), and maximum luminance (c) for a graininess object.

3.2 Subjective rating

The purpose of our experiment was to create a perceptual space to quantitatively control graininess. To achieve this, we designed an experiment based on the magnitude-estimation method—a psychophysical scaling technique that can reveal functional relationships between the physical properties of a stimulus and its perceptual attributes.

Observers are university students of men and women corrected to normal or normal eyesight. The number of participants was 9, and we performed same experiments for each observer. Observers observed pairs of graininess images that were generated by a CG renderer. These images were presented on a black background in a darkened room. The distance between the observer and monitor was about 40 inches, which was 3 times the height of display (Fig. 7).

Each experimental parameter for the images had three levels (Fig. 8). The depths of ruggedness (Amplitude) values (A) were 64, 128, or 256, the size of grain values (S) were 2, 3, or 4, and the maximum luminance values (L) were 11, 24, or 35. We randomly presented the 27 stimuli (3 amplitudes × 3 sizes × 3 luminances) to the observers and asked them to rate the graininess of each object on a scale of 0 to 100. Before the experiment, typical 0-graininess and 100-graininess objects were presented as reference. We normalized each observer's ratings from 0 to 1 to account for personal differences in the range of judgments (Eq. 4).

$$V_{\text{normalized}} = \frac{V_i - MIN}{MAX - MIN} \quad , \tag{4}$$

where $V_{\text{normalized}}$ is the result of a observer's subjective rating after normalization, V_i is their evaluation score for each image, MAX is the maximum value they used, and MIN is the minimum value they used.

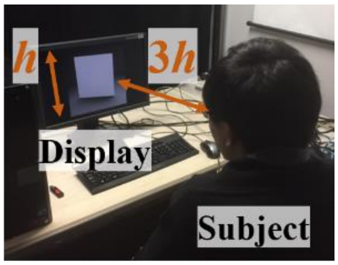


Figure 7. The conditions of the experiment.

3.3 The model for graininess reproduction

In the previous section, we performed experiments to evaluate a total of 27 stimuli by manipulating physical parameters (A, S, L) affecting the perception of graininess for observers (9 people). We summarize the rating results in Table 1. The table contains the physical parameters of the graininess objects and the average of the rating values for these experimental stimuli. The evaluation values of these graininess are shown in Figure 8 in 4D. Since there are 4 rows in Table 1, this figure is represented by 4D including a color bar for the graininess.

Equation 5 shows the result of a multiple regression analysis on the data obtained from the graininess rating task.

$$G = 0.254 \times \sqrt[3]{A} - 0.480 \times \sqrt{S} + 0.006 \times L - 0.121, \tag{5}$$

where the coefficient of determination (R^2) was 0.916. The relatively high R^2 indicates that this equation is reliable. G is the perceived graininess that is objective variable in Equation 5. Next, p-value is calculated to investigate a significant difference that each explanatory variable can explain the objective variable. Generally, when the p-value is less than 5% or 1%, the null hypothesis is rejected as false and the alternative hypothesis is adopted. Therefore, we summarize the p-value for each explanatory variable of Equation 5 in Table 2. Since the p-values for explanatory variables other than the intercept of the objective variable axis is less than 1%, it can be said that they cannot explain the objective variable with a probability of 1% or less. In other words, it is significant in explaining the objective variable with each explanatory variable.

This graininess model made it possible to generate objects that feel equal graininess on arbitrary curved surface. Figure 9 indicates these results as normalized graininess G = 0.2, 0.4, 0.6, 0.8, and 1.0. These surfaces can be used to equalize the perception of graininess by adjusting the values for A, S, and L. Therefore, when we select the value of A or S along the same surface according to the arbitrary maximum luminance of the display, a device-independent reproduction for graininess can be acquired. Larger sizes of grains are perceived as less grainy because the coefficient for S is negative. Conversely, large values for A and L lead to larger perceived graininess. The transition between the surfaces in Figure 9 represents these trends well. The shapes of the surfaces representing different levels of graininess are almost the same. The surfaces are drawn within the domain of the parameter treated in the experiment such as A, S and L, and the range for each coordinate axis in the graph is set without estimation.

