An Image Segmentation Method Based on Luminance Distribution and Its Application to Image Enhancement

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***Abstract*—This paper proposes a novel image segmentation method based on luminance distribution and its application to image enhancement. Many existing image segmentation methods focus on semantic segmentation which separates an image into some meaningful areas. However, those segmentation methods are not effective for image enhancement. The proposed segmentation method separates an image into some areas according to luminance values of pixels. To obtain those areas, the proposed method utilizes a clustering algorithm based on a Gaussian mixture model which is fit by using a variational Bayesian approach. By using the proposed segmentation method, an automatic exposure compensation method is also proposed. The proposed exposure compensation method enables to automatically produce pseudo multi-exposure images from a single image and to improve the image quality by fusing them. Experimental results show that the proposed segmentation method is effective for image enhancement. In addition, the image enhancement method using the proposed segmentation method outperforms state-of-the-art contrast enhancement methods, in terms of the entropy and statistical naturalness.**

I. Introduction

The low dynamic range (LDR) of modern digital cameras is a major factor preventing them from capturing images as well with human vision. This is due to a limited dynamic range which imaging sensors have. The limit results in the low contrast of images taken by digital cameras. The purpose of image enhancement is to show hidden details in such a image.

Various research works on image enhancement have so far been reported [1]–[5]. In image enhancement methods, histogram equalization (HE) has received the most attention because of its intuitive implementation quality and high efficiency. It aims to derive a mapping function such that the entropy of the distribution of output luminance values can be maximized. On the other hand, HE often causes loss of details in bright areas in images i.e. over-enhancement. To avoid the over-enhancement, a lot of image enhancement methods have been developed [1]–[4]. However, those methods cannot sufficiently enhance contrasts in dark regions. Recently, the pseudo multi-exposure image fusion (MEF) scheme has been proposed [5]. It is based on MEF methods which utilize a stack of differently exposed images, called multi-exposure images, and fuse them to produce an image with high quality [6]–[11]. The pseudo MEF scheme enables to produce pseudo multi-exposure images from a single image and to improve the image quality by fusing them. While the scheme is effective for image enhancement, the quality of enhanced images depends on parameter setting.

Because of such a situation, this paper proposes a novel image segmentation method. The proposed segmentation method makes it possible to automatically produce pseudo multi-exposure images for the pseudo MEF scheme. Conventionally, most image segmentation methods aim at semantic segmentation, namely, separating an image into meaningful areas such as “foreground and background”, “people and cars”, and so on [12], [13]. Despite those segmentation methods are effective for many fields e.g. object detection, they are not appropriate for image enhancement. For this reason, the proposed segmentation method separates an image into some areas such that each area has a particular luminance range. To obtain those areas, a clustering algorithm based on a Gaussian mixture model (GMM) of luminance distribution is utilized. In addition, a variational Bayesian algorithm enables us not only to fit the GMM but also to determine the number of the areas. Furthermore, an automatic exposure compensation method by using the proposed segmentation method is also proposed for the pseudo MEF scheme.

We evaluate the effectiveness of the proposed method in terms of the quality of enhanced images by a number of simulations. In the simulations, the proposed method is compared with typical contrast enhancement methods. Experimental results show that the proposed segmentation method is effective for image enhancement. In addition, the pseudo MEF scheme using the proposed segmentation method outperforms state-of-the-art contrast enhancement methods in terms of the entropy and statistical naturalness. It is also confirmed that the proposed enhancement method can produce high-quality images which represent both bright and dark areas.

II. Preparation

In this paper, a new image segmentation method for image enhancement is proposed. Here we postulate the use of the pseudo MEF scheme [5] as an image enhancement method. For this reason, the image enhancement method is summarized in this section.

A. Notation

The following notations are used throughout this paper.

