Enhancement of Low Light Level Images with Coupled Dictionary Learning

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Abstract—**Low Light Level Images (LLLIs) are captured with exceptionally low brightness and low contrast, and cannot be enhanced satisfactorily with ordinary methods. In this paper, we propose a LLLI enhancement method using coupled dictionary learning. During the training stage, a pair of dictionaries and a linear mapping function are learned simultaneously. The dictionary pair aims to describe the raw LLLIs and their enhanced versions, and the linear mapping function models the correspondence between the representations of the dictionary pair. In the enhancement process, the resulting image is generated through dictionary mapping from patches of the input LLLI. We adopt a clustering strategy to improve the robustness of coupled dictionary learning, and propose an improved algorithm for fast implementation. Experimental results on real images demonstrate the effectiveness of our method.**

I. INTRODUCTION

Low Light Level Images (LLLIs) are usually captured in the situation of dim light, for instance during the night. They have poor visual quality, low brightness and low contrast. Since lots of information is hidden in LLLIs, the enhancement of LLLIs is highly desired by consumers and computer vision application, such as object detection and recognition, scene analysis and so on. To the best of our knowledge, few researches have specially dealt with such LLLIs.

The difficulty of LLLIs' enhancement lies in the unknown relationship between LLLIs and their enhanced versions. The problem is under-constrained if only one LLLI is provided. Therefore, some methods have used multiple images for enhancement. In [1], images of the same scene at day and night time were fused together to remove the night effect. Zhuo et al. [2] and Matsui et al. [3] achieved context enhancement using multi-sensor images. Henrik et al. [4] and Bennett et al. [5] made use of image sequence with spatial and temporal information to restore details. However, the requirement of multiple images restricts their practicability, since mostly the input is only one LLLI.

The enhancement of LLLIs has also been tackled with assumptions on image statistics or transformation.

Traditional histogram based methods make assumptions on the intensity histograms of enhanced images, like uniform distribution, and then utilize local or global histogram to transform the raw images. Histogram equalization (HE) [6]

increases images' global contrast effectively while results in wash-out effect easily. As the improvement of HE, Tarik et al. [7] proposed a fusion framework integrating raw images with the enhanced results via HE to alleviate over enhancement. On the other side, local contrast methods divide the whole image or intensity histogram into several parts, and perform enhancement operations separately, e.g., contrast limited histogram equalization (CLAHE) [8], gray-level grouping (GLG) [9] and dualistic sub-image histogram equalization (DSIHE) [10]. Both CLAHE and DSIHE can produce more details than HE.

Methods with assumptions on transform function f turning a LLLI into a well illuminated style can also achieve impressive results.

Shan et al. [11] performed local linear adjustments with the assumption of linear mapping relationships between the corresponding images patches of input image and its enhanced version. However, this approach may fail at the brightness transition regions where the hypothesis is broken. The authors of [12]–[14] inverted a low light image and applied point-wise linear transformation function to achieve the "dehazing" effect with additional knowledge, named dark channel prior [15], and the final result was obtained by inverting the dehazed image. These methods lack a rigorous explanation, however, because an inverted low light image is different from a hazy image in nature.

In this paper, we propose a coupled dictionary learning approach for the enhancement of LLLIs. We do not estimate the transform function f directly, but address the LLLIs' enhancement from the perspective of example based approach instead. Our enhancement framework is formulated as an optimization problem for learning a pair of dictionaries and a linear mapping function simultaneously, and an iterative algorithm is developed to solve it. We integrate a clustering strategy to improve the robustness of our model, and develop an improved method for fast implementation.

The rest of this paper is organized as follows. Section II formulates the problem and details our approach. Section III presents the experimental results. Section IV makes the conclusion.

II. LLLI ENHANCEMENT APPROACH

A. Problem Formulation

The enhancement problem can be described as follows: given a Low Light Level image $\mathbf{y}$, how to restore the enhanced version $\mathbf{x}$ of the same scene. We assume that there exists a mapping function f from $\mathbf{y}$ to $\mathbf{x}$: $\mathbf{x} = f(\mathbf{y})$, and in most cases the transformation function f is unable to be acquired directly.

We are not intent to explore the exact form of mapping function f, but focus on the example based method to settle the problem. The example based methods have been successfully applied to other low level enhancement problems, such as image super-resolution [16]–[18] and deblurring [19].

