The Impact of Individual Observer Color Matching Functions on Simulated Texture Features

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ABSTRACT

We investigated the impact of simulating individual observer color matching functions (CMF) on texture features. Our hypothesis is that most people perceive texture in a similar manner, thus a texture indicator that is least dependent on individual physiology of human vision would be most likely a potential fit to visually perceived texture. To this end, the following strategy was implemented: Hyper-spectral images were converted into XYZ images for individual observer CMFs, estimated by an individual observer colorimetric model. Contrast sensitivity function (CSF) filtering was applied to the XYZ images for visual simulation. Two types of texture features were extracted from the filtered images. Finally, the difference between the texture features computed for two observer groups with different variance in CMFs was analyzed. The results obtained for this two simulated texture features could explain our hypothesis, however this is a preliminary investigation and requires further test and analysis to develop stronger observations.

KEYWORDS
texture features I *color matching functions* I *hyper-spectral images*

INTRODUCTION

The way we perceive, measure and model colour textures has been largely investigated, yet we still do not fully understand texture perception, e.g. Julez (1975), Tamura et al (1978), or Gibson and Bridgeman (1987). There are several texture such indicators that can be computed from a texture image, and the relation between those indicators and human judgement is a current topic of research at several institutes, e.g. Benco et al (2014), or Mirjalili and Hardeberg (2019). In this work, we propose to investigate the impact of individual Color Matching Functions (CMFs) on texture feature. The motivation of this work is based on the following hypothesis: If we can communicate about appearance, including texture, it means that, despite our individual differences, we have a similar representation of material appearance in our brain. In case of texture, this implies that the texture features that are consistent across various parameters of vision models, are more likely to be good candidate features to correlate better with visually perceived texture. If this hypothesis is verified, then we could investigate different features automatically based on simulation, assuming we have access to vision models. In this article we propose a method to investigate texture features following this procedure. We apply this method on two classes of texture features. The vision model we use is based on individual CMFs and a Contrast Masking method. The comparison between features is based on the measurement of differences between two clusters of individual observers.

Individual Observer Colorimetric Model

We recall here the individual observer color matching functions model by Asano (2015). The creation of the model involved three steps: color matching experiments, estimation of physiological parameters with an optimisation process using the individual observer colorimetric model, and generating the individual observer color matching functions. In the color matching experiment, the stimuli were made of four LEDs and there were 151 color-normal observers involved. For each observer, five color matches were implemented, and each match was repeated three times. The observers' ages ranged from 20 to 69 years old, and their inter-variability was tested by the Mean Color Difference from the Mean (MCDM). The results of the color matching experiments were fed to the individual observer colorimetric model, according to Equation 1:

$$\boxed{lms - CMFs = f\left(a, v, d_{lens}, d_{macula}, d_L, d_M, d_S, s_L, s_M, s_S\right)} \tag{1}$$

The input to the model was the ten physiological parameters: age, field size, deviation from an average for lens pigment density, deviation from an average for macular pigment density, deviations from averages for peak optical densities of L-, M-, S-cone photopigments, deviations [nm] from averages for $\boxed{\lambda_{max}}$ shifts of L-, M-, S-cone photopigments. The outputs were the cone fundamentals. A nonlinear optimisation was used to obtain the model. . The eight parameters were optimised by minimising the color difference between the results from the observers and the predicted CMFs by the model. After this step, the individual observer color matching functions could be reconstructed by the estimated parameters and ages. Each Individual lms-CMF was converted into the corresponding xyz-CMF (Figure 1) by a linear transform obtained from a linear regression between the CIE 1964 standard colorimetric observer and the average lms-CMFs.