- Lower case bold italic letters (e.g. $\boldsymbol{x}$) denote vectors or vector-valued functions and they are assumed to be column vectors.
- The notation $\{x_1, x_2, \cdots, x_N\}$ denotes a set with N elements. In situations where these is no ambiguity as to their elements, the simplified notation $\{x_n\}$ is used to denote the same set.
- The notation $p(x)$ denotes a probability density function of x.
- U and V are used to denote the width and the height of an input image, respectively.
- P denotes the set of all pixels, namely, $\mathrm{P} = \{(u, v)^\top | u \in \{1, 2, \cdots, U\} \wedge v \in \{1, 2, \cdots, V\}\}$.
- A pixel $\boldsymbol{p}$ is given as an element of P.
- An input image is denoted by a vector-valued function $\boldsymbol{x} : \mathrm{P} \to \mathbb{R}^3$, where its output means RGB pixel values. Function $\boldsymbol{y} : \mathrm{P} \to \mathbb{R}^3$ similarly indicates an image produced by an image enhancement method.
- The luminance of an image is denoted by a function $l : \mathrm{P} \to \mathbb{R}$.

B. Pseudo multi-exposure image fusion

The pseudo MEF consists of four operations: local contrast enhancement, exposure compensation, tone mapping, and MEF (see Fig. 1).

1) Local contrast enhancement: To enhance the local contrast of an input image $\boldsymbol{x}$, the dodging and burning algorithm is used [14]. The luminance l' enhanced by the algorithm is given by

$$l'(\boldsymbol{p}) = \frac{l(\boldsymbol{p})^2}{\bar{l}(\boldsymbol{p})}, \tag{1}$$

where $l(\boldsymbol{p})$ is the luminance of $\boldsymbol{x}$, and $\bar{l}(\boldsymbol{p})$ is the local average of luminance $l(\boldsymbol{p})$ around pixel $\boldsymbol{p}$. It is obtained by applying a bilateral filter to $l(\boldsymbol{p})$:

$$\bar{l}(\boldsymbol{p}) = \frac{\sum_{\boldsymbol{p}' \in \mathrm{P}} l(\boldsymbol{p}') g_{\sigma_1}(\|\boldsymbol{p}' - \boldsymbol{p}\|) g_{\sigma_2}(l(\boldsymbol{p}') - l(\boldsymbol{p}))}{\sum_{\boldsymbol{p}' \in \mathrm{P}} g_{\sigma_1}(\|\boldsymbol{p}' - \boldsymbol{p}\|) g_{\sigma_2}(l(\boldsymbol{p}') - l(\boldsymbol{p}))}, \tag{2}$$

where $g_\sigma(t)$ is a Gaussian function given by

$$g_\sigma(t) = \exp\left(-\frac{t^2}{2\sigma^2}\right) \text{ for } t \in \mathbb{R}. \tag{3}$$

2) Exposure compensation: In the exposure compensation step, multi-exposure images are artificially generated from a single image. To generate high quality images by fusing these pseudo multi-exposure ones, the multi-exposure ones should clearly represent bright, middle and dark areas of the scene. This purpose can be achieved by adjusting the luminance l' with multiple scale factors. A set $\{l''_1, l''_2, \cdots, l''_M\}$ of the scaled luminance is simply obtained by,

$$l''_m(\boldsymbol{p}) = \alpha_m l'(\boldsymbol{p}), \tag{4}$$

where the m-th scale factor α_m indicates the degree of adjustment for the m-th scaled luminance l''_m.

3) Tone mapping: Because the scaled luminance value $l''_m(\boldsymbol{p})$ often exceeds the maximum value of the common image format, pixel values might be lost due to truncation of the values. To overcome the problem, a tone mapping operation is used to fit the range of luminance values into the interval $[0, 1]$.

The luminance $\hat{l}_m(\boldsymbol{p})$ of an pseudo multi-exposure image is obtained by applying a tone mapping operator f_m to $l''_m(\boldsymbol{p})$:

$$\hat{l}_m(\boldsymbol{p}) = f_m(l''_m(\boldsymbol{p})). \tag{5}$$

Reinhard's global operator is used here as a tone mapping operator f_m [15].