Table 1. Physical parameters of the stimuli and mean of the rating value for these stimuli

Amplitude (A)	Size of Grain (S)	Maximum Luminance (L)	Graininess (G)
64	2	144	0.19
64	2	202	0.40
64	2	247	0.50
64	3	144	0.09
64	3	202	0.08
64	3	247	0.19
64	4	144	0.06
64	4	202	0.00
64	4	247	0.10
128	2	144	0.70
128	2	202	0.79
128	2	247	0.85
128	3	144	0.43
128	3	202	0.51
128	3	247	0.63
128	4	144	0.28
128	4	202	0.40
128	4	247	0.50
256	2	144	0.79
256	2	202	0.84
256	2	247	0.90
256	3	144	0.78
256	3	202	0.82
256	3	247	0.86
256	4	144	0.60
256	4	202	0.67
256	4	247	0.79

Table 2. P-values for each explanatory variable

	***p*-value**
$\sqrt[3]{A}$	**1.14E-12**
$\sqrt{S}$	**8.8E-07**
L	**0.001563**
Bias value	**0.161788**

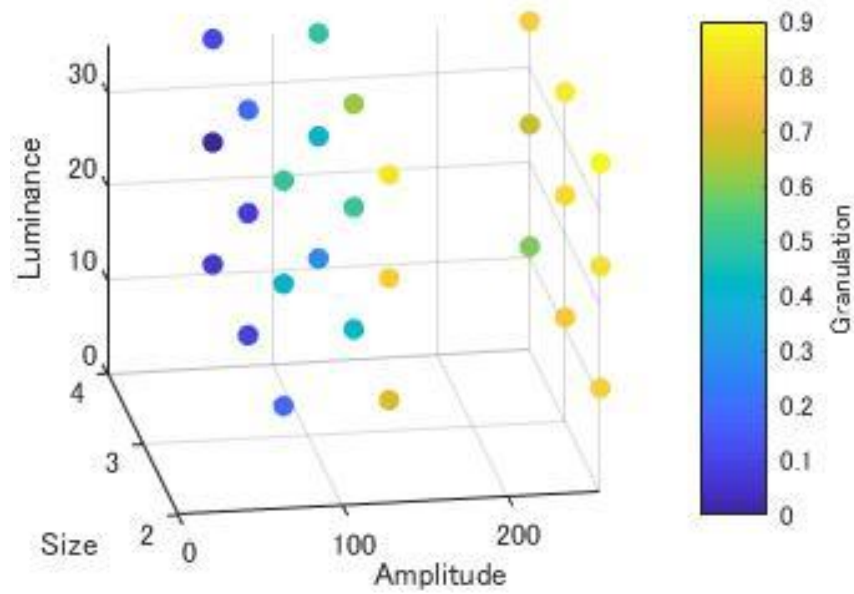


Figure 8. Mean of the rating value for each stimulus

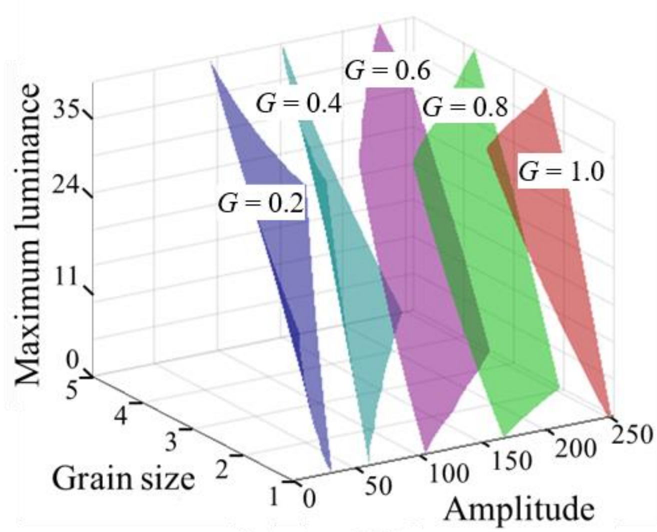


Figure 9. Surfaces of an equal graininess perception.

4. Management of Graininess Appearance

In this section, we use the model to adjust the image and equalize the perceived graininess. graininess. The graininess value is held constant by changing the physical parameters *A* and *S* in the graininess generation model according to maximum luminance value of the display being used.

