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3D CG Object Image Quality Assessment and Analysis for Glossy and Painted Based on Material Data Set of the Shitsukan Perception Standard Problem

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Abstract

Although humans perceive the luster of objects visually and sensuously on a daily basis, there is much debate as to how to express this numerically in order to obtain an index of luster. Gloss can be intentionally expressed by painting something on the 3D CG object. Therefore, we thought that we could somehow quantify the glossiness of 3D CG objects by studying the relationship between glossiness and paint. In this paper, we set parameters related to glossiness and paint on 3D CG object images in the Shitsukan Perception Standard Problem image dataset, performed texture analysis on these patterns, and discussed the results by classifying evaluation values using a Support Vector Machine (SVM) in relation to glossiness, paint, and image quality.

Index Terms

Glossy, Paint, Image Quality Assessment, Texture Analysis, Support Vector Machine (SVM)

1. Introduction

Traditionally, "Shitsukan" has had diverse meanings and interpretations. "Shitsukan" is defined as "the visual and tactile sensation of a material." However, there is no numerical evaluation or index of the degree to which a material has texture under certain conditions. In this study, we focus on glossiness, one of the components of Shitsukan. In our daily lives, we often perceive gloss when we recognize some objects. In this paper, we consider that glossiness can be classified into three types: natural gloss caused by optical phenomena such as specular or diffuse reflection of light on an object, gloss caused by the original surface texture of an object, and gloss caused by artificially created gloss by painting on an object. In our prior study, we conducted texture analysis on the relationship between texture information and image coding. Then, by using a support vector machine, we have discussed the classification method for image texture and clarified the relationship with image coding [1]. In addition, using luminance information, intercomparisons with texture analysis results were performed using heat maps [2]. As a results of the study, although the relationship between image encoding and texture was clarified, it was not clear whether the same could be said for 3D images or computer graphics when color information is taken into account, since the data set used was flat images where color information is not affected. Therefore, we thought that it might be necessary to take into account the material properties, contrast, and rotation factors of CG objects that include color and 3D information in order to measure texture more accurately. Based on these considerations, we conducted image analysis and evaluation of the materiality of 3D CG objects including contrast and rotation factors using images from dataset of the Shitsukan Perception Standard Problem [3]. The results showed that texture features, HEVC encoding, and rotation factors were effective, while contrasts related to the comparison stimuli did not change numerically with only a single parameter. Based on these results, we would like to consider glossiness, one of the other components of texture. In this study, we believe that it is easier to measure glossiness on 3D CG objects than on natural objects, and we will clarify the relationship between glossiness, paint, and image quality on artificial 3D CG objects. In this study, texture analysis was conducted for each pattern using 3D CG object images related to glossiness and paint in the image data set of the Shitsukan Perception Standard Problem [4]. And then, the relationship between glossiness, paint, and image quality is discussed by classifying the evaluation values using a Support Vector Machine (SVM).

2. Related work

2.1. Image and color engineering field

In the field of image and color engineering, formal modeling of texture from an optical approach and texture measurement have been studied as themes. Many of them have been measured under certain observational and environmental conditions, and their research includes estimation of texture from ergonomic viewpoints based on sensory evaluation and impression evaluation, as well as texture analysis of printed matter and cosmetics. In particular, the gloss and paint in this study are related to the formal modeling of texture and the texture analysis of printed materials [5, 6].

2.2. Computer graphics field

The field of computer graphics aims to visualize and mathematically model textures. Research on image-based visual prototyping of textiles [7], reflections and illumination [8], BRDF (Bidirectional Reflectance Distribution Function) [9], and multispectral light field [10], are discussed. In particular, the glossiness and paint in this study are seen to be related to the reflections, illumination, and light fields in the literature [8], [9], and [10].

2.3. Mathematical science, signal processing field

In the fields of mathematical sciences and signal processing, they are approached from the perspective of geometric approaches and applied mathematics. In particular, texture analysis on noise [11] and fractal descriptions [12], applied mathematics such as noise robust and rotation invariant frameworks [13], signal processing analysis on 2D multi-scale entropy processing analysis [14], 3D solid texture classification using locally oriented wavelet transforms [15], are discussed. Glossiness and paint in this study are seen to be related to noise and entropy in the literature [11],

