Single-image Dehazing using Detail Enhancement and Image Fusion

Nguyen D. Hien, Nguyen V. Tho*, Nguyen Q. Hieu, Nguyen H.H. Cuong, Tran T.M. Hanh, Tran H. Vu

Abstract—Haze is the suspension of atmospheric particles which is sufficient to reduce the visibility. Image dehazing refers to the processing tasks that lessen this negative effect. In this work, an alternative approach to single-image dehazing is developed which skips solving the haze formation equation, while still respects its hypothesis. In this method, we generated multiple under-exposed images from a single hazy input, followed by a detail enhancement process. Such resulting images were then merged using weights calculated based on the Dark Channel Prior assumption and overcame luminance enhancement. The visual improvement has been validated by both qualitative and quantitative evaluations.

Index Terms—image dehazing, multi-exposed, detail enhancement, image fusion, dark channel prior.

1. Introduction

RECENTLY, the fast expansion of computer vision and real-time image processing tasks has brought out higher requirements for input data. However, captured or recorded image visibility is always degraded due to the impact of the light transmission medium. This problem even becomes worse in bad weather and may lead to consequences such as poor-quality outputs, wrong detection, and false estimations. Thus, enhancement techniques are essential to improve the clarity of photos for better application performance.

Many algorithms have been proposed to enhance image quality degraded by the weather. Typical algorithms are rain removal [1]–[3], low-light image enhancement [4]–[6], image dehazing (or haze removal) [7]–[17]. The haze removal technique is one of the techniques developed to restore visibility. The use of haze removal techniques can improve not only the clarity of images but also the performance of later processes. Haze removal techniques play an important role in various fields such as remote sensing, object recognition, intelligent vehicles, and surveillance.

However, haze removal is a challenging problem because the haze is dependent on unknown depth information. Many methods have been proposed, but can be classified into two types: multi-image dehazing and single image dehazing. In multi-image dehazing, several input images are taken in different atmospheric conditions and processed to remove the haze. In [7]–[9], more constraints are obtained from multiple images of the same scene under different weather conditions. In [10], [11], the authors eliminated the haze effect using two or more images taken with different degrees of polarization. Multi-image dehazing can produce impressive outputs but requires rich information about the scene. This condition is not always ensured especially in real-time applications with strict limitations in processing time. Hence, single-image dehazing obtains greater interest from researchers due to the independence on external knowledge which is not usually available in most cases.

Recently, one popular approach for haze removal is proposing assumptions or priors derived from characteristic analysis on both hazy and haze-free images in particular circumstances. He et al. [7], through observing outdoor images in clear visibility, introduced the Dark Channel Prior (DCP) referring to the existence of very low intensities in at least one color channel of pixels in non-sky patches. With this theory, they can estimate atmospheric light and transmission map, then derive the haze-free image from the haze degradation equation. DCP can produce remarkable outputs, however, it is computationally intensive due to the soft matting and cannot deal with sky regions.

Zhu et al. [8] presented the Color Attenuation Prior (CAP) to create a linear model for the scene depth. With the recovered depth map by supervised learning technique, they can estimate transmission and remove

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the haze via the atmospheric scattering model. This technique works well in haze removing but it still has some disadvantages such as color distortion and high computational cost for a large guided filter.

For efficiency, Tarel et at. [9] limited the dehazing problem to road-specific enhancement with their planar road assumption. This method is much faster than the two techniques mentioned above since its complexity is only a linear function of the number of input image pixels. Nevertheless, the dehazed result suffers from halo artifacts due to the use of a filter called Median of Median Along Lines [10].

Considering from another point of view, Galdran et al. [11] proposed an alternative approach that handles haze removal as a spatially-varying contrast and saturation enhancement problem by using multi-scale fusion with a set of artificially under-exposed images. This method can simplify the dehazing process by skipping the complex estimations in the haze degradation model while still respecting its hypothesis. In spite of its impressive result, this algorithm still contains costly procedures such as Laplacian pyramid decomposition and histogram equalization.

In this paper, we contribute a hardware-friendly and powerful algorithm based on multi-exposure image fusion. Firstly, under-exposed images are generated from an original hazy one before being detail-intensified. Then, fusion is performed as a summation which is guided by weights calculated using Dark Channel Prior assumption. At last, luminance enhancement and color emphasis by Adaptive Tone Remapping (ATR) [18] [18] are performed on the fused image to achieve the final dehazed result.

In the next part of the paper, we describe our solution for image dehazing based on multi-exposure image fusion. Section 3 presents simulation results and evaluates our proposed solution. Conclusions are made in section 4.

