

[P2-22]

On the relation between contrast and the perception of visual complexity

André Cavalcante¹, Ahmed Mansouri², Lemya Kacha Epe Mansouri², Allan Kardec Barros³, Yoshinori Takeuchi¹, Naoji Matsumoto² and Noboru Ohnishi¹

¹ Ohnishi Lab, School of Information Science, Nagoya University

² Graduate School of Architecture, Nagoya Institute of Technology

³Laboratory for Biological Information Processing, Universidade Federal do Maranhao, Brazil

E-mail: andre@ohnishi.m.is.nagoya-u.ac.jp

Abstract— We propose a measure of visual complexity for real-world images. Specifically, our measure is based on the statistics of contrast distribution of the visual compositions. Here, we use a dataset of 74 streetscapes consisting of dayscapes and nightscapes captured in Algeria and Japan. The proposed objective measure and subjective ratings exhibit correlation coefficient of 0.66 whilst the state-of-art only exhibits 0.36 of correlation for this dataset.

Keywords— Image contrast, Visual complexity, Perception

1 Introduction

One problem in psychology and perception is to create mathematical measures which can predict when humans judge visual scenes as simple or complex. Many studies have investigated the design such measures [1,2,3] focusing only on images such as radar images, simple drawings, icons and paintings. In this regard, these works shows that for such images, a measure highly correlated with subjective complexity is the size of the image file in JPEG format. In this work, we focus on real-world images. Specifically, we use here database of dayscapes and nightscapes.

2 Methods

In this work, 74 streetscape images were used. Half of the images were acquired in Al-Kantara and Batna cities in Algeria. The other half was acquired in the cities of Kyoto and Tokyo in Japan. Within the dataset, 40 images were acquired in daytime and 34 images in nighttime. The image quality is 4288 x 2848 14 bit pixels.

2.1 Subjective raking

Images in the dataset were analyzed by 15 subjects in high resolution displays. The participants were asked to analyze and compare the images sorting from the most simple to the most complex streetscape. After gathering data from all subjects, images were ranked according to the following procedure.

Firstly, c-scores are used to represent 74 rank positions, i.e.,

$$c(k) = 2 \cdot \frac{k - 37.5}{21.5} + 5, \quad k = 1, 2, \dots, 74. \quad (1)$$

The rank of an image is then calculated based on its

average positioning, i.e.,

$$r = \frac{1}{\sum_k v(k)} \cdot \sum_k [v(k) \cdot c(k)], \quad (2)$$

where $v(k)$ is the number of times the specific image was voted or located by the subjects at position k .

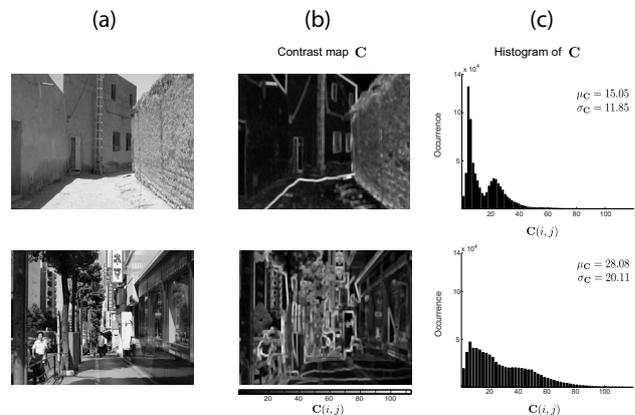


Figure 1: **Statistics of contrast maps.** (a) Original images. The first image was ranked as the most simple streetscape. The second streetscape was considered the most complex scene. (c) Respective contrast maps and (c) their histograms.

2.2 Objective ranking

For objective ranking, images were transformed to grayscale and resampled to 1072 x 712 pixels.

2.2.1 Contrast map

Around every pixel $\mathbf{I}(i, j)$ of the input image, let us consider a neighborhood of $2N \times 2N$ pixels denoted by the vector \mathbf{x}_{ij} . The contrast map \mathbf{C} is calculated as

$$\mathbf{C}(i, j) = \sqrt{E\{(\mathbf{x}_{ij} - \mu_{\mathbf{x}_{ij}})^2\}}, \quad (3)$$

where $\mu_{\mathbf{x}_{ij}}$ is the mean value of \mathbf{x}_{ij} . The above measure is also called the RMS contrast of luminance values in \mathbf{x}_{ij} .

2.2.2 Measure of visual complexity α

For objective evaluation of visual complexity, this works considers the following measure

$$\alpha = \mu_{\mathbf{C}} \cdot \sigma_{\mathbf{C}}, \quad (4)$$

where $\mu_{\mathbf{C}}$ and $\sigma_{\mathbf{C}}$ are the mean and standard deviation of RMS contrast values $\mathbf{C}(i, j)$.