Reinhard's global operator is given by

$$f_m(t) = \frac{t}{1+t}\left(1 + \frac{t}{L_m^2}\right) \text{ for } t \in [0, \infty), \tag{6}$$

where parameter $L_m > 0$ determines a value t as $f_m(t) = 1$. Because Reinhard's global operator f_m is a monotonically increasing function, truncation of the luminance values can be prevented by setting L_m as $\max l''_m(\boldsymbol{p})$.

Combining $\hat{l}_m$, the input image $\boldsymbol{x}$, and its luminance l, we obtain the pseudo multi-exposure images $\hat{\boldsymbol{x}}_m$:

$$\hat{\boldsymbol{x}}_m(\boldsymbol{p}) = \frac{\hat{l}_m(\boldsymbol{p})}{l(\boldsymbol{p})}\boldsymbol{x}(\boldsymbol{p}). \tag{7}$$

4) Fusion of pseudo multi-exposure images: Generated pseudo multi-exposure images $\hat{\boldsymbol{x}}_m$ can be used as input for any existing MEF methods [7], [16]. A final image $\boldsymbol{y}$ is produced as

$$\boldsymbol{y} = \mathscr{F}(\hat{\boldsymbol{x}}_1, \hat{\boldsymbol{x}}_2, \cdots, \hat{\boldsymbol{x}}_M), \tag{8}$$

where $\mathscr{F}(\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_M)$ indicates a function to fuse M images $\boldsymbol{x}_1, \boldsymbol{x}_2, \cdots, \boldsymbol{x}_M$ into a single image.

C. Scenario

The literature [5] pointed out that it is effective for image enhancement to generate pseudo multi-exposure images. To produce high-quality images from pseudo multi-exposure ones, it is necessary that the multi-exposure ones clearly represent the whole area of the scene. However, the following respects in the exposure compensation have never been discussed.

- Determining the number of pseudo multi-exposure images.
- Estimating appropriate parameter α_m.

Because of such a situation, a new image segmentation method is proposed. Applying the proposed segmentation method to the exposure compensation enables us not only to determine the number of pseudo multi-exposure images, but also to estimating appropriate parameter α_m.

III. Proposed Image Segmentation and its Application to Exposure Compensation

The goal of the proposed image segmentation is to separate an image into M areas $\mathrm{P}_1, \cdots, \mathrm{P}_M \subset \mathrm{P}$, where each of them has a specific brightness range of the image, and satisfies $\mathrm{P}_1 \cup \cdots \cup \mathrm{P}_M = \mathrm{P}$ (see Fig.2). By using these results, pseudo multi-exposure images, where the m-th image clearly represents area P_m, are generated as shown in III-B and Fig. 3.

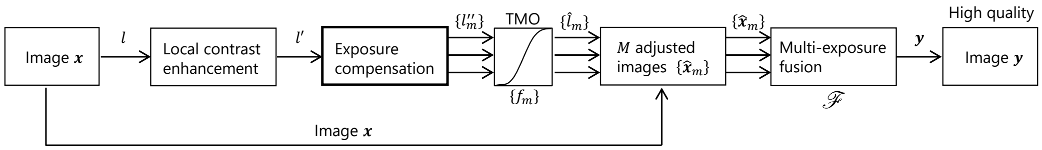


Fig. 1: Pseudo multi-exposure image fusion

A. Image segmentation based on luminance distribution

The proposed segmentation method differs from typical segmentation ones in the following points.

- Drawing no attention to structure of the image (e.g. edges).
- Allowing P_m to include spatially non-contiguous regions.

For the segmentation, a Gaussian mixture distribution is utilized to model the luminance distribution of the input image. After that, pixels are classified by a clustering algorithm based on a GMM [17].