2. Proposed Algorithms

The overall block diagram of the proposed method is shown in Fig. 1. Multi-exposed images (I_{gc}^1, I_{gc}^2, I_{gc}^3, I_{gc}^4) produced by gamma correction from the input image. The enhanced detail images (I_{de}^1, I_{de}^2, I_{de}^3, I_{de}^4) are weighted and fused. Finally, the fused image (J) is luminance-enhanced to obtain dehazed output image.

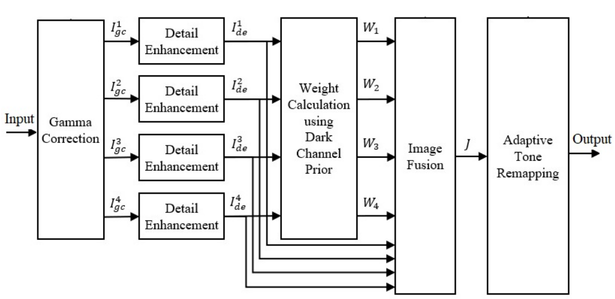


Fig. 1: Overall block diagram

Equation (1) is the Kosmeider's model of haze degradation

$$I(x) = J(x)t(x) + [1 - t(x)]A \tag{1}$$

where $I(x)$ is the hazy image, $J(x)$ is the haze-free image, $t(x)$ is the medium transmission, and A is atmospheric light. By inverting equation

$$t(x) = \frac{A - I(x)}{A - J(x)} \tag{2}$$

Since $t(x) \in [0, 1]$, it can be derived that $J(x) \leq I(x), \forall x$ or pixels in a hazy image always have equal or higher values than in its corresponding haze-free version.

2.1. Gamma Correction

Gamma correction is one of the simplest algorithms used in image enhancement. It is known that a haze-free image always has higher contrast than its hazy form, thus, only under-exposed images are generated from original input for haze-free regions seeking. In some cases, a hazy photo may contain well-exposed parts, thus we also included it in the set of multi-exposed images. The gamma correction for each color channel of a RGB image should be as below:

$$I_{gc}^c(x, y) = I^c(x, y)^\gamma, \gamma \geq 1 \tag{3}$$

where I^C is a color channel of RGB image I, (x, y) is the coordinates of pixels. We also include the hazy image ($\gamma \geq 1$) in the under-exposed sequence since it may contain useful information in some cases.

2.2. Detail Enhancement

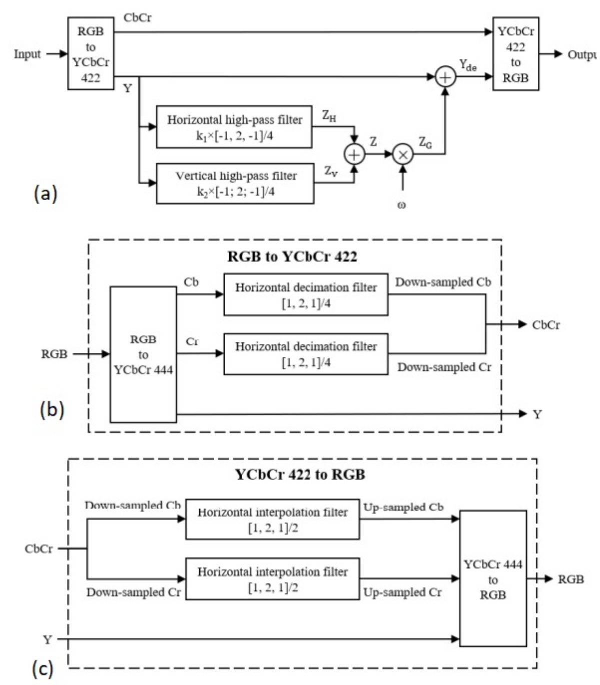


Fig. 2: (a)Detail enhancement block (b)RGB to YcbCr block. (c)YcbCr to RGB block.

In hazy images, objects are usually hidden behind high-intensity hazy layers. Gamma correction can lessen this effect but it also reduces the intensity of useful information. Thus, detail enhancement is necessary to improve the clarity of the dehazed result.

Fig. 2 demonstrates the structure of the detail enhancement block in which edge-enhancement is performed in YCbCr color space. It is efficient to strengthen only the luminance since this component is more sensitive to human eyes compared to chrominance. Features are extracted by using two Finite Impulse Response (FIR) high-pass filters before being intensified.

Filtered data is then amplified before being added to the original Y value. The amplifying parameter ω may vary between different images due to the difference in extracted detail.

