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# Development of a Font Comparison System Using Similarity Metrics

Sho Takizawa\*, Taisei Hoshi \*\* and Qiu Chen \*\*\*

\* Kogakuin University, 1-24-2, Nishi-shinjuku, Sinjuku-ku , Tokyo, 163-8677, Japan  
c515067@ns.kogakuin.ac.jp

\*\* Graduate School of Engineering, Kogakuin University, 1-24-2, Nishi-shinjuku, Sinjuku-ku , Tokyo, 163-8677, Japan  
cm18033@ns.kogakuin.ac.jp

\*\*\* Kogakuin University, 1-24-2, Nishi-shinjuku, Sinjuku-ku , Tokyo, 163-8677, Japan  
chen@cc.kogakuin.ac.jp

**Abstract:** Various measures are being used to select the best font for the content. However, the degree of similarity calculated using different measures is different for the same font. In this research, we propose a font comparison system considering different similarity comparison methods by ranking similarities for each font. For measuring similarity, we use MSE, PSNR, SSIM, and MSSSIM for image quality assessment, as well as Euclidean distance and cosine similarity in t-SNE for dimensionality reduction. Relative relations among fonts are obtained by averaging similarity rankings of different similarity comparison methods.

**Keywords:** Font comparison, Similarity Metric, MSE, PSNR, t-SNE

## 1. INTRODUCTION

The expansion of information transmission means has increased the use of digital fonts as a medium for expressing information such as advertisements on webs and movies, subtitles on television, posters and the like. At the time of content creation, the creator selects and uses from a large number of expression fonts for the purpose of emphasizing more information to be conveyed. However, it is getting more difficult to select fonts to the characters of the information you want to convey, such as Web font service and fonts provided free of charge, due to the increase in choices.

In this research, we compare images of each character generated from fonts, and developed the system which proposes font having similarity similar to that of user selected font by using the result of comparing similarity for each character .

## 2. RELATED WORKS

In this paper, we use MSE, PSNR[1], SSIM[2,3], MSSSIM[4] for image quality evaluation, as well as Euclidean distance and cosine similarity in t-SNE[5] for dimensionality reduction.

### 2.1 MSE(Mean Squared Error)

Measure the error of each pixel value of the image and obtain the average.

The MSE between  $m \times n$  image A and image B sets each pixel value to  $A = \{A_{11}, A_{12}, \dots, A_{mn}\}$  and  $B = \{B_{11}, B_{12}, \dots, B_{mn}\}$  is defined as:

$$MSE(A, B) = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n (A_{ij} - B_{ij})^2 \quad (1)$$

### 2.2 PSNR(Peak signal-to-noise ratio)

This is a method of obtaining the maximum pixel value that each pixel value of an image can take and the ratio of degradation due to noise.

PSNR between image A and image B is given by

$$PSNR = 10 \log_{10} \frac{L^2}{MSE(A, B)} \quad (2)$$

where  $L$  is the dynamic range of the pixel values, it will be  $L=2^8-1=255$  if it is 8bit/pixel gray scale images.

### 2.3 SSIM(Structural Similarity)

Luminance  $l(x, y)$ , contrast  $c(x, y)$ , structure  $s(x, y)$  for the local region  $x$  of the image A and the local region  $y$  of the image B extracted between the images based on the window size , And combines these to calculate the similarity  $SSIM(x, y)$ .

Assuming that the parameters of luminance, contrast, and structure are  $\alpha, \beta, \gamma$ , then

$$SSIM(x, y) = [l(x, y)]^\alpha \cdot [c(x, y)]^\beta \cdot [s(x, y)]^\gamma \quad (3)$$

In this implementation, referring to [3], the window size of the local area is  $11 \times 11$ ,  $\alpha = \beta = \gamma = 1$ ,  $C_1 = (K_1L)^2$ ,  $C_2 = (K_2L)^2$ ,  $K_1 = 0.01$ ,  $K_2 = 0.03$  is used as the constant.

For comparison between images with  $M$  as the number of local regions, mean SSIM (MSSIM) is used as follows.

$$MSSIM(A, B) = \frac{1}{M} \sum_{j=1}^M SSIM(x_j, y_j) \quad (4)$$

#### 2.4 MSSSIM(Multi-Scale Structural Similarity)

MSSSIM is an improved method of calculating the SSIM in the local region. A contrast comparison function  $c_1(x, y)$  and a structure comparison function  $s_1(x, y)$  are obtained for the local region  $x$  of the image  $A$  and the local region  $y$  of the image  $B$  extracted from among the images based on the window size. Then,  $c_2(x, y)$  and  $s_2(x, y)$  are calculated by passing low pass filter and down sampling on the input. This process is repeated until  $M-1$  iterations of  $c_{M-1}(x, y)$ ,  $s_{M-1}(x, y)$  by low pass filter and down sampling. Finally, in addition to  $c_M(x, y)$ ,  $s_M(x, y)$  and luminance comparison function  $l_M(x, y)$  is calculated.

