Computational Classification of Texture Contents in the Shitsukan Research Database

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Keywords: Texture, HEVC, Texture Features, Gray-Level Co-Occurrence Matrix, Support Vector Machine

ABSTRACT

In this paper, we used the Shitsukan Research Database from Web for free of charge. First, we generated the texture evaluation images by H.265/HEVC. And then, we assessed the generated images by texture analysis, and discussed results. Next, based on experimental results, we considered for classification method of texture types by Support Vector Machine (SVM). Finally, we discussed including assumption of system's automation.

1 INTRODUCTION

In Japan, by starting Quad FHDTV (QFHDTV: 4K) quality broadcasting in 2018 four times more than that of Full HDTV (FHDTV: 2K) in previous, the image texture is improved in addition to image quality improvement and high-definition of 3D image and video. On the other hand, since even if 4K broadcasting is started, all broadcasting video contents are not in 4K video quality, it is difficult to represent texture or Shitsukan of images originally. Therefore, for an example, HDTV quality video is transformed to 4K quality by processing of super-resolution [1], and then, we will need to reproduce texture of 4K quality as possible in the near future. Up to now, in “Shitsukan (in Japanese)”, there are a lot of meaning and interpretation. In [2], “Shitsukan” is defined as “material appearance or quality”. On the other hand, “Texture” is defined as using to represent (1) how to weave fabric, textile, cloth. (2) touch of wood and stone, material feeling. (3) material appearance of object surface in 3D Computer Graphics images. Of course, these definitions can be understood as interpretation of expression. However, actually, there is no numerical assessment or index how much Shitsukan or Texture is satisfied for requirement. Therefore, in each research fields, the development of the texture quantitative assessment system is demanded.

For texture of images, there were many studies by approaching from optics and color engineering field [3], [4]. In most of them, texture is estimated by measuring for optics under certain conditions. On the other hand, texture is estimated by Kansei assessment for ergonomics [5]. Therefore, it is not always possible to assess and measure correctly on real time. For examples, in the transportation and information system field, in the case of measuring traffic road surface condition, their conditions are affected by environmental condition (sun, rain, snow etc.) and the volume of traffic [6]. Therefore, in the transportation and information system field, it is required that information system which it is possible to assess and measure on real time. As a result, it is needed for objective assessment of texture to road surface condition, vehicle parts, and background. On the other hand, in the medical image engineering field, in case a medical specialist observes internal organs or body region, the image diagnosis result depends on state of progress for lesions [7]. Therefore, in the medical image engineering field, the information system that it is possible to diagnose and assess in real time, is required, and it is needed for the objective assessment of texture in the internal organ or body region. In this study, we consider image texture (equal to Shitsukan) as these common points. We studied on coded image quality assessment up to now. Particularly, we clarified to the relation among the multi-view 3D image, high-definition image, and image coding. However, these are not considered for texture. Actually, it is not clarified quantitatively for the relation between image coding and texture. Therefore, we consider that we are able to contribute for various fields in addition to broadcasting, transportation and information system, and medical image engineering by clarifying the relation between image coding and texture.

In this paper, first, we generated texture evaluation images by using the Shitsukan Research Database [8]. And then, we assessed these images by quantifying objectively based on texture analysis, and considered results. Next, from experimental result, we considered whether we are able to classify or not for texture types by using Support Vector Machine (SVM). Finally, we discussed assuming automation based on these results.

2 EXPERIMENTAL SET

2.1 Evaluation images in this study

Figs. 1 to 8 are the evaluation images used in this study. These images are encoded and decoded by H.265/HEVC in the Shitsukan Research Database (4170 images) for no charge from Web [8]. Overall, we used eight texture types: bark (1-530), sand (531-992), fabric (993-1501), fur (1502-2041), leather (2042-2566), stone (2567-3091), water (3092-3629), wood (3630-4170), and for Quantization Parameter (Q), we used seven types: $Q = ref, 20, 25, 30, 35, 40, 51$.

2.2 Experimental procedure

As experimental procedure, we show (1)-(4) in the following.