2.3. Weight Calculation and Fusion

From the statistics of observed images in clear days, He et al. [4] proposed a popular Dark Channel Prior, which imposed the existence of pixels that have very low intensity in at least one color channel inside most of the local regions except sky scene. The dark channel of an image I is defined as below:

$$I_{dark}(x,y) = \min_{i,j\in\Omega(x,y)} \{ \min_{c\in\{R,G,B\}} [I^c(i,j)] \} \quad (4)$$

where I^c is a color channel of I, $\Omega(x,y)$ is a local patch centered at (x,y). The fact that pixels in a hazy image usually have higher intensity than in haze-free one can be applied to derived dark channels. To imply the effect of haze-free components on the final result, weight is computed as the inversion of the produced dark channel. Hence, low-haze regions will possess higher weights and vice versa. Weights are then normalized to prevent the overflow occurrence in later processes. Image fusion is a weighted summation of all detail-enhanced images. Equation (5) describes image fusion as a weighted summation of all detail-enhanced images

$$W_k(i,j) = \frac{W^k_{dcp}(i,j)}{\sum_{k=1}^{k} W^k_{dcp}(i,j)} \quad (5)$$

where k is the number of multi-exposure images, (i,j) is the coordinates of pixels weight of the dark channel:

$$W^k_{dcp}(i,j) = 1 - I^{dark}_k(i,j) \quad (6)$$

By including the hazy image in the fusion process, the result of merging procedure can preserve the naturally haze-free areas inside the original scene

2.4. Luminance Enhancement

Haze removal output is a dark image due to the strong impact of high-contrast regions and it is needed to be enhanced in luminance and color. We employed the Adaptive Tone Remapping -ATR (Fig. 3) developed by Cho et al. [2] based on adaptive nonlinear curves of luminance to improve the visibility of low light images. This method generates a nonlinear curve for the tone mapping according to the pixel distribution and the luminance average. The weight values increased in low-light regions and reduced in high-light ones.

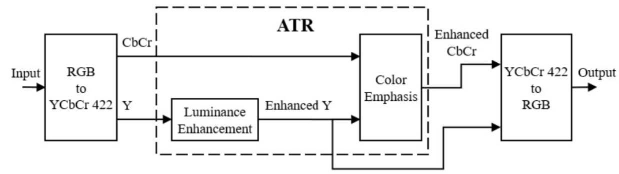


Fig. 3: Luminance enhancement with ATR

3. Result and Evaluation

To evaluate the performance of the proposed algorithm, we have to use particular applications for each procedure in the workflow. Initially, Mathworks Matlab is used for algorithm development in both floating-point and fixed-point forms. After that, hardware design is described in Verilog hardware description language. Then, Mentor Graphics ModelSim is utilized for functional simulation. Finally, hardware synthesis and timing simulation are performed by Xilinx ISE.

In our simulation, the selected parameters are $\gamma = \{1, 1.3, 1.7, 4\}$, $k1 = k2 = 1$, and $\omega = \{1, 1.5, 2, 2.5\}$. Algorithm performance is evaluated by comparing with several previous works by He et al. [7], Tarel et al., and Zhu et al. [9]. The datasets used are O-HAZE [19] and I-HAZE [20] that contain pairs of haze-free and corresponding hazy images in outdoor and indoor conditions. In Fig. 4, the algorithms of Tarel et al. and Zhu et al. left thick fog with a strong artifact and false color. He et al. successfully eliminated the haze but came at the cost of a dark image. Our approach, despite the remaining of a slight hazy layer, was able to recover the clear scene in a natural way.

TABLE 1: Measurements of O-HAZE database

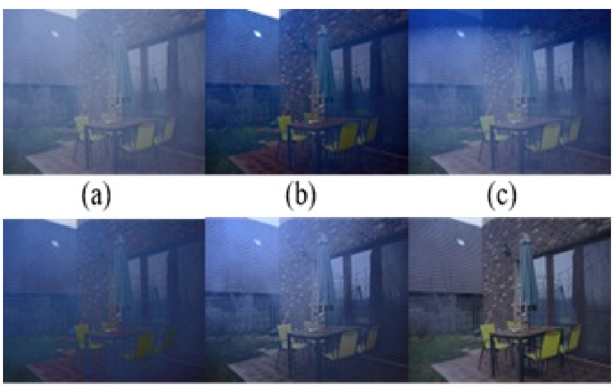
Method	SSIM	TMQI	FSIMc	FADE
He et al.	0.7709	0.8403	0.8423	0.3719
Tarel et al.	0.7235	0.8455	0.7940	0.6514
Zhu et al.	0.6647	0.8118	0.7738	0.6531
Ours	0.7764	0.8842	0.8306	0.4029

TABLE 2: Measurements of I-HAZE database

Method	SSIM	TMQI	FSIMc	FADE
He et al.	0.6580	0.7319	0.8208	0.8328
Tarel et al.	0.6849	0.7481	0.8091	1.5558
Zhu et al.	0.6864	0.7512	0.8252	1.0532
Ours	0.7783	0.7994	0.8544	0.9907