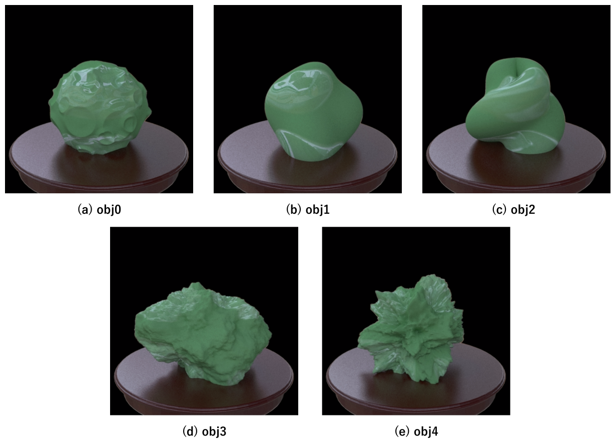

Figure 1. *Image content for texture perception evaluation used in this study*

[13], [14].

2.4. Medical image engineering field

The field of medical image engineering often deals with human life and urgent cases in hospitals and other medical institutions. Therefore, more accurate and reliable content is required. Under such conditions, research is being conducted on texture analysis for automatic recognition, discrimination, detection, evaluation, and estimation of in vivo sites and lesions. Specifically, estimation of cause of death, adaptive prediction of contour parameters using convolutional neural networks and texture analysis [16], and texture analysis of CT images to predict the risk of gastrointestinal malignancy [17] are have been discussed. In particular, glossiness and paint in this study are not directly related to the field of medical image engineering, but are seen as relevant for texture analysis, image discrimination, and evaluation.

2.5. Conclusion

From the related studies, there are no studies or examples that focus on real-time and large-scale texture measurement and quality evaluation from an information-theoretic approach that considers the relationship between glossiness, paint, and image quality. Therefore, based on the author's previous work in the literature, this study aims to gain new insights into texture informatics related to glossiness, paint, and HEVC coding using the image data set of the Shitsukan Perception Standard Problem.

3. Experimental set

3.1. 3D CG contents used in this study

In this study, we used the Shitsukan Perception Standard Problem: image dataset, which is freely available in the Shitsukan Research Database, as shown in Fig. 1. The dataset is divided into six datasets, Task 1 through Task 6, and all of Task 6 (Glossy vs. Painted) was used in this study.

3.2. Experimental procedure

The experimental procedure is shown below.

1. Shitsukan Perception Standard Problem: Select 200 images from Task 1-6 of the image dataset, the content of the Glossy vs Painted Task 6 dataset (Object (5 types), Depth (4 types), Target Stimulus (2 types), Rotation (5 types)). The image resolution is 512×512.
2. H.265/HEVC coding is performed on the 200 images in Task 6. Seven quantization parameters are used: $Q = ref, 20, 25, 30, 35, 40, 51$. The total number of image contents used in this study was 1400.
3. Texture analysis is performed on the generated evaluation images. In this study, the evaluation items are Energy, Entropy, Contrast, Correlation, and Homogeneity.
4. Based on the results obtained from the texture analysis, the relationship between glossiness, paint, and image quality was discussed by using a Support Vector Machine (SVM) to perform evaluation classification.

3.3. Experimental method and assessment method

In this study, the following two types of experiments were conducted:

- Experiment 1: H.265/HEVC image quality (called as Exp.1)
- Experiment 2: Rotation angle (called as Exp.2)

In this study, an HEVC encoder was built using CMake, and a solution running on Visual Studio 2022 was created and compiled to generate the encoder and decoder applications. The encoded image was generated by setting encoding parameters and resolution for the encoder and decoder and performing YUV4.2.0 8 bit conversion. As an evaluation method, we analyzed images using Gray-Level Co-Occurrence Matrix (GLCM), which is one of texture features in this study. Given a grayscale image f of size $W \times H(pixels)$ with L steps of luminance values (gray levels) as pixel values, if V_{ij} is the component of the i rows and j columns of the gray-level coincidence matrix V, then V_{ij} is the component of the i rows and j columns of the gray-level coincidence matrix V.

$$V_{ij} = \frac{\sum_{x,y \in \Omega} \left(\delta\left(i - f\left(x, y\right)\right) \delta\left(j - f\left(x + \Delta x, y + \Delta y\right)\right)\right)}{|\Omega|} \tag{1}$$

Here, the displacement vector $(\Delta x, \Delta y)$ represents how far away from the pixel of interest (x, y) the pixel value is viewed, and the set Ω is a collection of (x, y) such that the position after displacement $(x + \Delta x, y + \Delta y)$ will not deviate from the pixel value. Since different displacement vectors yield different GLCMs, the displacement vector must be chosen appropriately. Also,

$$P_{ij} = \frac{V_{ij} + V_{ji}}{2 \sum_{i,j=0}^{L-1} V_{ij}} \tag{2}$$

The matrix P obtained by denotes the normalized symmetric GLCM. Using the expressions (1) and (2), the statistical texture features can be expressed as (3)-(7).