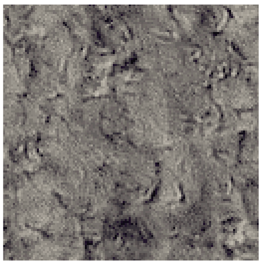
Fig. 1: bark

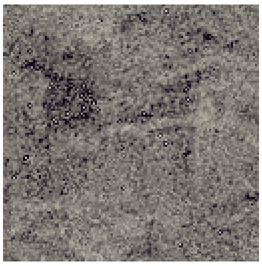
Fig. 2: sand


Fig. 3: fabric

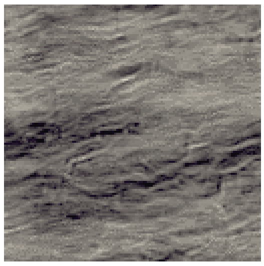
Fig. 4: fur

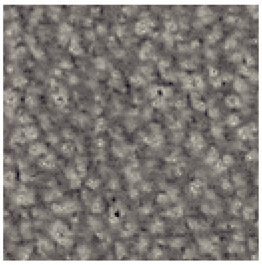
Fig. 5: leather

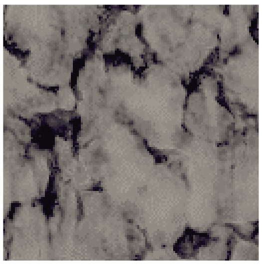
Fig. 6: stone


Fig. 7: water

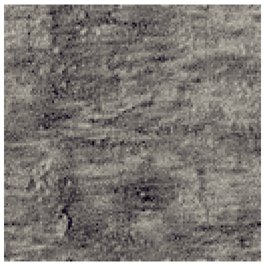
Fig. 8: wood

(1). There are 10,355 images in the Shitsukan Research Database [8]. These are included original images (4,170 images), interpolation images by texture composition parameter (6,185 images). In this study, we experimented using 4,170 images of original images.

(2). Next, we encoded and decoded the original images by H.265/HEVC, and then, we generated evaluation images. In this study, we analyze big data since we use 4,170 images. Therefore, the image sequences cannot be encoded and decoded in certain image pattern, certain types of Quantization Parameter. In this case, we defined as removing this pattern. On the other hand, we included the coded missing or defect as evaluation images.

(3). For generated evaluation images, we carried out texture analysis. In detail, we explain in Subsection 2.3 and Section 3.

(4). Based on results of texture analysis, we classified texture types of pattern in each texture features by using Support Vector Machine (SVM). In detail, we explain in Section 4. Finally, we discussed from experimental result. In detail, we explain in Section 5.

2.3 Evaluation method

As the evaluation method in this study, we carried out image analysis using Gray Level Co-Occurrence Matrix (GLCM) which is one of texture features. Here, in case there is a gray scale image f (size $W \times H$ (pixels)) which is L level luminance value (gray level) as pixel value, row i column j component of GLCM V is V_{ij}. In this case, we calculate in the following Eq. (1).

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

Here, the displacement vector $(\Delta x, \Delta y)$ represented that there is pixel value in position how long is departed from pixel of interest (x, y). Set Ω is (x, y) that the position after displacement is not deviated from pixel value. Since the different GLCM is obtained by the different displacement vector, we need to select the displacement vector appropriately. On the other hand, the matrix P as shown in Eq. (2) is represented as the normalized symmetry GLCM.

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

By using Eqs. (1) to (2), the statistical texture features used in this study are shown in Eqs. (3) to (7) of the following.

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

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

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

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

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

Here, μ, σ^2 are represented as shown in Eqs. (8) and (9).