Four measurements are used for quantitative assessment. Structural SIMilarity (SSIM) [21] assesses the impact of luminance, contrast, and structure. Tone Mapped Image Quality Index (TMQI) [22] evaluates the structural information preserving characteristics . Feature SIMilarity Index extended to color image (FSIMc) [23] appraises image quality based on salient low-level and chromatic features. Fog Aware Density Evaluator (FADE) [24], which is a referenceless perceptual fog density prediction model, is used to assess de-hazed images without requiring their haze-free scenes. Different from other measurements that show the better results for higher values, in FADE, the lower the number is, the lower haze density in the scene is. Among these metrics, FSIMc and FADE are designed for color images while the others only evaluate grayscale photos.

The average results are provided in Table 1 and 2, in which the proposed method acquires the best score in most fields. For the O-HAZE database, our results - with advantages from multi-exposure fusion and DCP assumed, attains good grades in FSIMc, FADE and best mark in terms of SSIM, TMQI. For I-HAZE databases, the proposed method is the best performing algorithm in the fields of SSIM, FSIMc and TMQI. Due to the effect of luminance enhancement on the low-light de-hazed images in indoor environment, locates at the second place in the field of FADE, just below the DCP method from He.



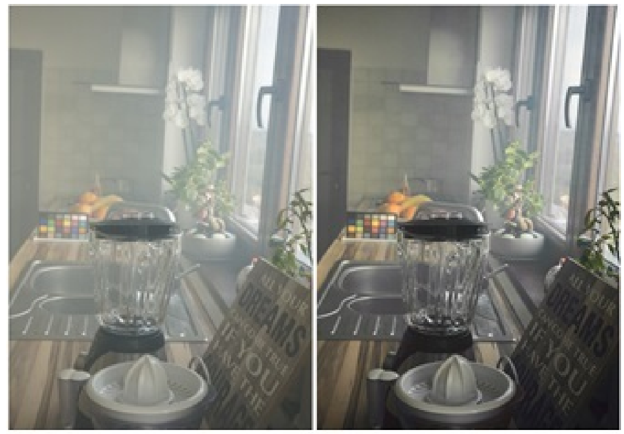
(a) (b) (c)
(d) (e) (f)

Fig. 4: a) Hazy image, (b) He et al., (c) Tarel et al., (d) Zhu et al., (e) ours, and (f) haze-free image

In Fig. 4, Tarel's results usually have very dark regions at the top while Zhu's method leaves color distortions. He's algorithm successfully eliminated the haze but came with false color and cannot handle the sky scenes. The technique from He obtained impressive haze-free images in all cases but these scenes were darkened and slightly blurred. The proposed design, although it still leaves a thin hazy layer from thick fog scenes, was able to produce a bright and detailed image. Moreover, our approach can also deal with sky scenes, even though it uses the DCP assumption for weight calculation.

Some of our other simulations with indoor images (Fig. 5) and outdoor images (Fig. 6 and Fig. 7) both give good results.

Table 3 provides the results when fitting proposed design to a specific device (xc7z045-2-ffg900). The total number of registers and look-up tables stands for

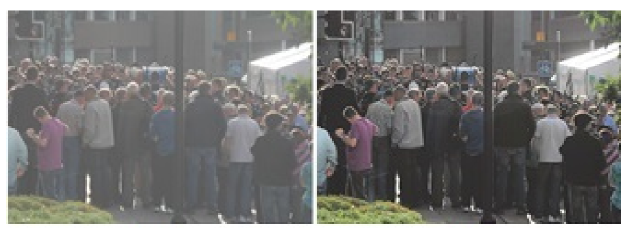


(a) (b)

Fig. 5: (a)Hazy image (b) Dehazed image

(a) (b)

Fig. 6: (a)Hazy image (b) Dehazed image



(a) (b)

Fig. 7: (a)Hazy image (b) Dehazed image

logic gate areas. The percentage of look-up tables used as memory is only 1%. RAM36E1 value refers to the memory usage.

TABLE 3: Xilinx Synthetic Results

Xilinx Design Analyzer			
Device	xc7z045-2-ffg9		
Slice Logic Utilization	**Available**	**Used**	**Utilization**
Slice Registers	437200	15911	3 %
Slice LUTs	218600	25882	11 %
Used as Memory	70400	747	1 %
RAMB36E1/FIFO36E1s	545	64	11 %
RAMB18E1/FIFO18E1s	1090	0	0 %

4. Conclusion

An alternative approach for haze removal from a different point of view has been proposed. The method can produce high-quality dehazed images while bypassing complex estimations in traditional techniques. The visual improvement has been validated by both qualitative and quantitative evaluations.

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