Estimation of Helmholtz-Kohlrausch Effect using Deep Learning

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ABSTRACT

The purpose of this study is to estimate the Helmholtz-Kohlrausch effect by using deep neural networks. Data augmentation and fine-tuning based on empirical knowledge of subjective evaluation experiments enable deep neural networks to estimate this effect.

1 INTRODUCTION

The Helmholtz-Kohlrausch effect (H-K effect) is a phenomenon that occurs in the human visual system (HSV), in which the brightness perceived by human changes with saturation even if the lightness value remains the same. This phenomenon affects many display devices and projectors. Quantifying provides us a useful parameter for the development and evaluation of display devices [1]. Nayatani et al. quantified the H-K effect by expressing it as a ratio of the perceived brightness and lightness of an actual image (B/L ratio) [2]. The authors also have reported on the estimation of the H-K effect in IDW [3]-[8].

In recent years, access to high computing powers has led to deep learning being popular for research and development. Deep learning models outperformed conventional models in an image classification challenge called ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [9]. Since then, deep learning models have been applied actively for various research tasks. In general, deep learning provides high accuracy by using a large amount of data. For instance, ImageNet dataset for ILSVRC contains around 10 million static images.

With regard to the application of deep learning to estimate the H-K effect, a large number of images and their experimental data are required. To obtain the B/L ratio, subjective evaluation experiments must be performed. However, experimentation is difficult owing to the various costs involved [3]-[8]. Thus, applying deep learning to an estimation model based on subjective evaluation experiments is a challenge. This study aims to take up this challenge and estimate the H-K effect.

Therefore, the purpose of this study is to estimate Helmholtz-Kohlrausch effect by using deep learning with augmented data and fine-tuning based on the knowledge of subjective evaluation experiments.

2 LEARNING METHOD

2.1 Fine-tuning

In the deep learning method, deep neural models are often fine-tuned to shorten the learning time and simultaneously improve the accuracy. For fine-tuning a deep neural model, the model is pre-learned with a large amount of dataset, and learned weights are used for the specific task. For example, VGG16 is a model that was pre-learned on ImageNet dataset, and the pre-learned weights are used for fine-tuning the model with a different task [10]. Meanwhile, the H-K effect in natural images **is** estimated by correcting the estimation for monochromatic images [3]-[8]. The model learns about the estimation for the monochromatic images by pre-learning the pseudo-monochromatic images as shown in Fig. 1. Then, learning is performed for estimating the natural images by learning the pixel-arrangement random images and the natural images in order. As stated above, fine-tuning of deep neural models is based on the knowledge obtain in previous studies.

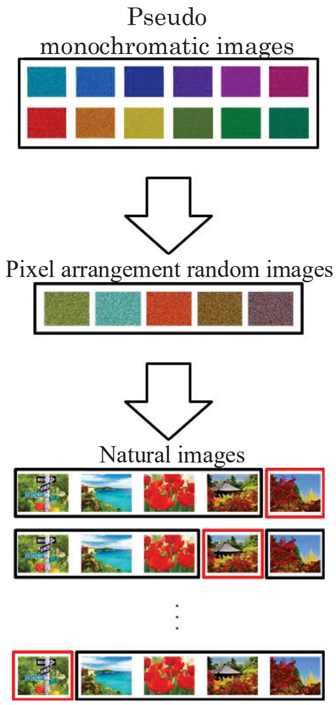


Fig. 1 Fine-tuning

2.2 Data Augmentation

Many images and their correct experimental values are required to realize high performance when applying deep learning models to estimate the H-K effect. Therefore, in this study, data were augmented based on the knowledge obtained in subjective evaluation experiments.

2.2.1 Augmentation of images

Data augmentation techniques, such as random cropping, adding noise, and horizontal flipping, are commonly used in deep learning to augment data. For instance, as shown in Fig. 2, noise is added to the original image to create another image [11]. Humans perceive these different images, which exceed the limit of the human resolution, as identical [12]. To augment the image dataset, we used pseudo-monochromatic images and pixel-arranged random images. A pseudo-monochromatic image is an image in which although each pixel has a different color, as shown in Fig. 3, the image is generally perceived as a monochromatic image. Such images were used in subjective evaluation experiments conducted by Hayami [7], because the variation between the subjects in the experiment when using these images was small. Therefore, a large number of images can be created by the rearrangement of pixels of pseudo-monochromatic images, and thus, image data can be augmented.