Using the above results, MSSSIM is obtained by

$$SSIM(x, y) = [l_M(x, y)]^{\alpha_M} \cdot \prod_{j=1}^M [c_j(x, y)]^{\beta_j} \cdot [s_j(x, y)]^{\gamma_j} \quad (5)$$

SSIM is calculated by equation (5), and equation (4) is used for comparison between images. Also, we use  $\beta_1 = \gamma_1 = 0.0448$ ,  $\beta_2 = \gamma_2 = 0.2856$ ,  $\beta_3 = \gamma_3 = 0.3001$ ,  $\beta_4 = \gamma_4 = 0.2363$ ,  $\alpha_5 = \beta_5 = \gamma_5 = 0.1333$  from [4].

#### 2.5 t-SNE(t-distributed stochastic neighbor embedding)

A nonlinear dimensionality reduction method that estimates a low-dimensional space that holds the data structure of a high-dimensional space as much as possible by minimizing the Kullback-Leibler divergence. The high-dimensional space probability distribution as  $P$ , the low-dimensional space probability distribution we want to estimate as  $Q$ , let  $X = \{x_1, x_2, \dots, x_n\}$  be the image data in the high dimensional space,  $Y = \{y_1, y_2, \dots, y_n\}$  be the image data in the low dimensional space, let the proximity of the data of  $x_i$  and  $x_j$  be the joint probability  $P_{ij}$  and the closeness of the data of  $y_i$  and  $y_j$  be the joint probability  $q_{ij}$ .

By using the fact that the distribution is similar as the Kullback-Leibler divergence amount for  $P$  of  $Q$  becomes

smaller, the objective function  $C$  is defined as below and minimized.

$$C = KL(P||Q) = \sum_i \sum_j p_{ij} \log \frac{p_{ij}}{q_{ij}} \quad (6)$$

### 3. PROPOSED FONT COMPARISON SYSTEM

Figure 1 shows the proposed font comparison system (FCS), by which the most similar font will be output compared with input fonts selected by the user.

In FCS, the comparisons will be carried out by the following procedure.

1. Create images of selected characters from fonts.
2. Extract data, file path, and font name from the images.
3. MSE, PSNR, SSIM, MSSSIM, Euclidean distance and Cosine similarity after adaptation of t-SNE are calculated according to the image data and stored as csv.
4. Using the results of csv, we propose similar ranking of fonts for user selected fonts on a web application created using Dash[6], applied strings. Let  $R$  be the ranking of a font for a font,  $R_i$  in a similarity comparing method,  $x_j$  the ranking of the comparison result of the same character,  $n$  the number of character types to be compared and  $m$  the number of similarity comparison methods, calculate the font rank for each similarity comparison method by the following,

$$R_m = \frac{1}{n} \sum_{j=1}^n x_j \quad (7)$$

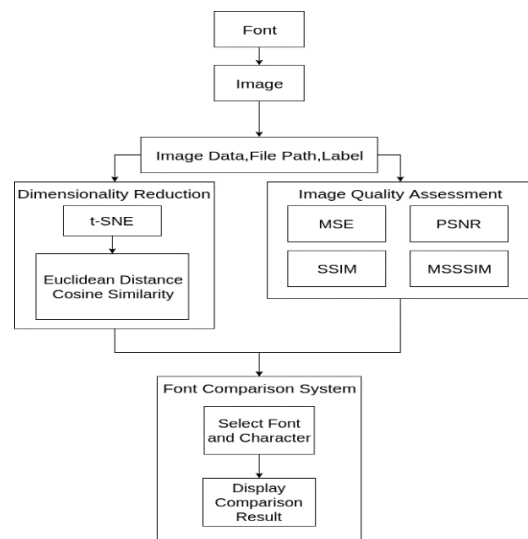


Figure1: Proposed Font Comparison System

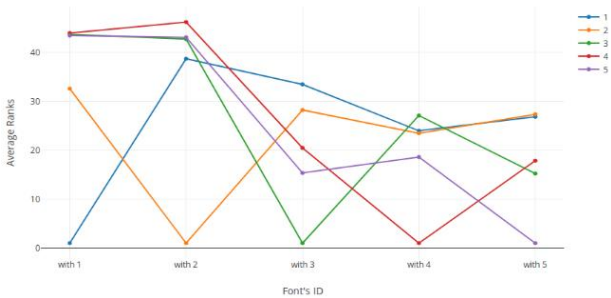
Also,  $R$  is calculated by averaging each similarity comparison method by the following equation.