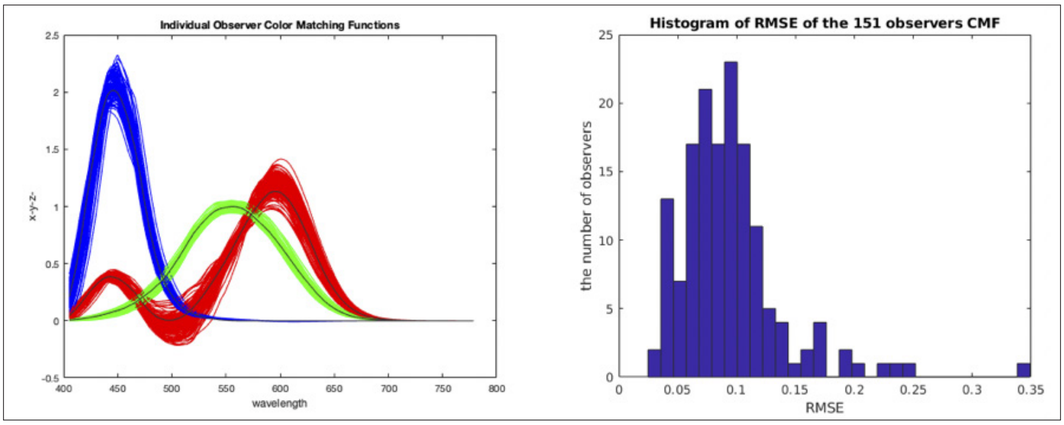

Figure 1 (Left) the 151 individual observer color matching functions used in our experiment. The black line is the average CMFs from those data. (Right) We plot the histogram of RMSE of the 151 observers CMFs compared to the average CMFs. This provides a visualisation of the dispersion of the individual observers CMFs. Note that no instance is exactly at the average position.

Contrast Sensitivity Function Filtering

Before the filtering, a color space transformation from XYZ into YCbCr is performed. The conversion follows the method by Pedersen and Farup (2012). They proposed a series of transformations by defining a specific set of primaries as follows: sRGB → XYZ → RGB → YCbCr → sRGB. In the study, the transformation from XYZ to YCbCr is adopted.

Next, the YCbCr images are decomposed into a set of low pass bands and several sets of high pass bands by the shearlets tool. The high pass bands are filtered by CSF from Barten (2003), with separate luminance Y channel, and chrominance Cb and Cr channels. The filtering method by Nadenau (2000) is used for considering local activity in the intra channel masking.

Texture Features

We calculate several texture features of luminance and chromatic channels. Feature extractions are implemented on YCbCr images after CSF filtering.

Gray Level Co-occurrence Matrix (GLCM) is used for calculating texture features for luminance channel of the images (Y in YCbCr), by: computing the co-occurrence matrix and calculating the feature vectors. The co-occurrence matrix is computed by counting the number of neighbouring pair of pixels having the same intensities. Five texture features including energy, contrast, correlation, homogeneity, and entropy of the images are subsequently calculated from the co-occurrence matrices using the MATLAB function *graycoprops*. Additionally, for all luminance and chrominance channels of the images, the mean and standard deviation of the pixel values are computed as the first-order statistical texture features. The Mean-Standard Deviation feature represents the distribution of intensity of pixels in an image, while GLCM features indicate the spatial relationship of pixels.

EXPERIMENT

Data Processing

We conducted our experiment on the HyTexiLa dataset by Khan et al (2018), including 4 types of hyper-spectral images, textile, wood, stone, food, and vegetation. The images are obtained by a line-scan hyper-spectral camera (HySpex VNIR-1800, Norsk Elektro Optikk). We select five textile images and two images from each other category. The RGB rendering of the hyperspectral images used in this experiment are shown in Figure 2. The HyTexiLa dataset provides the reflectance factors of image pixel, within the range of 405.37 to 780 nm with a 3.19 nm interval. The pixel size of the hyper-spectral camera is 5~6x10-3 cm.

The individual observer color matching functions of 151 observers are obtained through Asano (2015), and their average are calculated. Half of them are training set and half of them are testing set when estimating the parameters through the model. The Root Mean Square Error (RMSE) of each CMF from the average of CMFs are determined. The histogram of such RMSE values are depicted in Figure 1.

Before performing CSF filtering, the reflectance images are first converted into individual observer XYZ images using the corresponding individual xyz-CMFs. The equal-energy illuminant is used as the reference white point. The XYZ images are then converted into RGB images by linear transformation. The individual RGB images are finally converted into the corresponding individual observer YCbCr images using a specific set of RGB stimulus. The variability of the CMFs between individual observers is assumed to be maintained in the YCbCr color space because we use linear transforms. The sRGB images shown in Figure 2 are not used in the experiment, only used for display. They are converted from individual observer YCbCr image whose CMF is the closest to the average CMF in the observer dataset.

In order to reduce the computational time, the images are downsampled to 205 × 205 pixels before CSF filtering, which are originally 1024x1024 in the dataset. If we display images in 10cmx10cm, the dot per inch for the filtering is 52 dpi. The viewing distances that has been experimented are 50cm (common reading distance) and 200cm (remote observation in a real scene). The illuminance of the screen and the surround illumination as the input of the filtering are set into 80 cd/m^2 and 20 cd/m^2, respectively. Thus, in total, with 13 images, 151 CMFs, and 2 viewing distances, 3926 CSF filtering are conducted.