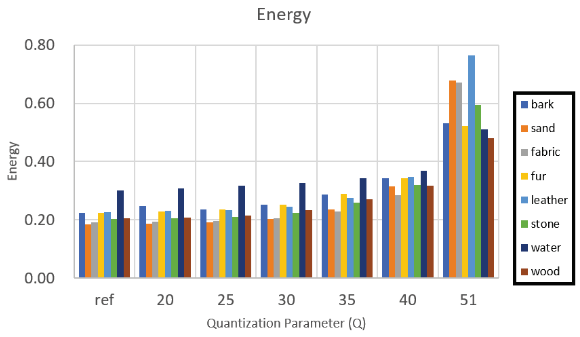

Fig. 9: Experimental Result (Energy)

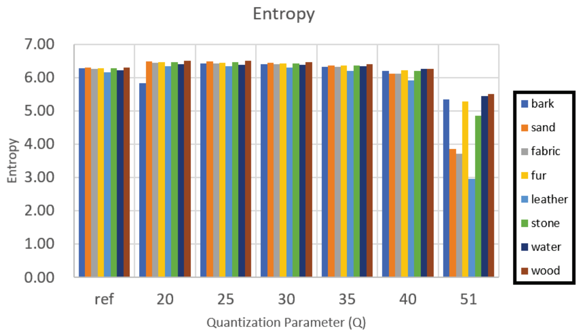

Fig. 10: Experimental Result (Entropy)

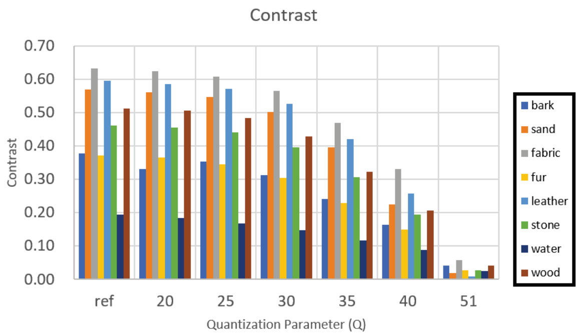

Fig. 11: Experimental Result (Contrast)

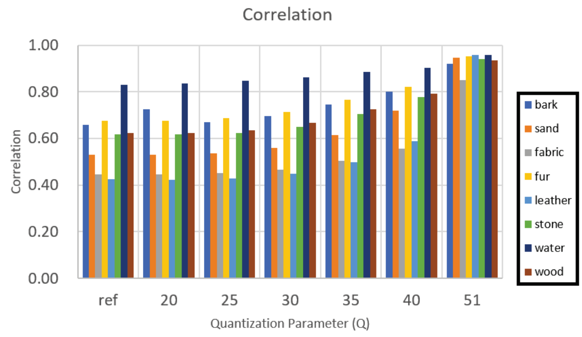

Fig. 12: Experimental Result (Correlation)

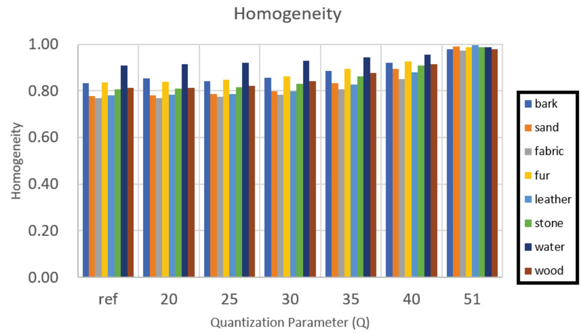

Fig. 13: Experimental Result (Homogeneity)

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

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

3 EXPERIMENTAL RESULTS

Figs. 9 to 13 are experimental results for “Energy,” “Entropy,” “Contrast,” “Correlation,” and “Homogeneity”. Here, the vertical axis is each statistical texture features, the horizontal axis is Quantization Parameter (Q), and the graph legend is contents type of the Shitsukan Research Database.

For “Energy” of Fig. 9, in the case of $Q = 51$, the feature of “leather,” “sand,” and “fabric” are tend to high rapidly. On the other hand, in the case of $Q \leq 40$, the feature of “water” is the highest of all contents. In the case of $Q \leq 35$, the feature of “sand,” and “fabric” are before and after 0.20, and this is tend to low among contents. In the case of $Q \geq 40$, the difference among contents is large. In the case of $Q = 40$, the difference between minimum and maximum value is about 0.1, however, in the case of $Q = 51$, this is about 0.3.

