Color Constancy Using Amplitude Information of AC Light

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Abstract

In this paper, multiple frames captured with a high-speed camera~~s~~ were used to estimate the illuminant of the image. The proposed method exploits amplitude map generated from sinusoidal regression to estimate the varying intensity of the AC light. The proposed network consists of two subnets that estimate local illuminant and their respective confidence maps which are combined into a weighted sum to estimate the illuminant of the image.

I. Introduction

The color of an object captured by a camera is influenced by factors such as the presence, number, color, and intensity of surrounding lighting. Color constancy is a method for estimating the intrinsic color of an object by eliminating the effects of lighting [1].

기In previous studies, confidence maps representing the reliability of color estimation were extracted through learning and used as weights for illumination estimation [2]. These studies primarily used single images as input. However, the proposed method utilizes high-speed video captured in environments influenced by AC-powered lighting. A preceding study extracted temporal gradient maps by using the maximum difference between consecutive frames and applied these maps for confidence map training to estimate illumination [6].

This paper shares similarities with previous research in leveraging high-speed captured images. However, it introduces a novel approach by estimating the sine waveform of the brightness of AC lighting to learn confidence. This approach provides more detailed information about the influence of lighting on each region of an image, enabling more effective training.

II. Proposed Method

AlexNet [4] and FC4 [2] estimate illumination using a single network. Since the brightness of AC lighting varies sinusoidally over time, the changes in the brightness of reflected light can be observed using a high-speed camera. In previous studies on AC lighting, confidence maps were estimated using maps generated from the brightness differences of high-speed video frames [3] and U-Net [8] [6].

In this paper, we perform sine wave fitting for the brightness variations of each pixel in high-speed video frames. To ensure that only brightness information, independent of color information, is used, we employ frames created by averaging the R, G, and B channels of each video frame for sine wave fitting. Assuming that the amplitude of the estimated sine wave reflects the influence of illumination, we propose using the amplitude values to generate an amplitude map, which serves as the input for a deep learning network. The proposed amplitude map is fed into a U-Net [8] to estimate the confidence map.

Ⅲ. Implementation

3.1 Proposed network

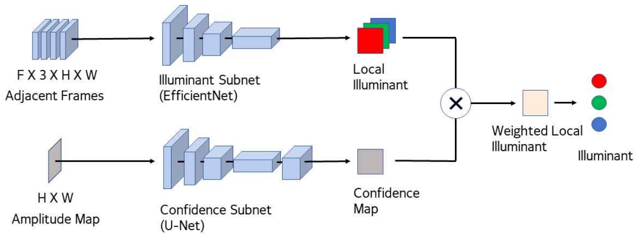

Figure 1 . Network Structure

Figure 1 illustrates the structure of the proposed network. For each scene, nine consecutive frames are used as input to EfficientNet [7] to estimate the illumination of local regions. The amplitude map, calculated from the brightness changes across the frames, is used as input to a modified U-Net [8] to extract confidence. The final illumination is estimated by taking the weighted sum of the estimated illumination and confidence.

3.2 Results

The proposed network was implemented using PyTorch. The results of the proposed network were compared with those of FC4 [2] and Temporal Gradient [6] under the same experimental conditions. In all three experiments, the batch size was set to 16, the learning rate to 0.001, and the same dataset was used. The dataset consisted of 225 high-speed videos, each comprising 10 frames. Of these, 150 videos were used for training, and 75 videos were used for performance evaluation.

Table 1 shows the performance evaluation results of the proposed method compared to the baseline methods. The proposed method outperformed AlexNet [4] and FC4 [2] in all aspects. Notably, in the Worst 25% Error metric, the proposed network demonstrated a significant improvement over the Temporal Gradient network. This indicates that the proposed network is less affected by outliers and exhibits more stable performance compared to Temporal Gradient.

Table 2 presents the inputs, amplitude maps, confidence maps, and the illumination-adjusted images for each network.

Network	AlexNet [4]	FC4 [2]	Temporal Gradient [6]	Proposed
Mean Angular Error(°)	1.79	2.26	**0.95**	1.03
Median Angular Error(°)	1.12	2.05	**0.24**	0.37
Best 25% Error(°)	0.36	0.76	**0.12**	0.16
Worst 25% Error(°)	4.42	4.17	2.84	**1.43**
Closed Setting(°)	1.44	2.30	**0.35**	0.52
Ambient Setting(°)	1.97	2.25	**1.25**	1.28

Table 1. Results from Different Networks

Ⅳ. Conclusion

Additional brightness information obtained through high-speed camera captures was used to construct t he amplitude map, which enabled more effective lear ning based on this data. By using multiple frames a s input to EfficientNet to estimate local illumination, and combining it with the confidence estimated by a modified U-Net [8] that takes the amplitude map as input, illumination could be estimated with high accu racy through the weighted sum of these values.

Acknowledgements

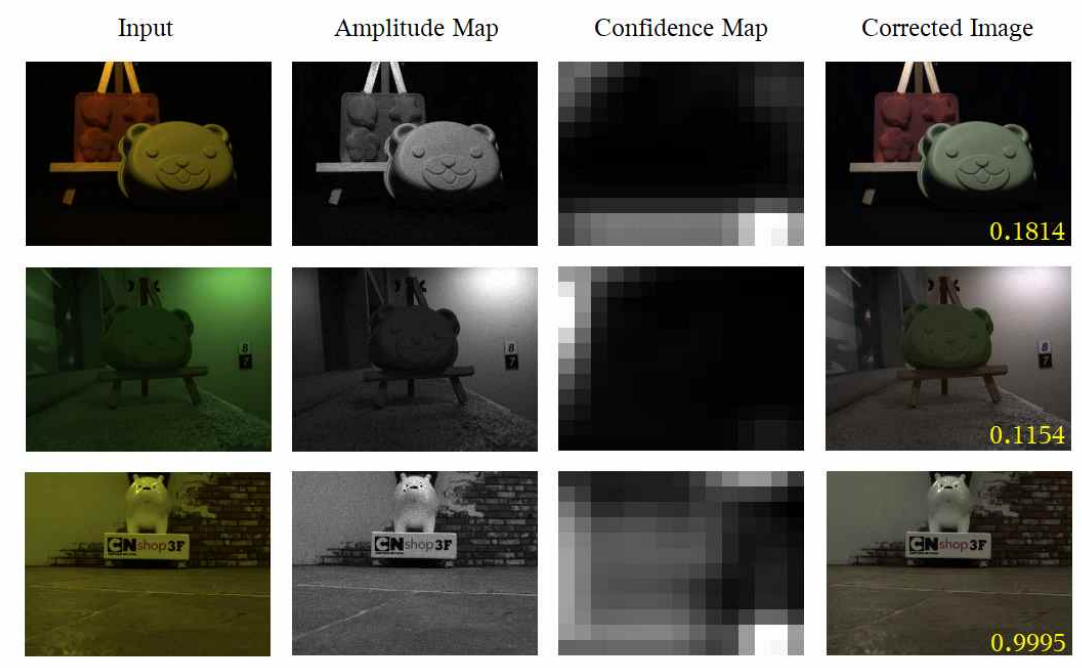

Figure 2 . Results of Proposed Method

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