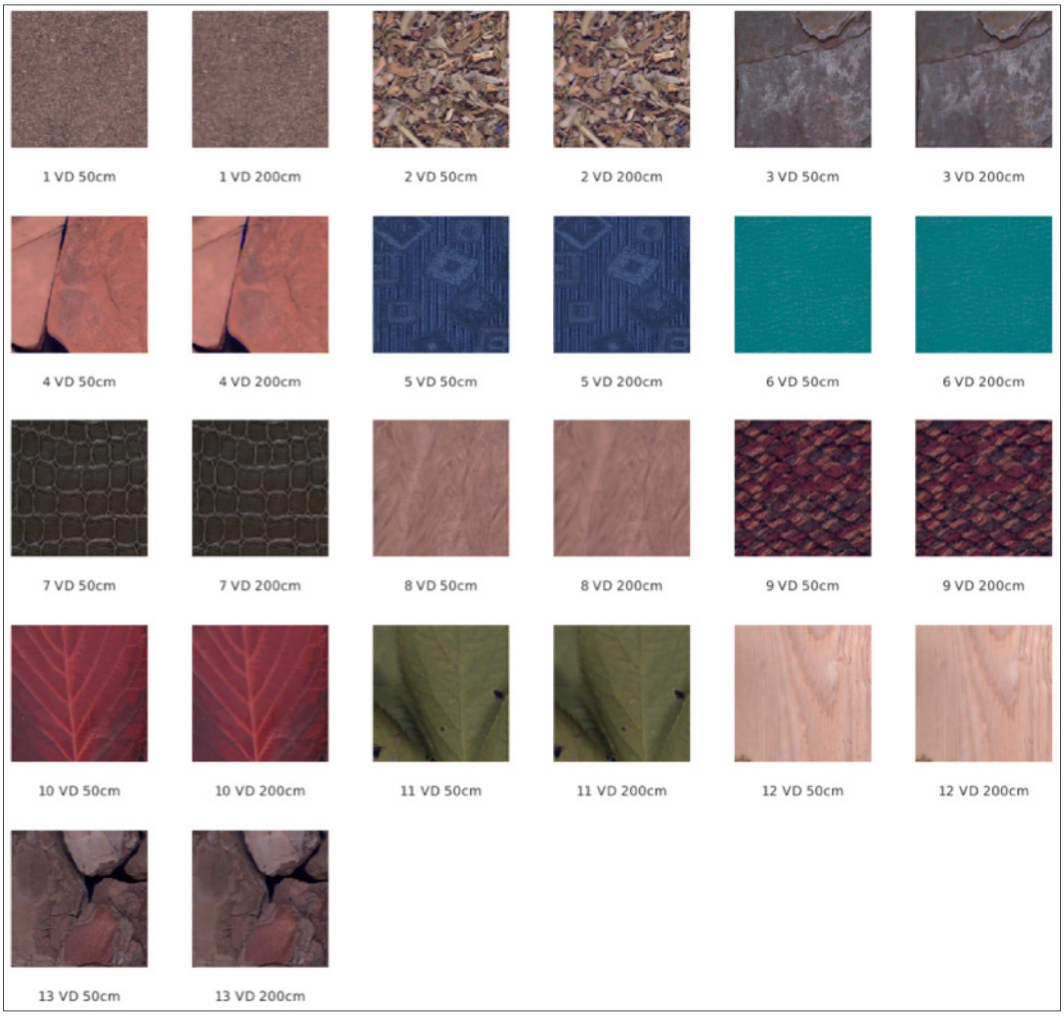

Figure 2 the HyTexiLa images with CSF filtered in viewing distances (VD) of 50cm and 200cm

Before extracting the features, the output YCbCr images from the CSF filtering are linear tone-mapped into [0,255] and rounded into integers, in order to build the co-occurrence matrix. For each YCbCr image, the GLCM feature vector is an array of five features, including energy, contrast, correlation, homogeneity, and entropy. The Mean-Standard Deviation feature vector is an array of six features including the mean and standard deviation of three channels.

Comparison of Texture Features

In order to test the hypothesis, a comparison of the texture features is implemented between two observer groups, one with lower RMSE in CMFs as the average observers, and the other containing all observers with the most variance in CMFs. The criteria to consider the average observers' group is that they have CMFs with RMSE smaller than the 50th percentile. Then, the volume of the feature vectors in their vector spaces is calculated by convnhull function in MATLAB, for both groups. The volume ratio of equation (2) between the two groups represents the comparison.

$$\boxed{Volume\ Ratio = 10 \times log_{10}\left(\frac{Volume\ of\ all\ observers'\ texture\ features}{Volume\ of\ average\ observer\ s'\ texture\ feature}\right)} \quad (2)$$

RESULTS AND DISCUSSION

When computing the volumes of the texture feature vectors in their vector spaces, the results have the order of magnitude of from -15 to -31. Thus, the study used the logarithm with the base 10 to obtain the difference between the order of the magnitude of the volumes. The factor 10 in equation (2) is used to visualize one more digit of the values and makes it easier to analyze the results with a figure.