4.1 Matching graininess using the model

As an example of how we modified the perceived graininess, consider the graininess object generated by the parameters: A = 128, S = 3, and L = 35 shown in Figure 10(a). This object has a graininess score (G) of 0.54 on the graininess surface. We defined this image as the original image in this evaluation. *A* represents the depth of ruggedness on the surface of the graininess object. This is defined as the amplitude in this paper. *S* is the size of the grains of the graininess object. *A* and *S* control the texture in the bump mapping by image processing. *L* represents the maximum luminance value of the display used in the experiment. In this method, the same display was used to avoid the influence due to the difference in display characteristics. Therefore, *L* virtualizes the change in the maximum luminance value of the display by scaling the pixel value of the scene image including the graininess object. In this method, *A*, *S* and *L* are generated with the same value in the object. A detailed explanation is given in 3.1.

Next, we generated the modified example for a display with low maximum luminance. This object was rendered by changing the parameters to: A = 128, S = 3, and L = 11 shown in Figure 10(b), in which only the maximum luminance is lowered. We assume that changes in the maximum pixel values in the images are variations of the maximum luminance of the displays. The *G* of this example was 0.43, which was the average of added subjective rating to confirm graininess. The lower luminance clearly resulted in a lower perception of graininess. This result indicates that observers have difficulty sensing the graininess when the maximum luminance of the display is low. Human has a difficulty to discriminate features of texture in dark scenes. In a bright display, the contrast is large that expresses features such as the amplitude of the graininess object. On the other hand, the contrast is small in a dark display. Therefore, it can be said that the features of a texture can be recognized more clearly in the bright display. However, from the viewpoint of the Just Noticeable Difference (JND), it can be said that the difference in features can be more discriminated in dark displays. In this experiment, the observers could detect the little graininess with a dark display. Because of the balance between the contrast and the JND that are events by the human sensory organs in eyes, the observer noticed the difference even in a dark display.

Next, we modified the image so that its perceived graininess would equal that of the original image. In the first operation, we define the plane such that all values are equivalent according to the maximum luminance $L = 11$. The cross line between this plane and the graininess space is calculated as shown in Figure 11. Although the graininess for the original image decreased with the lower the maximum luminance value, it can be increased to match the original perception by changing the physical parameters and returning to this cross line. Therefore, we selected three positions: $A = 232$ and $S = 4$, $A = 179$ and $S = 3$, and $A = 126$ and $S = 2$ on the equal graininess surface for $G = 0.54$. The three right images in Figure 11 show the results. The proposed operation was effective in equalizing graininess perception even when the luminance of the display was different from the original display.

To evaluate whether the graininess of the modified objects was equal that of the original object, we again asked observers to rate the graininess as described in section 3. After normalizing and averaging the ratings, the resulting evaluation scores were $G = 0.54$,

G = 0.58, and 0.57, for the three sets of A and S values, respectively. We can see that the change in ruggedness A is more important for generating the equalized perception for graininess than is the change in gain size S.

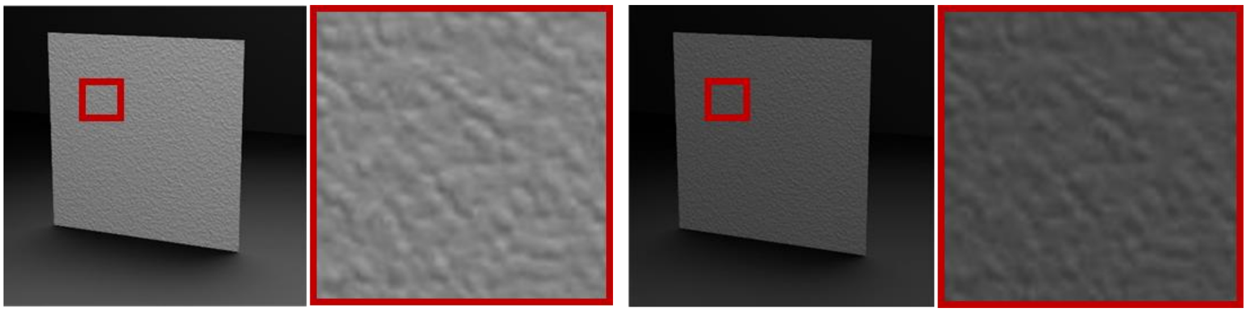


Figure 10. Sample of objects to revise the graininess. (a) Part of the graininess object with high maximum luminance, mean = 129, variance = 324, skewness = 0.006, kurtosis = 2.98. (b) Part of the graininess object with low maximum luminance, mean = 75, variance = 40, skewness = -0.271, kurtosis = 3.57