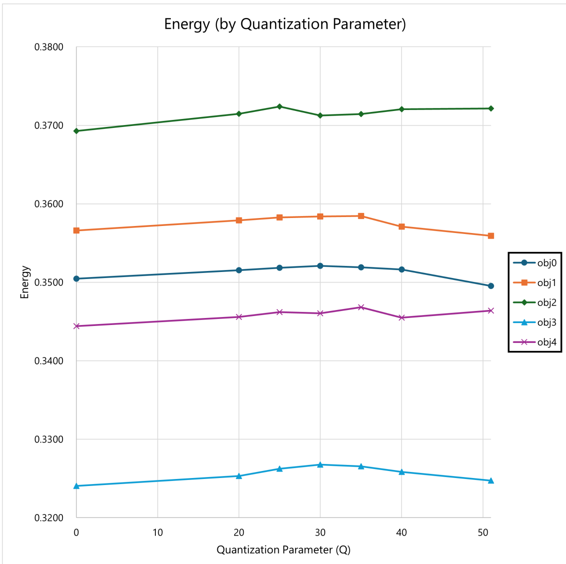

Figure 2. *Result of Exp.1 (H.265/HEVC) (Energy)*

$$Energy: \quad F_1 = \sum_{i,j=0}^{L-1} (P_{ij})^2 \tag{3}$$

$$Entropy: \quad F_2 = -\sum_{i,j=0}^{L-1} P_{ij} \log P_{ij} \tag{4}$$

$$Contrast: \quad F_3 = \sum_{i,j=0}^{L-1} (i-j)^2 P_{ij} \tag{5}$$

$$Correlation: \quad F_4 = \sum_{i,j=0}^{L-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \tag{6}$$

$$Homogeneity: \quad F_5 = \sum_{i,j=0}^{L-1} \frac{P_{ij}}{1+(i-j)} \tag{7}$$

where μ and σ^2 can be expressed as in equations (8) and (9).

$$\mu = \sum_{i,j=0}^{L-1} iP_{ij} \tag{8}$$

$$\sigma^2 = \sum_{i,j=0}^{L-1} P_{ij}(i-\mu) \tag{9}$$

4. Experimental results and discussion

The results of Exp. 1 (H.265/HEVC image quality) are shown in Figures 2 to 6. The vertical axis in Figures 2 to 6 represents the respective texture feature values and the horizontal axis represents the quantization parameter Q. The results of Exp. 2 (rotation angle) are shown in Figs.7 to 11. The vertical axis in Figs. 2 to 6 represents each texture feature, and the horizontal axis represents the quantization parameter Q and the rotation angle.

Table 1: SVM (SMO, Class Quantization Parameter)

Class Q Correctly Classified Instances 61/175 34.9%			
Precision	Recall	F-Measure	Class (Q)
0.73	0.76	0.75	Q_ref
0.17	0.12	0.14	Q_20
0.17	0.16	0.16	Q_25
0.04	0.04	0.04	Q_30
0.04	0.04	0.04	Q_35
0.33	0.44	0.38	Q_40
0.92	0.88	0.9	Q_51
0.34	0.35	0.34	Weighted Avg.

Table 2: SVM (SMO, Class Rotation)

Class Rotation Correctly Classified Instances 25/175 14.3%			
Precision	Recall	F-Measure	Class (R)
0.19	0.26	0.22	0
0.03	0.03	0.03	36
0.09	0.06	0.07	72
0.25	0.34	0.29	108
0.05	0.03	0.04	144
0.12	0.14	0.13	Weighted Avg.

4.1. Exp.1: H.265/HEVC image quality

From the results of experiment 1, for “Energy”, we can divide it into three groups: “obj2” (highest), “obj1”, “obj0”, “obj4”, and “obj3” (lowest) from Fig. 2. For “Entropy”, we can judge as “obj3” (the highest, but with a drop at $Q > 30$), “obj1” (the lowest, but with a drop at $Q > 30$) for “obj1” (lowest, but with a drop for $Q > 30$), “obj0” (highest, but with a drop for $Q > 30$) The three groups are “obj0”, “obj4” and “obj2” (almost monotonically increasing). For “Contrast”, all the patterns are monotonically decreasing, but can be divided into two groups: “obj4” and “obj3” (upper), and “obj0”, “obj2” and “obj1” (lower). As for the “Correlation”, it is monotonically increasing in all patterns. It was shown that the correlation increases as Q increases, regardless of the content. For “Homogeneity”, the correlation increased monotonically for all patterns. As for “Correlation”, it was shown that the uniformity increased as Q increased, regardless of the content.