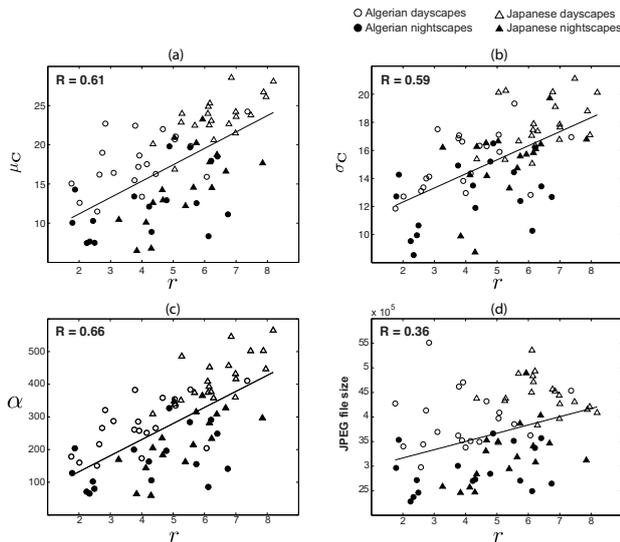


Figure 2: **Objective rank analysis.** Objective measures are given in function of r -values. (a) Mean contrast μ_C . (b) Standard deviation σ_C of contrast values. (c) Measure α . (d) Size of the image file in JPEG format (bytes). Correlation coefficient between objective and subjective ranks are given at top right corner of each plot. All correlation significant $p < 0.01$. Solid lines in the plots represent the best least-squares-sense first-order polynomial fit.

3 Results

3.1 Statistics of contrast maps

Figure 1 shows examples of contrast maps for streetscape images. In Figure 1.a, the top scene was ranked as the most simple streetscape and the second one as the most complex. Figure 1.b shows the respective contrast maps for each streetscape and their histograms.

In the contrast maps, sharp changes of luminance receive very high values. In this way, the contrast map highlights features such as image contours. Notice the differences between the contrast maps of the most simple and most complex streetscapes. These differences are quantified by their histograms. Notice that α -parameters, i.e., μ_C and σ_C , almost double from the most simple to the most complex. The next section provides a more rigorous analysis of how α -parameters change along the entire streetscape database.

3.2 Objective rank analysis

Figure 2 shows how each objective measure correlates with subjective rank given by r -values. The mean RMS contrast μ_C is shown in Figure 2.a. The correlation coefficient between this α -parameter and r -values is $R = 0.61$. Notice that in comparison to dayscapes, most of nightscapes have lower mean contrast.

Plot 2.b shows the standard deviation σ_C of contrast values in function of subjective ranks. The correlation coefficient with subjective ranks for this measurement is $R = 0.59$. Nightscapes also exhibit lower σ_C values than those of dayscapes.

Plots 2.c and 2.d show measure α and the size of image files when converted to JPEG format, respectively.

The proposed measure has the highest correlation with subjective ranks ($R = 0.66$). Notice that for both, measure α and JPEG file size, dayscapes consistently generate lower values.

4 Discussion

Firstly, let us analyze the proposed measure of visual complexity α . The mean RMS contrast μ increases as the number of high-contrast features increases. Since μ exhibits a positive correlation with subjective ranks, the perceived complexity is likely to increase with the presence of high-contrast features.

The standard deviation σ_C increases due to the presence of features that generate $C(i, j)$ values either higher or lower than μ . In this way, σ_C is a measure of contrast variety within the visual composition. This α -parameter is also positively correlated with subjective ranks. Therefore, streetscape complexity is more likely to increase with higher contrast variety.

Although measure α has a far higher correlation with subjective ranks than JPEG file size, it is also biased by nightscapes. The reason is that contrast is naturally lower during the night due the lack of light. Since many nightscapes have indeed high r -values, humans should not be judging visual complexity based only on parameters derived from contrast information.

Interestingly, the proposed measure does not use information about color distribution, which is likely to have an important role for the analysis of participants. Notice that JPEG file was created for the original colored images. In this way, measure α requires less information from the original images.

5 Conclusion

Here, we have proposed a new measure of visual complexity based on the use of contrast information. This measure has a correlation coefficient with subjective ranks of $R = 0.66$ for a set of 74 streetscapes. This correlation coefficient widely surpasses the performance of JPEG file size, which exhibits correlation coefficient of only $R = 0.36$. The main reason that the image file size fails to provide a good indication of visual complexity is because it is highly biased in the presence of photos shot during night period. In this regard, it is important to notice that the proposed measure still present biases but less than image file size. At this moment, the authors are analyzing other statistical parameters which can help to eliminate these bias.

References

- [1] Forsythe, A., Nadal, M., Sheehy, N., Cela-Conde, C.J. & Sawey, M. (2011), Predicting beauty: Fractal dimension and visual complexity in art. *British Journal of Psychology*, 102, 49–70.
- [2] Donderi, D.C. (2006). An information theory analysis of visual complexity and dissimilarity. *Perception*, 35, 823–835.
- [3] Forsythe, A., Mulhern, G., & Sawey, M. (2008). Confounds in pictorial sets: The role of complexity and familiarity in basic-level picture processing. *Behavior Research Methods*, 40(1), 116–129.