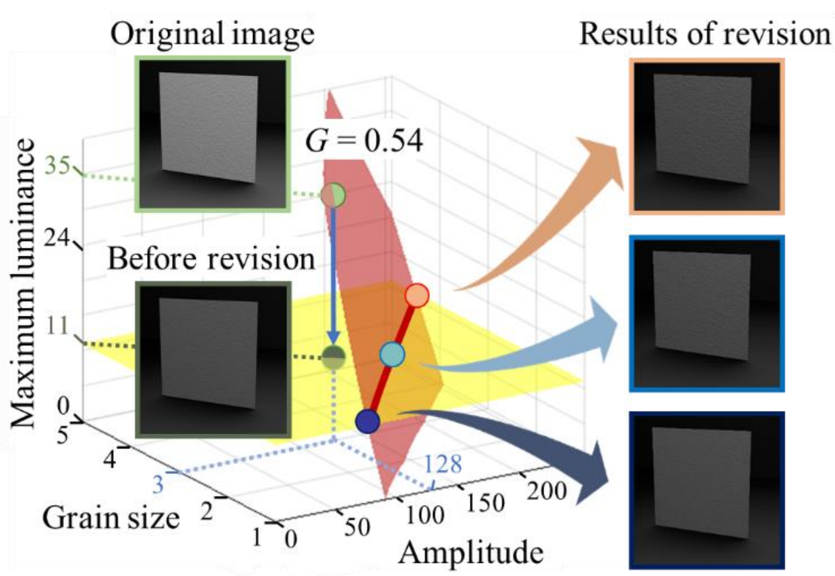


Figure 11. Schematic process for equalizing graininess G to 0.54.

4.2 Evaluation for the Accuracy

The graininess evaluation scores obtained by magnitude estimation is uneven because subjective rating is hard to compare under different luminance conditions. Therefore, we must check whether the numerical difference in evaluation score (G = 0.54 ~ 0.58) for the revised image is an appropriate result. We considered the variance of the graininess scores and determined the acceptable range. A standard deviation was calculated from the evaluation scores for each of the 27 images used in the rating task as shown in Table 3. The Table 3 indicates a tendency for variance to be large if both the size of the grains and the maximum luminance are small (Fig. 12). Similarly, Figure 13 indicates that the variance is small when both the size of the grains and the maximum luminance are large. The average of each graininess object's standard deviations (SD_{ave}) was 0.12. A difference in evaluation score for a revised image is therefore inappropriate if it is more than 0.12. In the example above, the target graininess for the image after revision was G = 0.54, and thus acceptable evaluation scores would be in the range of 0.42 to 0.66 (0.54 ± 0.12). Thus, in this paper, the acceptable boundary for graininess is within SD_{ave} of the target graininess value.

As shown in Fig 14(c-e), the perceived graininess of the image after revision ranged from G = 0.54 to 0.58 (a range of 0.04), which is well within the ± 0.12 boundary. The color of the outer frame of the graininess images shown in Figure 14 correspond to what is shown in Figure 11. This result is evidence that our proposed method for graininess space is useful for matching the perception of graininess even if the maximum luminance of display is changed.

Table 3. Graininess for the stimuli and its standard deviation

Amplitude	*Size*	*Maximum luminance*	*Graininess*	*Standard deviation*
64	2	11	0.19	0.0967384
64	2	24	0.4	0.1393901
64	2	35	0.5	0.1233472
64	3	11	0.09	0.0477231
64	3	24	0.08	0.0531899
64	3	35	0.19	0.0656472
64	4	11	0.06	0.0571663
64	4	24	0	0
64	4	35	0.1	0.0941271
128	2	11	0.7	0.1850335
128	2	24	0.79	0.1653805
128	2	35	0.85	0.1218958
128	3	11	0.43	0.1804283
128	3	24	0.51	0.0871989
128	3	35	0.63	0.1124477
128	4	11	0.28	0.1145117
128	4	24	0.4	0.1225348
128	4	35	0.5	0.1623673
256	2	11	0.79	0.1812379
256	2	24	0.84	0.1707873
256	2	35	0.9	0.1606013
256	3	11	0.78	0.1052932
256	3	24	0.82	0.135659
256	3	35	0.86	0.0862342
256	4	11	0.6	0.124508
256	4	24	0.67	0.1749642
256	4	35	0.79	0.1784082

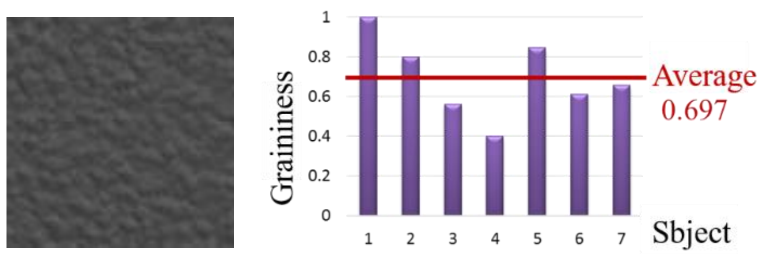


Figure 12. (left) Image with small grain size and small maximum luminance. (right) Variance in graininess perception for 7 observers.