4.2. Exp.2: Rotation angle

From the results of Exp. 2, for “Energy” in particular, “obj3” showed the largest difference between the rotation angles. For “Entropy”, in particular, the differences between rotation angles at $Q = 51$ were large regardless of the content. For “Contrast”, the contrast decreased monotonically for all patterns in Experiment 1, but not for each rotation angle, indicating that the contrast increased with the rotation angle. For “Correlation”, all patterns were monotonically increasing in Experiment 1, but not for each degree of rotation, indicating that the correlation decreased with the degree of rotation. For “Homogeneity”, it was shown that, as in the case of “Correlation”, the uniformity decreased with the

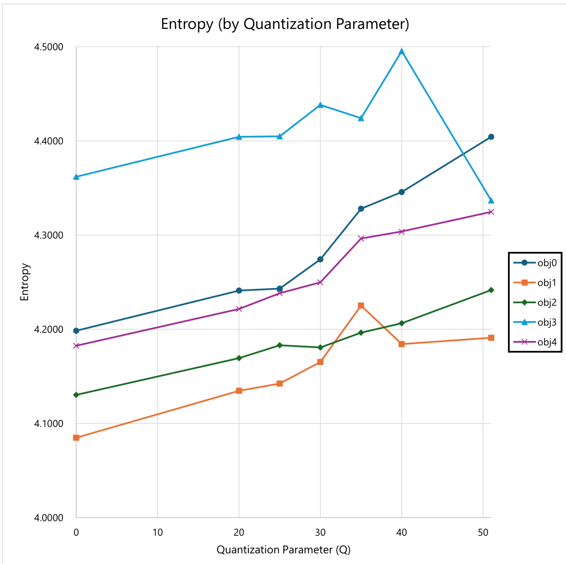

Figure 3. *Result of Exp.1 (H.265/HEVC) (Entropy)*

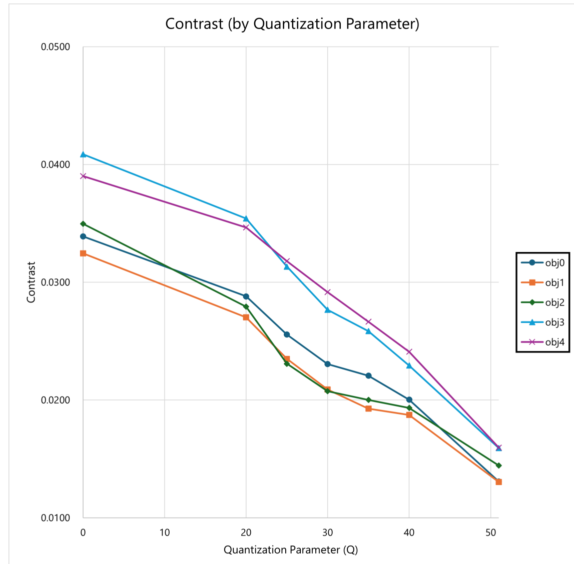

Figure 4. *Result of Exp.1 (H.265/HEVC) (Contrast)*

degree of rotation.

4.3. Discussion on classification using Support Vector Machine (SVM)

Based on the experimental results, the results of classification (by Q, by Rotation) by Support Vector Machine (Weka3.8.6) are shown in Table 1, 2. Precision, Recall, F-Measure, and Weighted Avg. in the tables 1 and 2 are "Precision", "Recall", "F-Measure", and "Weighted Avg". In this study, the SMO (Sequential Minimize Optimization) method was used to classify each of the classes Q and Rotation, and a score of 0.9 or higher was considered "very classifiable," a score of 0.8 or higher was considered "classifiable," and a score of 0.7 or higher was considered 0.7 or more, it is "Somewhat classifiable". From Table 1, the accuracy, recall, and F-value of Q_ref are all above 0.7, indicating that it is somewhat classifiable. For Q51, the accuracy and F-value exceed 0.9, making it very classifiable, and the reproducibility exceeds 0.8, making it classifiable. For the other Q patterns, accuracy, recall, and F value were all less than 0.7, and they were not classifiable. The classification correctness rate was 61/175, or 34.9 percent. On the other hand, Table reftb:SVM-R shows that the accuracy, recall, and F value for Rotation were all below 0.7, indicating that the patterns were not classifiable. The classification correctness rate was also lower than Class (Q) at 25/175, or 14.3 percent. The support vector machine classification results show that Class (Q) has a higher classification correctness rate than Class (R) and is closer to being classifiable, indicating that there is more relationship between the quantization parameters than between the rotation angles.