2.2.2 Augmentation of experimental values

Although the same image is used for evaluation, the experimental values differ depending on the subject in the subjective evaluation experiment. Each image has experimental values for the number of subjects. Hence, it is also necessary to augment the experimental value data when augmenting the image data described in Section 2.2.1. Experimental data were obtained by performing subjective evaluation experiments. Labels were augmented based on the assumption that the result of the subjective evaluation experiment follows the normal distribution, as shown in Fig. 4 [13]. This assumption was made based on the knowledge of the successive category method and Thurstone's law. Therefore, the experimental value data were artificially augmented using the parameters mean (μ) and standard deviation (σ).

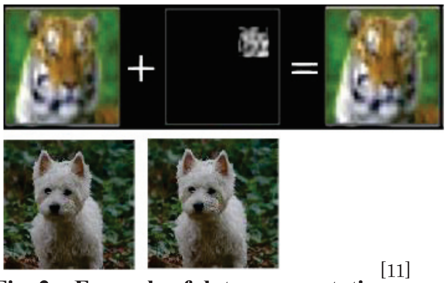
3 EXPERIMENT

3.1 Experiment conditions

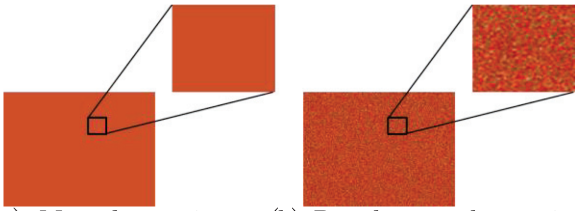
Experiment conditions is shown in Table 1. In this study, we used a model based on VGG16, which is a general model of the convolutional neural network. The model structure is shown in Fig. 5. The input images are "Signboard," "Sea," "Tulip," "Temple," and "Autumn leaves." The image size was 800×600 which is the same as the size of the original image. Learning/Evaluating the model was performed cross-validation leave-one-out. Pseudo-monochromatic images and pixel-arrangement random images were used for fine-tuning. In the experiment, Intel (R) Core (TM) i7-9750H CPU @ 2.60GHz and NVIDIA GeForce RTX 2070 GPU were used. The memory size was 32 GB. The squared error was used as the loss function.

3.2 Experimental result

Natural images were evaluated as shown in Fig. 6. The results are summarized in Table 2. The comparative estimator was derived by Nakagawa et al [14]. The horizontal axis in Fig. 6 (a)-(e) shows the evaluation image number corresponding to changes in lightness and saturation. Fig. 6 shows that the B/L ratio is proportional to saturation and is negatively proportional to lightness. This indicates the properties of the H-K effect.



[11]
Fig. 2 Example of data augmentation



(a) Monochromatic images (b) Pseudo monochromatic images

Fig. 3 Monochromatic images and Pseudo monochromatic images

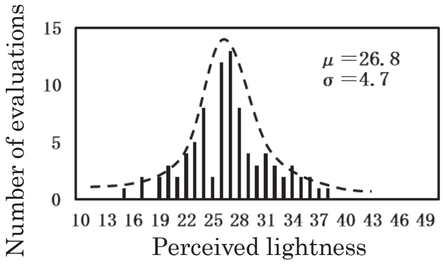


Fig. 4 Example of experimental value distribution

Table. 1 Experiment conditions

Model	Refer to VGG16
Train data	Nature images "Signboard", "Sea", "Tulip", "Temple", and "Autumn leaves"
Evaluation data	Nature images excluding train data
Image size	800×600
CPU	Intel(R) Core（TM) i7-9750H CPU @ 2.60GHz
GPU	NVIDIA GeForce RTX 2070
Memory	32GB
Fine-tuning	Pseud-monochromatic images, Random pixel arrangement images
Activation function	Identity function
Loss function	Squared error
Learning late	$lr_{epoch} = \frac{lr_1}{2}\cos\left(\frac{epoch}{10}\pi\right) + \frac{lr_1}{2}$ initial value $lr_1 = 0.001$