Figure 3 shows the volume ratios of the two texture features, i.e. GLCM feature and Mean-Standard Deviation features, separately for each image at 50cm and 200cm viewing distances. A volume ratio near zero indicates that there is no difference between the two observer groups in terms of their corresponding simulated texture features, while volume ratios greater than 10 indicate that there is at least one order of magnitude difference between volumes of texture feature vectors of the two observer groups. In the graph of volume ratio of GLCM features, 7 out of 13 images have the volume ratios greater than 10, 6 of which correspond to the smaller viewing distance i.e. 50cm. And 6 out of that 7 images have lower volume ratios down to less than 10, with the higher viewing distances. That could be explained by GLCM takes into account only luminance channel where the most textures information of the image is preserved. With higher viewing distance, textures are blurred and the disparity of individual observers in higher spatial frequency information also decreases. Because the texture perception depends on the intensity gradient perception. For image 1, 8 and 12 in viewing distance of 200 cm, the values of the volume ratio are -13.80, -14.16 and -13.50. They are not showing in the graph because they are negative, meaning that the volumes of the average observer groups are bigger. That indicates that the feature vectors between two observer groups are similar enough so that the noise through the computation makes the results fluctuated. Image 1, 6, 9, 11 and 13 shows similar GLCM feature between two observer groups in both viewing distances. If combining the assumption that GLCM features represent human observer texture feature perception and the assumption of individual observers tend to have similar texture perception although various with color matching functions, the results of the GLCM graph can infer that the similar texture perception trend depends on the images and viewing distances.

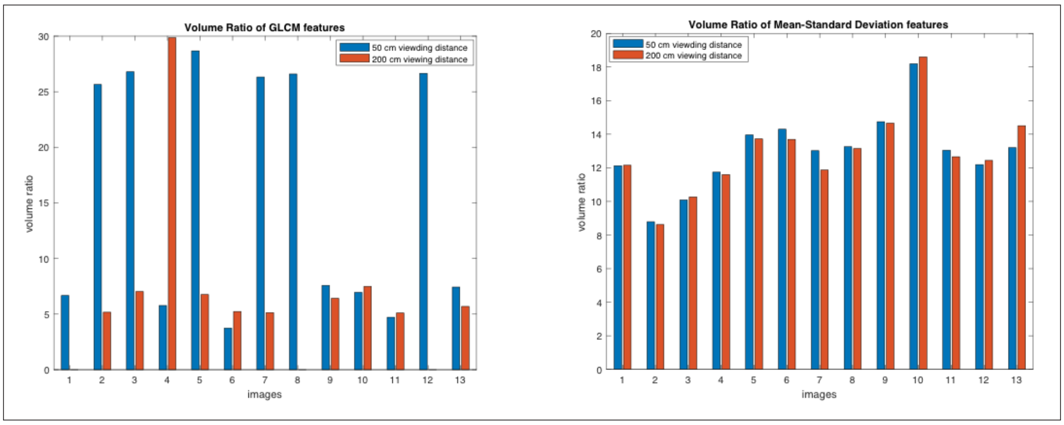

Figure 3 the volume ratio between two observers groups in Gray-level Cooccurrence Matrix and Mean-Standard Deviation feature vectors. The two observer groups have different variance in color matching functions. The feature vectors are extracted by the images with contrast sensitivity function filtered in two viewing distances.

In the graph of volume ratios of Mean-Standard Deviation feature, most of images have the volume ratios around 10 while image 2 and 3 have the volume ratio below 10. Mean-Standard Deviation features' volume ratios of all images in 200 cm except #4 and of some images in 50cm are bigger than the GLCM's. The one order of magnitude difference in texture feature volumes appear to be small compared to their original orders of magnitude. But the definition of the similar texture features needs to be further explored. However, there are no obvious difference in volume ratio when increasing the viewing distance. The reason is that the contrast sensitivity function filtering with different viewing distances does not change the intensity distribution of the images.

CONCLUSION

The study explores a methodology to investigate the impact of the individual observer color matching function on the simulated texture features. With the hypothesis that individual observers with various color matching functions tend to have similar perceives textures, the results by the two simulated features can be explained in the view of our hypothesis, however this is preliminary and require further test and analysis to develop strong observations. GLCM features are better representatives for visual texture perception than Mean-Standard Deviation Features. For the particular images we have studied, and for the particular set of CMFs, texture features are more similar in larger viewing distance.

Future work includes the verification of the hypothesis. It is important to develop also the test of several texture features on huge databases.

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