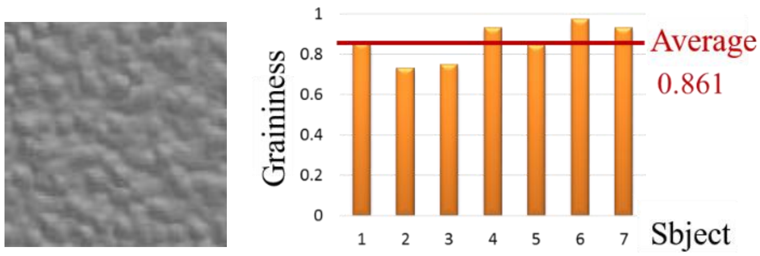


Figure 13. Image with large grain size and large maximum luminance. (right) Variance in graininess perception for 7 observers.

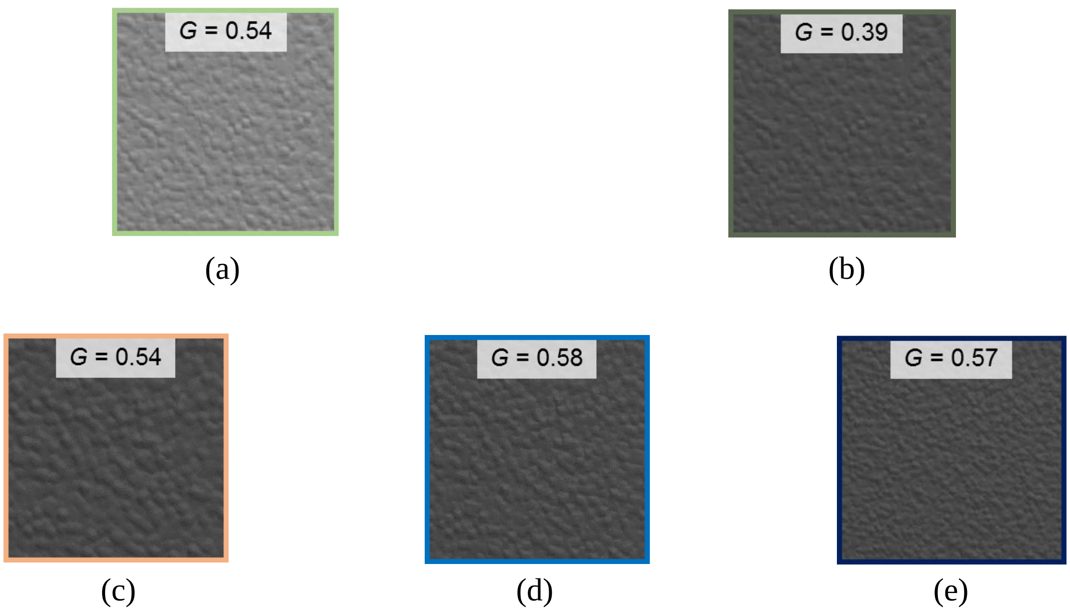


Figure 14. (a) An original image. (b) Lower luminance but before revision. (c-e) After revision with three different pairs of grain size and depth of ruggedness.

5 Conclusion and Future work

Here, we produced a psychophysically-based model of graininess perception for generating device-independent graininess. This model was used to match the graininess perception across displays with varying maximum luminances. The objects generated by the model were perceived as having equal graininess with a high accuracy.

This model is the result based on regression analysis. It is interesting that the result converged to the third root. This is because $L*$ indicating the luminance in the CIE $L*a*b*$ color space can be represented by the third root of Y indicating the luminance in the CIE XYZ color space. The $L*a*b*$ color space is designed to approximate human vision. Among them, the L component value is very close to the human perception of brightness. The amplitude (A) in this method represents the depth of the ruggedness by the contrast of the pixel value. Therefore, we guess it can be said that the difference in brightness of the graininess object leads to the graininess. In the future, we will investigate the relationship between the graininess due to the amplitude and the graininess due to the difference in brightness.