For “Entropy” of Fig. 10 in the case of $Q \leq 40$, there is no difference among contents, and then, $6.00 < Entropy < 6.30$ is satisfied. In the case of $Q = 51$, the features of “sand,” “fabric,” and “leather” are declined. In the case of “sand,” “fabric”, the difference for decline is about 2, in the case of “leather”, the difference for decline is about 3. On the other hand, in the case of “bark,” “fur,” “stone,” “water,” and “wood”, the difference for decline is the only between 1 and 1.5. To decline Entropy is the decrease of information content, and this is meaning as decrease of texture information. From this, in case the texture pattern is included complex content, the decrease of Entropy is tend to high.

For “Contrast” of Fig. 11, in the case of $Q = 51$, there is no feature. For “water”, in the case of $Q \leq 40$, feature is less than 0.20 among contents. From this, the feature of low Contrast can be seen. Focused on Fig. 7, we estimate for “water” case as low contrast subjectively, since there is stripped pattern compared to other contents, and pattern is not dark or deep.

For “Correlation” of Fig. 12, the more Q is increasing, the more correlation is high, however, there is the difference among contents. Particularly, for “fabric,” “leather”, in the case of $Q \leq 35$, “Correlation” is less than 0.5. Therefore, we can judge that there is no “Correlation” compared to other contents. On the other hand, for "water", in the case of all Q, "Correlation" is more than 0.8. Therefore, we can judge that there is "Correlation".

For "Homogeneity" of Fig. 13, for "water", in the case of Q, "Homogeneity" is more than 0.9, therefore, this is tend to high. For other patterns, "Homogeneity" is more than 0.75. Therefore, we can judge there is "Homogeneity" constantly.

4 CLASSIFICATION METHOD OF TEXTURE TYPES

4.1 Definition

In this subsection, we carried out the Support Vector Machine (SVM) of Sequential Minimal Optimization (SMO) method by data mining tool Weka based on texture analysis results, and then, we discussed texture types (for classification among contents). In this study, we focused on the only texture types, and for coded image quality, we defined as starting after having finished to classify appropriately in advance. For classification, we evaluated "Precision," "Recall," and "F-Measure". If the evaluation score is more than 0.7, we represent this as bold point, and then, we define this as "Classified".

4.2 Classification for texture types

From result of SVM, in the case of except for $Q = 51$ and "Correlation", "Recall" of "water" is more than 0.7. Others are less than 0.7. In the case of $Q = 51$ and "Correlation", "Precision" of "fabric" and "Recall" of "fur" are more than 0.7. As a result, we obtained that there is the difference in the case of $Q = 51$ and others.

For result of SVM correctly classified percentage for texture types, in the case of patterns except for $Q = 51$, the correctly classified percentage is between 24 and 26%, in the case of $Q = 51$, this percentage is 14.3%. We consider that we need to advance analysis for parameter between $Q = 40$ and $Q = 51$ which is not still investigated in this study.

5 DISCUSSION

From experimental results, we can judge that there is relationship of trade-off between "Energy" and "Entropy". For "Energy", in the case of $Q = 51$, feature is raised rapidly. On the other hand, for "Entropy", in the case of $Q = 51$, feature is declined rapidly. This shows that the defect of information contents is occurred by increasing the amount of energy which is the degree of coded quality. Particularly, in the Shitsukan Research Database, this phenomenon is often seen in the case of $Q = 51$. In this study, we use the only original images, and we are not able to carry out experiments to try overlapping some texture tile or multiple combination. If the image resolution in texture images is increased, we estimate that we are able to obtain the different results in this experiment. Particularly, in this study, there is some evaluation images which are defected or degraded since the coded region is limited, although the correct images can be generated in good condition (for relationship of high resolution or texture types). Therefore, actually, there is possibility that prospective results cannot be output well, and we will try in high resolution in the near future.

6 CONCLUSIONS

In this paper, first, we carried out the texture analysis for original texture images encoded and decoded by H.265/HEVC by using the Shitsukan Research Database [20]. Next, from results, we estimated classification method for texture types by using SVM. From experimental results, we obtained three knowledges that (1) To relate between "Energy" and "Entropy". (2) To change feature rapidly in the case of $Q = 51$. (3) To be able to classify before and after 25% in SVM correctly classified percentage for texture types. As our future works, we will carry out the improvement of precision applied super-resolution processing, signal processing and deep learning, and medical application.

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