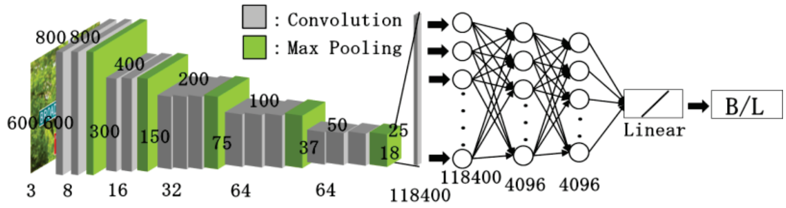
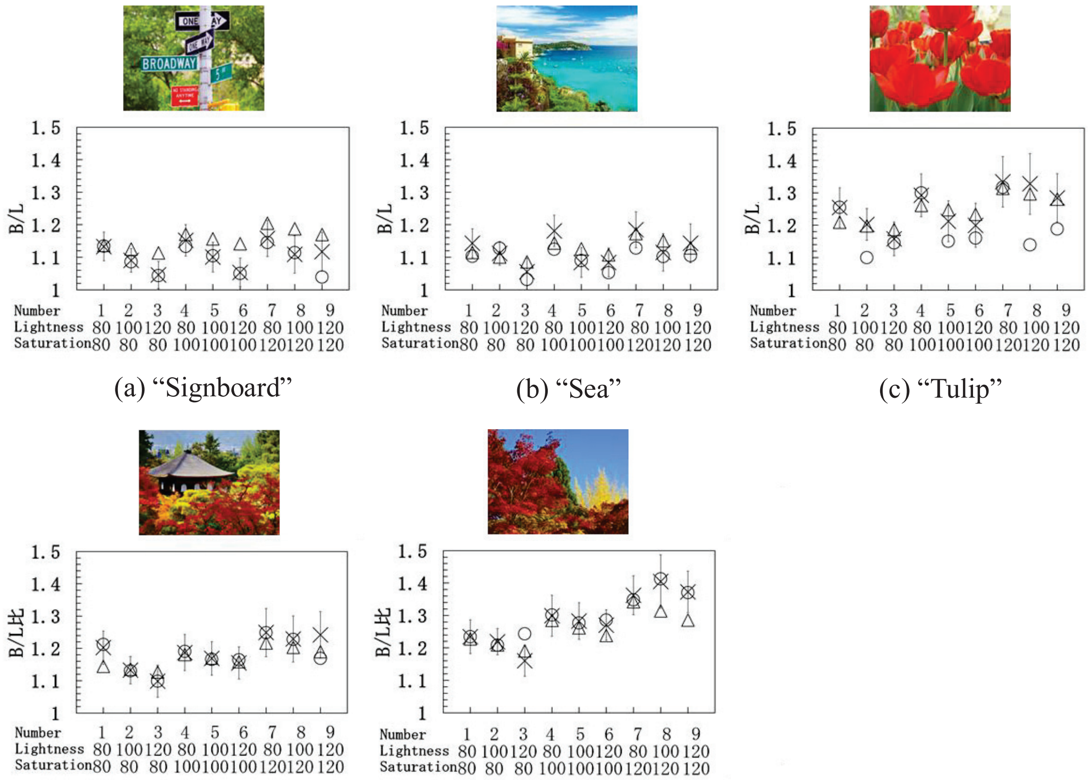


Fig. 5 The model structure



(a) “Signboard” (b) “Sea” (c) “Tulip”

(d) “Temple” (e) “Autumn leaves”

Fig. 6 Experimental results

○ : This method △ : Nakagawa’s estimated value
× : Experimental value I : 95[%]confidence interval

However, the results for (c) Tulip 2, 8 and (e) Autumn leaves 8, 9, do not agree with the properties of the H-K effect, and further improvement is required. The data in Table 2 shows that this method is more accurate than the estimation method[14] for (a) Signboard, (d) Temple, and (e) Autumn leaves, and is not better than that of the estimation [14] for (b) Sea and (c) Tulip. The average error rate of this method is smaller than that of the previous estimation [14]. Experimental results show that deep learning may be used to estimate the H-K effect.

4 CONCLUSION

The estimation of the H-K effect using deep learning based on the knowledge obtain in previous studies was investigated. Deep neural models require a large amount of dataset. It is difficult to obtain a large amount of data through subjective evaluation experiments for H-K effect estimation. Data were augmented based on the assumption that humans perceive different images that are beyond the limit of human resolution as the same images. Further, labels were augmented based on the assumption that the result of subjective evaluation

Table. 2 Experimental results

						All data
The average of the error rate (This method)	1.27	2.73	4.63	0.94	1.29	2.17
The average of the error rate (The estimation formula)	4.55	2.34	2.09	1.93	2.61	2.70

experiment follows the normal distribution. The deep neural network was trained from monochromatic images to natural images according to the complexity. The experimental results show that the proposed method is good, and that the H-K effect may be estimated using deep learning. In other words, it may be feasible to apply deep learning to the estimation model based on subjective evaluation experiments.

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