This model is useful for cases in which the graininess object is affected by a limited amount of luminance. The limitations of our model should be explored with additional evaluations. This model is useful for cases in which the graininess object is affected by a limited amount of luminance. The limitations of our model should be explored with additional evaluations. ·

Our model has limitations on the generated images. Since this model is an application of technology to map uniform graininess, it is preferable to apply to an object with uniform texture. As a basic research, we excludes the material appearance other than the graininess. Therefore, this model cannot be applied to the material appearance containing other elements such as gloss. The fineness / roughness is greatly affected by image contrast. However, the modulation of the texture is effective only under the condition that the intensity contrast or the shape of the intensity histogram match the characteristic of the fine texture.[11)] Since the size of the device affects the size of grain of the graininess object, the device used for the material appearance control is preferably the same size as the device before the control. Moreover, our model is only applicable to objects with a plane surface. As many kinds of objects with complex shapes exist in the world, future studies will have to achieve a more practical way to match appearance so that e-commerce can progress.

Acknowledgements

We thank Adam Phillips, PhD, from Edanz Group (www.edanzediting.com/ac) for editing a draft of this manuscript.

References

1. M. Ludwig, G. Meyer, “Effects of Mesoscale Surface Structure on Perceived Brightness”, Electron. Imaging Meas. Model. Reprod. Mater, 1–7 (7), 2016
2. Jie Guo, Jingui Pan, Real-time multi-scale refraction under all- frequency environmental lighting. CAD/Graphics, 2013.
3. Jie Guo, Jinghui Qian, Yanwen Guo, and Jingui Pan, Rendering Thin Transparent Layers with Extended Normal Distribution Functions, IEEE Transactions on Visualization and Computer Graphics, 2016
4. Fabio Pellacini, James A. Ferwerda, and Donald P.Greenberg, “Toward a psychophysically-based light reflection model for image synthesis”, In Proc. SIGGRAPH ’00, pp.55-64, 2000-07-01.

5. Busing F., Commandeur J., and Heiser W. (1997), “PROXSCAL: a multidimensional scaling program for individual differences scaling with constraints.”, In W. Bandilla and Faulbaum (Eds.), Advances in Statistical Software, 6, Lucius & Lucius: Stuttgart, 67-73.

6. G.J.Ward, ”Measuring and modeling anisotropic reflection”, ACM SIGGRAPH Computer Graphics, 26(2), pp.265-272(1992).Joseph B. Kruskal et al., “Multidimensional Scaling”, SAGE PUBLICATIONS, 1978.

7. Matt Pharr et al., “Physically Based Rendering: From Theory to Implementation”, http://www.pbrt.org/consumers-guide.html, (2017/01/03 access).

8. Hunter, R.S. and Harold R.W. (1987), “The Measurement of Appearance (2nd edition)”, Wiley, New York.

9. Norimichi Tsumura, Tetsuo Ikeda, Yoichi Miyake, ”Device Independent Gloss Reproduction Model for E-Commerce: Estimation of Radiance on Display”, PICS, 2003

10. B. Phong, “Illumination for computer-generated pictures”, Communications of the ACM Vol.18 No.6, pp.311-317, 1982.

11. Sawayama, M., Nishida, S., & Shinya, M. (2017). Human perception of subresolution fineness of dense textures based on image intensity statistics. Journal of Vision, 17(4):8, 1-18, doi:10.1167/17.4.8.

Caption List

Fig. 5 A graininess object before processing (a), after smoothing (b), and after inversing the luminance (c).

Fig. 6 Change in the depth of ruggedness (a), size of the grains (b), and maximum luminance (c) for a graininess object.

Fig. 7 The conditions of the experiment.

Fig. 8 Mean of the rating value for each stimulus.

Fig. 9 Surfaces of an equal graininess perception.

Fig. 10 Sample of objects to revise the graininess.

Fig. 11 Schematic process for equalizing graininess G to 0.54.

Fig. 12 I Image with small grain size and small maximum luminance. (right) Variance in graininess perception for 7 observers.

Fig. 13 Image with large grain size and large maximum luminance. (right) Variance in graininess perception for 7 observers.

Fig. 14 (a) An original image. (b) Lower luminance but before revision. (c-e) After revision with three different pairs of grain size and depth of ruggedness.