By using a GMM, the distribution of $l'(\boldsymbol{p})$ is given as

$$p(l'(\boldsymbol{p})) = \sum_{k=1}^{K} \pi_k \mathcal{N}(l'(\boldsymbol{p})|\mu_k, \sigma_k^2), \tag{9}$$

where K indicates the number of mixture components, π_k is the k-th mixing coefficient, and $\mathcal{N}(l'(\boldsymbol{p})|\mu_k, \sigma_k^2))$ is a Gaussian distribution with mean μ_k and variance σ_k^2.

To fit the GMM into a given $l'(\boldsymbol{p})$, the variational Bayesian algorithm [17] is utilized. Compared to the traditional maximum likelihood approach, one of the advantages is that the variational Bayesian approach can avoid overfitting even when we choose a large K. For this reason, unnecessary mixture components are automatically removed by using the approach together with a large K. $K = 10$ is used in this paper, as the maximum of the partition number M.

Here let $\boldsymbol{z}$ be a K-dimensional binary random variable having a 1-of-K representation in which a particular element z_k is equal to 1 and all other elements are equal to 0. The marginal distribution over $\boldsymbol{z}$ is specified in terms of a mixing coefficient π_k, such that

$$p(z_k = 1) = \pi_k. \tag{10}$$

In order for $p(z_k = 1)$ to be a valid probability, $\{\pi_k\}$ must satisfy

$$0 \le \pi_k \le 1 \tag{11}$$

together with

$$\sum_{k=1}^{K} \pi_k = 1. \tag{12}$$

A cluster for an pixel $\boldsymbol{p}$ is determined by the responsibility $\gamma(z_k|l'(\boldsymbol{p}))$ which is given as the following conditional probability:

$$\gamma(z_k|l'(\boldsymbol{p})) = p(z_k = 1|l'(\boldsymbol{p})) = \frac{\pi_k \mathcal{N}(l'(\boldsymbol{p})|\mu_k, \sigma_k)}{\sum_{j=1}^{K} \pi_j \mathcal{N}(l'(\boldsymbol{p})|\mu_j, \sigma_j)}. \tag{13}$$

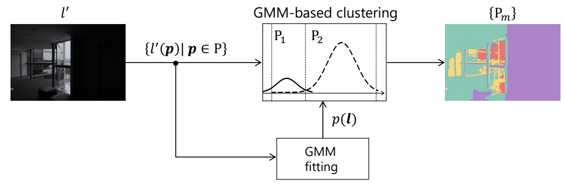
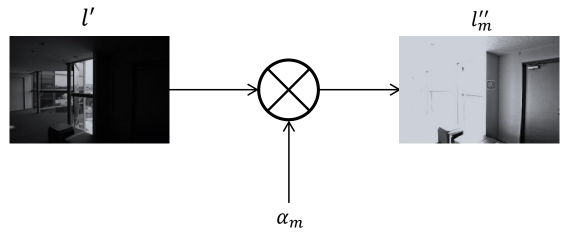
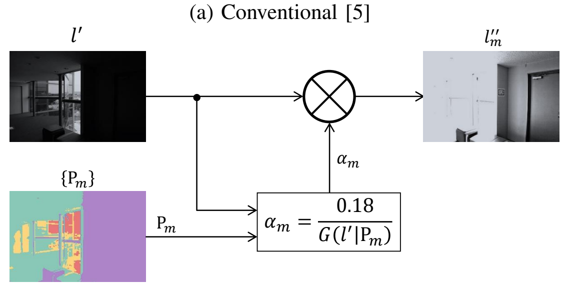


Fig. 2: Proposed image segmentation



(a) Conventional [5]



(b) Proposed

Fig. 3: Proposed segmentation-based exposure compensation. The proposed method can automatically calculate M parameters $\{\alpha_m\}$ although the conventional method cannot.

When an pixel $\boldsymbol{p} \in \mathrm{P}$ is given and m satisfies

$$m = \arg\max_{k} \gamma(z_k|l'(\boldsymbol{p})), \tag{14}$$

the pixel $\boldsymbol{p}$ is assigned to a subset $\mathrm{P_m}$ of P.