$$R = \frac{1}{m} \sum_{i=1}^m R_i \quad (8)$$

#### 4. EXPERIMENTAL RESULTS

Five kinds of fonts expressing each emotion proposed in [7], Angry (HOT-bukotsu Std U, ID 1), fear·contempt·contempt (Manyokoin Std B, ID 2), expressionless (HG kyokasyotai, ID 3), pleasure·surprise (HGS soueikaku pop tai, ID 4), And sorrow (HGS gyousyotai, ID 5), we compare ranking using the font comparison system on the generated characters and the similarity of the original font using a system that generates fonts by combining two kinds. The letters to be used are 62 types including the numbers 0 to 9, alphabets a to z, and A to Z. 62 types of characters were deduced from two types of fonts and generated as  $256 \times 256$  images at ratios of 0:100, 25:75, 50:50, 75:25 and 100:0, respectively.

As 55 kinds of fonts with 62 characters per font together with the original font, we compared how similar the other original fonts are to the five original fonts. For example, font similarity rankings of IDs 2, 3, 4, and 5 are compared with fonts of ID 1 defined in 4 to investigate what kind of similarity is possessed. Table 1 shows the ranking of similarity of the original font for each of the five original fonts, and the result is shown graphically in Figure 2.

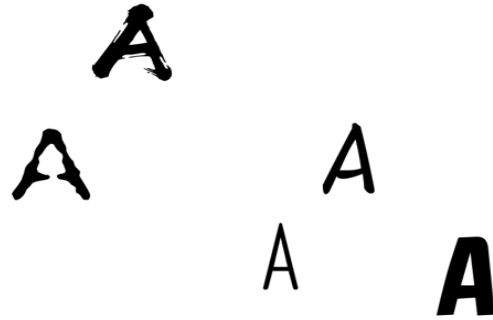


**Figure 2:** Relationship of similarity rank order among five kinds of original fonts

From the results in Table 1, the similarity relationship among the five original fonts is  
 ID 2, 5, 3, 4 for ID 1,  
 ID 1, 3, 5, 4 for ID 2,  
 ID 5, 4, 2, 1 for ID 3,  
 ID 5, 2, 1, 3 for ID 4,  
 ID 3, 4, 1, 2 for ID 5.

**Table 1:** Similarity ranking among five types of original fonts

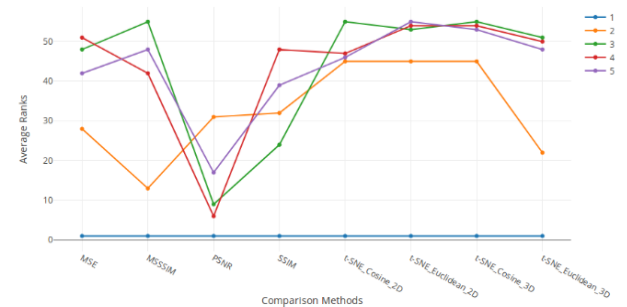
Font's ID	1	2	3	4	5
With 1	1	32.625	43.75	44	43.5
With 2	38.75	1	42.75	46.25	43.125
With 3	33.5	28.25	1	20.5	15.375
With 4	24	23.5	27.125	1	18.625
With 5	26.875	27.375	15.25	17.875	1



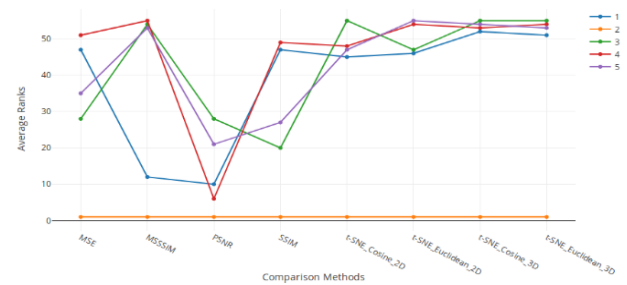
**Figure 3:** Relative positional relationship of five kinds of original fonts

When expressed by letters of A generated from each font, the result as shown in Figure 3 was obtained.