5. Conclusion

The results of this study suggest that the research results show that the influence of quantization parameters is more significant than the rotation angle in the texture evaluation regarding gloss and paint. As future works, we will continue to utilize image processing for more optical analysis.

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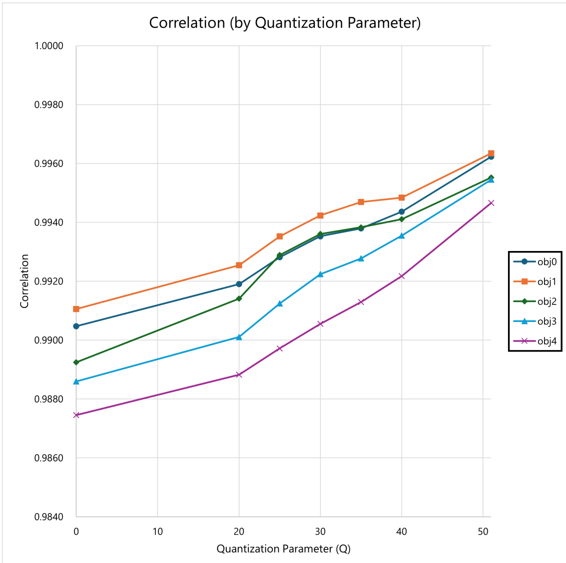

Figure 5. *Result of Exp.1 (H.265/HEVC) (Correlation)*

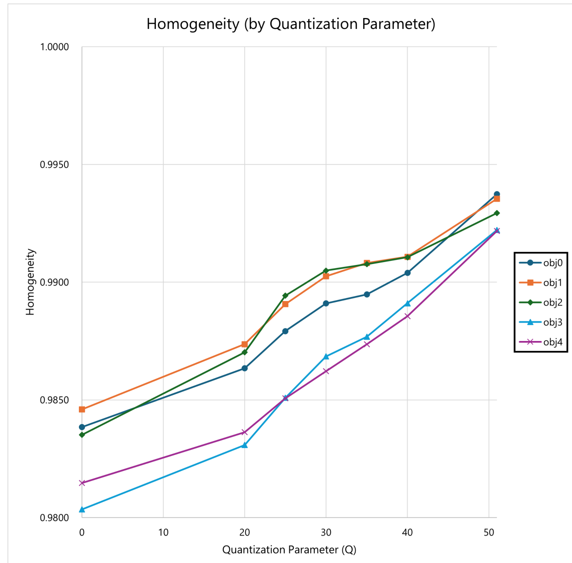

Figure 6. *Result of Exp.1 (H.265/HEVC) (Homogeneity)*

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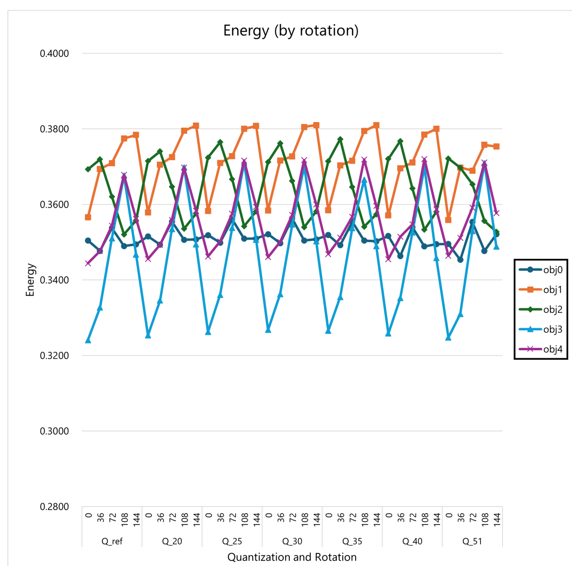