B. Segmentation-based exposure compensation

The flow of the proposed segmentation-based exposure compensation is illustrated in Fig. 3. The proposed one is applied to the luminance l' after the local contrast enhancement as shown in Fig. 1. The scaled luminance l''_m is obtained according to eq. (4). In the following, how to determine parameter α_m is discussed.

Given P_m as a subset of P, the approximate brightness of P_m is calculated as the geometric mean of luminance values on P_m. We thus estimate an adjusted multi-exposure image

$l''_m(\boldsymbol{p})$, so that the geometric mean of its luminance equals to middle-gray of the displayed image, or 0.18 on a scale from zero to one, as in [15].

The geometric mean $G(l|\mathrm{P}_m)$ of luminance l on pixel set P_m is calculated using

$$G(l|\mathrm{P}_m) = \exp\left(\frac{1}{|\mathrm{P}_m|}\sum_{\boldsymbol{p}\in\mathrm{P}_m}\log\left(\max\left(l(\boldsymbol{p}),\epsilon\right)\right)\right), \quad (15)$$

where ϵ is set to a small value to avoid singularities at $l(\boldsymbol{p}) = 0$.

From eq. (15), parameter α_m is calculated as

$$\alpha_m = \frac{0.18}{G(l'|\mathrm{P}_m)}. \quad (16)$$

The scaled luminance l''_m, calculated by using eq. (4) with parameters α_m, is used as input of the tone mapping operation described in II-B3. As a result, we obtain M pseudo multi-exposure images.

C. Proposed procedure

The procedure for generating an enhanced image $\boldsymbol{y}$ from an input image $\boldsymbol{x}$ under the use of the proposed method with the pseudo MEF is summarized as follows (see Figs. 1, 2, and 3).

1) Calculate luminance l from the input image x.
2) Enhance the local contrast of l by using eq. (1) to eq. (3), then obtain the enhanced luminance l'.
3) Separate P into M areas $\{\mathrm{P_m}\}$ by using eq. (9) to eq. (14).
4) Estimate α_m by using eqs. (15) and (16).
5) Calculate $\{l''_m\}$ by using eq. (4) with α_m.
6) Map $\{l''_m\}$ to $\{\hat{l}_m\}$ according to eqs. (5) and (6).
7) Generate $\{\hat{\boldsymbol{x}}_m\}$ according to eq. (7).
8) Obtain an image $\boldsymbol{y}$ with a MEF method $\mathscr{F}$ as in eq. (8).

Note that the number M of P_m satisfies $1 \leq M \leq K$.

IV. Simulation

We evaluated the proposed method in terms of the quality of enhanced images $\boldsymbol{y}$.

A. Comparison with conventional methods

To evaluate the quality of the images produced by each method, objective quality assessments are needed. Typical quality assessments such as the peak signal to noise ratio (PSNR) and the structural similarity index (SSIM) are not suitable for this purpose because they use the target image with the highest quality as the reference one. We therefore used the tone mapped image quality index (TMQI) [18] and discrete entropy as quality assessments.

TMQI represents the quality of an image tone mapped from an HDR image; the index incorporates structural fidelity and statistical naturalness. An HDR image is used as a reference to calculate structural fidelity. A reference is not needed to calculate statistical naturalness. Since the processes of tone mapping and photographing are similar, TMQI is also useful for evaluating photographs. Discrete entropy represents the amount of information in an image.

B. Simulation conditions

In the simulation, 22 photographs taken by Canon EOS 5D Mark II camera and 16 photographs selected from an available online database [19] were used as input images $\boldsymbol{x}$. Note that input images are taken with zero or negative exposure values (EVs). The following procedure was carried out to evaluate the effectiveness of the proposed method.

1) Produce $\boldsymbol{y}$ from $\boldsymbol{x}$ using the proposed method.
2) Compute TMQI values of $\boldsymbol{y}$.
3) Compute discrete entropy of $\boldsymbol{y}$.