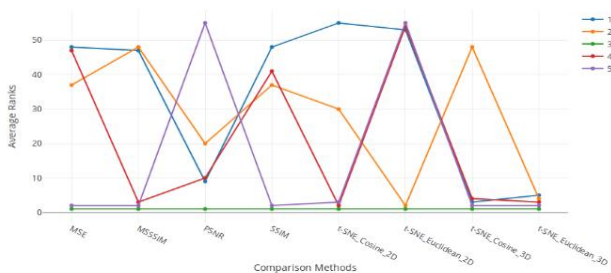
The results of comparing the similarity rankings for each similarity comparison method in one font are shown in Figure 4 to 8.



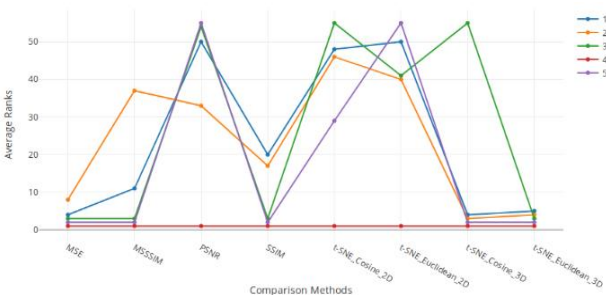
**Figure 4:** Similarity ranking for each comparison method for ID 1



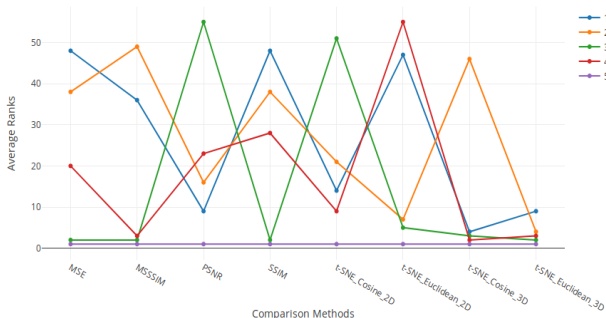
**Figure 5:** Similarity ranking for each comparison method for ID 2



**Figure 6:** Similarity ranking for each comparison method for ID 3



**Figure 7:** Similarity ranking for each comparison method for ID 4



**Figure 8:** Similarity ranking for each comparison method for ID 5

Table 2 shows the comparison method in which the similarity relationship between the original fonts for each comparison method shown in 4 to 8 is the same as the similarity relation obtained from Table 1.

**Table 2:** Comparative method to maintain similarity relations

Font's ID	Comparison Methods
1	MSE
2	None
3	t-SNE_Euclidean_3D
4	t-SNE_Cosine_2D,3D
5	MSSSIM

### 5. CONCLUSION

We developed a system that calculates similarity between five kinds of fonts by multiple similarity comparison methods and proposes similar fonts for each font. The similarity comparison method that maintains the same relation as the ranking of the similarity between fonts according to the ranking of ranking of each similarity comparison method differs for each font to be compared. Therefore, by increasing the number of identification characters for one font from 62 types, the average ranking of each similarity comparison method that maintains the same similarity relationship becomes more stable, or by increasing the type of font, Find similarity relationships between fonts showing close similarity.

### REFERENCES

- [1] Z. Wang, A. C. Bovik; Mean squared error: Lot it or leave it? A new look at signal fidelity measures, IEEE Signal Processing Magazine, 26(1), pp. 98-117, 2009.
- [2] Z. Wang, A. C. Bovik, H. R. Sheikh, E. P. Simoncelli; Image Quality Assessment : From Error Visibility to Structural Similarity, 13(4), pp. 1-14, 2004.
- [3] A. N. Avanaki; Exact global histogram specification optimized for structural similarity, Optical Review, 16(6), pp. 613-621, 2009.
- [4] Z. Wang, E. P. Simoncelli and A. C. Bovik; Multi-scale structural similarity for image quality assessment, IEEE Asilomar Conference Signals, Systems and Computers, Nov. 2003.
- [5] L. Maaten, G. Hinton; Visualizing Data using t-SNE, Journal of Machine Learning Research, 9, pp. 2579-2605, 2008.
- [6] Dash by plotly <<https://plot.ly/products/dash/>> Accessed, 2019-02-06.
- [7] A. Nakamura, S. Takizawa, T. Hoshi, H. Tsunashima, Q. Chen; Automatic Font Generation Algorithm Based on Image Kansei, Transactions of Japan Society of Kansei Engineering, 17(5), pp. 523-529, 2018.