Figure 7. *Result of Exp.2 (Rotation) (Energy)*

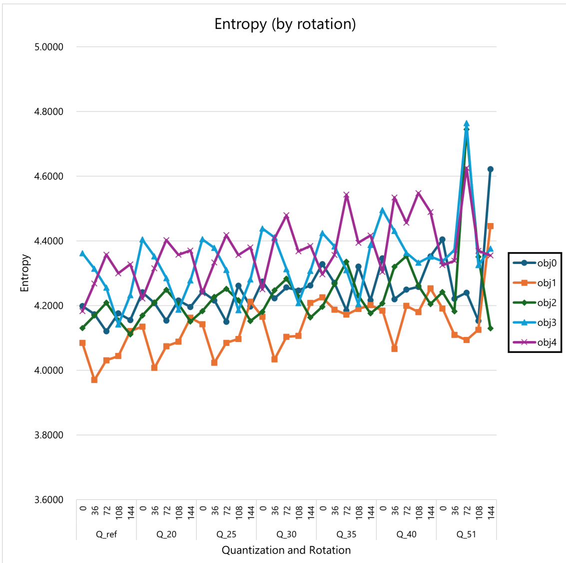

Figure 8. *Result of Exp.2 (Rotation) (Entropy)*

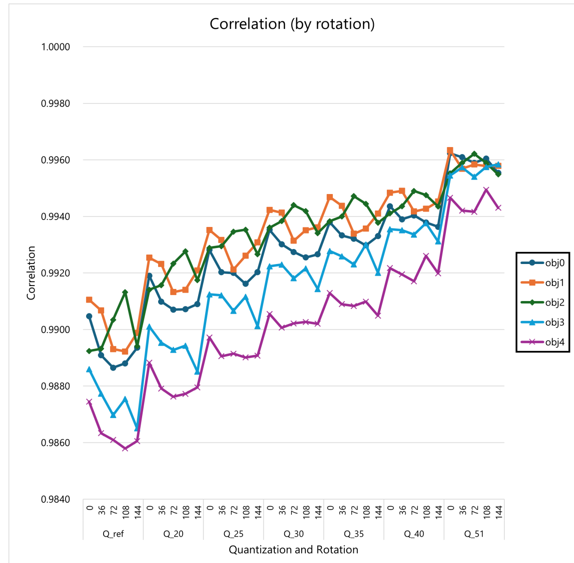

Figure 10. *Result of Exp.2 (Rotation) (Correlation)*

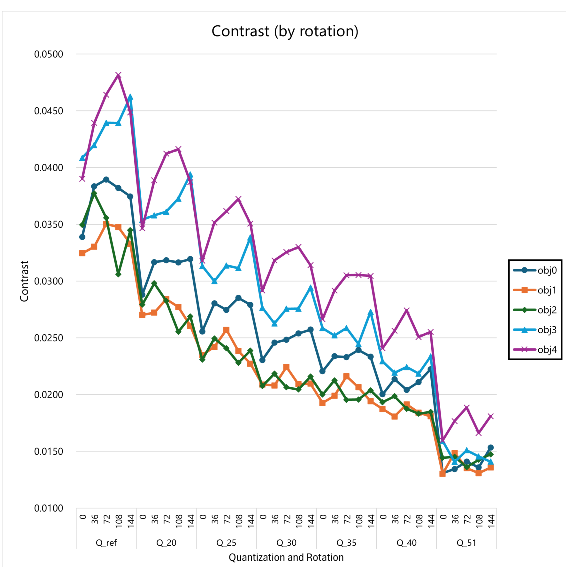

Figure 9. *Result of Exp.2 (Rotation) (Contrast)*

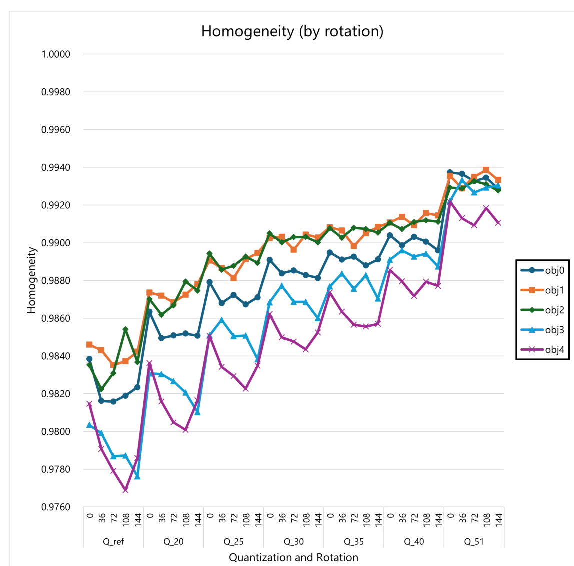

Figure 11. *Result of Exp.2 (Rotation) (Homogeneity)*