The following six methods were compared in this paper: histogram equalization (HE), the contrast limited adaptive histogram equalization (CLAHE) [1], the adaptive gamma correction with weighting distribution (AGCWD) [2], the contrast-accumulated histogram equalization (CACHE) [3], the low light image enhancement based on two-step noise suppression (LLIE) [4], and the proposed method. In the proposed method, Nejati's method [16] is used as $\mathscr{F}$.

In addition, structural fidelity in the TMQI could not be calculated due to the non-use of HDR images. Thus, we used only statistical naturalness in the TMQI for the evaluation.

C. Simulation results

Images enhanced from the input image "Laurenziana" are illustrated in Fig. 4. This figure shows that the proposed method can strongly enhance the details in dark areas. Conventional enhancement methods have certain effects of enhancement. However, those effects are not sufficient to visualize shadow areas. In addition, the proposed method can improve the quality of images without loss of details in highlight areas (i.e. over-enhancement) while the loss often occurs by some conventional methods, as shown in Fig. 5. The results indicate that the proposed method enables us not only to enhance the details in dark areas, but also to keep the details in bright areas clear.

Figures 6 and 7 summarize scores for 38 input images in terms of discrete entropy and statistical naturalness, as box plots. The boxes span from the first to the third quartile, referred to as Q_1 and Q_3, and the whiskers show the maximum and minimum values in the range of $[Q_1-1.5(Q_3-Q_1), Q_3+1.5(Q_3-Q_1)]$. The band inside the box indicates the median i.e. the second quartile Q_2. For each score (discrete entropy $\in [0,8]$, and statistical naturalness $\in [0,1]$), a larger value means higher quality.

From Fig. 6, it is confirmed that the proposed method provided high scores which are distributed in an extremely narrow range, regardless of scores of input images. In contrast, ranges of scores for conventional methods are wider than that of the proposed method. Therefore, the proposed method can generate an higher-quality image from any input image in terms of discrete entropy, compared with conventional enhancement methods.

Figure 7 denotes that most of the images produced by the proposed method and HE have higher quality than most images generated by other methods. This result reflects that

(a) Input image $\boldsymbol{x}$ (-2EV). Entropy: 4.895 and Naturalness: 0.0974.

(b) HE. Entropy: 6.831 and Naturalness: 0.9042.

(c) CLAHE [1]. Entropy: 6.647 and Naturalness: 0.8001.

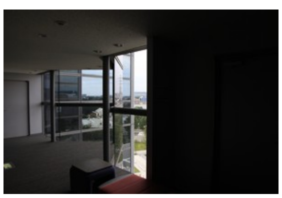
(d) AGCWD [2]. Entropy: 6.018 and Naturalness: 0.7287.

(e) CACHE [3]. Entropy: 6.967 and Naturalness: 0.8263.

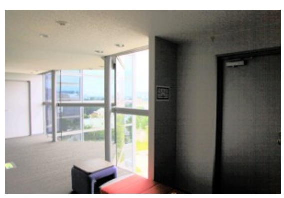
(f) LLIE [4]. Entropy: 5.950 and Naturalness: 0.7524.

(g) Proposed. Entropy: 6.429 and Naturalness: 0.6024.

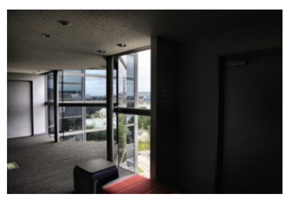
Fig. 4: Comparison of the proposed method with image enhancement methods (Laurenziana). The proposed method can produce clear images without under or over enhancement.



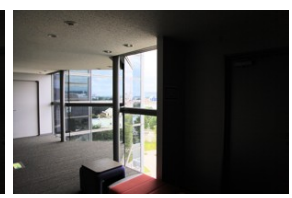
(a) Input image $\boldsymbol{x}$ (-1EV). Entropy: 3.811 and Naturalness: 0.0058.



(b) HE. Entropy: 5.636 and Naturalness: 0.6317.



(c) CLAHE [1]. Entropy: 5.040 and Naturalness: 0.0945.



(d) AGCWD [2]. Entropy: 5.158 and Naturalness: 0.1544.

(e) CACHE [3]. Entropy: 5.350 and Naturalness: 0.1810.

(f) LLIE [4]. Entropy: 4.730 and Naturalness: 0.0608.

(g) Proposed. Entropy: 6.652 and Naturalness: 0.7695.

Fig. 5: Comparison of the proposed method with image enhancement methods (Window). The proposed method can produce clear images without under or over enhancement.

the proposed method and HE can strongly enhance images, as shown in Figs. 4 and 5. In particular, the proposed method never causes the loss of details in bright areas.

For these reasons, it is confirmed that the proposed image

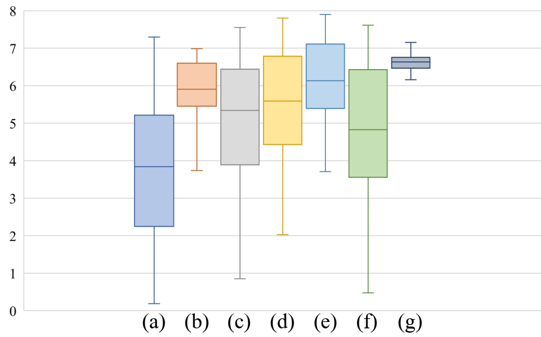


Fig. 6: Experimental results for discrete entropy. (a) Input image, (b) HE, (c) CLAHE, (d) AGCWD, (e) CACHE, (f) LLIE, and (g) Proposed. The boxes span from the first to the third quartile, referred to as Q_1 and Q_3, and the whiskers show the maximum and minimum values in the range of $[Q_1 - 1.5(Q_3 - Q_1), Q_3 + 1.5(Q_3 - Q_1)]$. The band inside the box indicates the median.

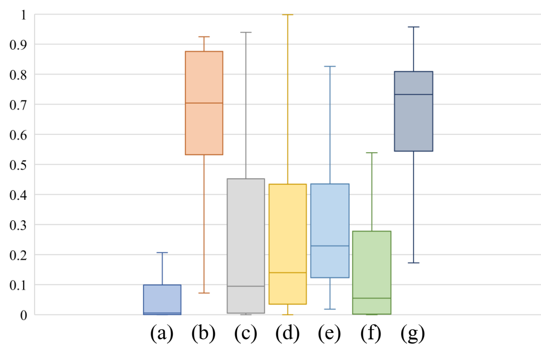


Fig. 7: Experimental results for statistical naturalness. (a) Input image, (b) HE, (c) CLAHE, (d) AGCWD, (e) CACHE, (f) LLIE, and (g) Proposed. The boxes span from the first to the third quartile, referred to as Q_1 and Q_3, and the whiskers show the maximum and minimum values in the range of $[Q_1 - 1.5(Q_3 - Q_1), Q_3 + 1.5(Q_3 - Q_1)]$. The band inside the box indicates the median.

segmentation method is effective for image enhancement. In addition, the pseudo MEF using the proposed segmentation method is useful to produce high quality images which represent both bright and dark areas.

V. Conclusion

This paper has proposed a novel image segmentation method based on luminance distribution. The proposed method separates an image into some areas according to luminance values of pixels. To obtain those areas, the proposed method utilizes a clustering algorithm based on a GMM which is fit by using a variational Bayesian approach. In addition, an application of the segmentation method to the pseudo MEF method is also proposed. Experimental results showed that the proposed segmentation method is effective for image enhancement. In addition, the pseudo MEF using the proposed segmentation method outperforms state-of-the-art contrast enhancement methods, in terms of the entropy and statistical naturalness. It is also confirmed that the proposed enhancement method can produce high-quality images which represent both bright and dark areas.

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