The basic idea of the example based method on LLLIs enhancement problem is to construct the proposed results with examples from image dataset. A brief example is illustrated as follows: for any patch $\mathbf{y}_i$ of an image $\mathbf{y}$ to be enhanced, we search the most similar patch $\hat{\mathbf{y}}_i$ in the image pairs dataset for $\mathbf{y}_i$, and take the corresponding enhancement part $\hat{\mathbf{x}}_i$ of $\hat{\mathbf{y}}_i$ as the enhanced style $\mathbf{x}_i$ of $\mathbf{y}_i$. A more reasonable way is to improve the enhanced result $\mathbf{x}_i$ with a group of examples. We can first search the most T similar patches $\hat{\mathbf{y}}_i(n)(n = 1, ..., T)$ in the image pairs dataset as the neighbours of $\mathbf{y}_i$, and $\mathbf{y}_i$ will be reconstructed from $\hat{\mathbf{y}}_i(n)(n = 1, ..., T)$. If we also know the corresponding patches $\hat{\mathbf{x}}_i(k)$ of $\mathbf{x}_i$, we will have $\mathbf{y_i} = \mathbf{R}^{y_i}\hat{\mathbf{Y}}_i, \mathbf{x_i} = \mathbf{R}^{x_i}\hat{\mathbf{X}}_i$, where $\hat{\mathbf{Y}}_i$ and $\hat{\mathbf{X}}_i$ are matrices made up by the neighbours of $\mathbf{x}_i$ and $\mathbf{y}_i$, respectively, $\mathbf{R}^{y_i}$ and $\mathbf{R}^{x_i}$ are the reconstruction coefficients matrices. Shan et al. [11] and Dong et al. [12] hypothesized the linear mapping relationship between local patches $\mathbf{y_i}$ and $\mathbf{x_i}$. Different from their approach, we adopt the linear mapping hypothesis for the coefficient $R_k^{y_i}$ and $R_k^{x_i}$, which gives

$$\mathbf{R}^{x_i} = \mathbf{W_i} \cdot \mathbf{R}^{y_i}. \tag{1}$$

The easiest way to get the coefficient $\mathbf{R}^{x_i}$ is making the matrix $\mathbf{W_i}$ equal to identity matrix. However, this assumption is strict and leads to unsatisfactory enhancement result. On the other side, the search for most K similar patches in the image dataset of any input patch is time consuming, and we will use dictionary learning to replace this step for acceleration.

Based on the above analysis, we develop a coupled dictionary framework to solve the LLLI enhancement problem. Let $\mathbf{X}$ and $\mathbf{Y}$ denote the training datasets made up of the image patch pairs from the LLLIs and their well illuminated counterparts, respectively. We process the patches of all images in raster-scan order, from left to right and top to bottom, and the pixels in each patch are concatenated into a vector. Consider image pair reconstruction and mapping simultaneously, the enhancement of LLLI can be formulated into the following model:

$$\min_{\mathbf{D}_x, \mathbf{D}_y, \mathbf{W}} \|\mathbf{X} - \mathbf{D}_x\Theta_x\|_F^2 + \|\mathbf{Y} - \mathbf{D}_y\Theta_y\|_F^2$$
$$+ \gamma \|\Theta_x - \mathbf{W}\Theta_y\|_F^2 + \lambda(\|\Theta_x\|_1 + \|\Theta_y\|_1) + \lambda_w \|\mathbf{W}\|_F^2$$
$$\text{s.t.}\|d_{x,i}\|_2 \leq 1, \|d_{y,i}\|_2 \leq 1, \forall i, \tag{2}$$

where $\gamma, \lambda, \lambda_w$ are regularization parameters, $d_{x,i}, d_{y,i}$ are the atoms of dictionary $\mathbf{D}_x$ and $\mathbf{D}_y$, respectively, and $\mathbf{W}$ is the linear mapping matrix of coefficients Θ_x and Θ_y. Though the objective function is not jointly convex to $\mathbf{D}_x, \mathbf{D}_y, \mathbf{W}$, it is convex with regard to one of them if the other two are fixed. Thus, we exploit an iterative strategy to optimize the variables alternatively.

B. Learning

To obtain the solution, we separate the target function 2 into three sub-problems:

The first sub-problem is to get the Θ_x, Θ_y by fixing $\mathbf{D}_x, \mathbf{D}_y$ and $\mathbf{W}$. For fast convergence, we initialize the $\mathbf{D}_x$ and $\mathbf{D}_y$ as the matrices learned via 2 without the item $\|\Theta_x - \mathbf{W}\Theta_y\|_F^2$. After the initialization of $\mathbf{D}_x, \mathbf{D}_y$ and $\mathbf{W}$, the optimization problem is:

$$\min_{\Theta_x, \Theta_y} \|\mathbf{X} - \mathbf{D}_x\Theta_x\|_F^2 + \|\mathbf{Y} - \mathbf{D}_y\Theta_y\|_F^2$$
$$+ \gamma \|\Theta_x - \mathbf{W}\Theta_y\|_F^2 + \lambda(\|\Theta_x\|_1 + \|\Theta_y\|_1). \tag{3}$$

We further separate the above sub-problem into the following forms:

$$\min_{\Theta_x} \|\mathbf{X} - \mathbf{D}_x\Theta_x\|_F^2 + \gamma \|\Theta_x - \mathbf{W}\Theta_y\|_F^2 + \lambda \|\Theta_x\|_1. \tag{4}$$

$$\min_{\Theta_y} \|\mathbf{Y} - \mathbf{D}_y\Theta_y\|_F^2 + \gamma \|\Theta_x - \mathbf{W}\Theta_y\|_F^2 + \lambda \|\Theta_y\|_1. \tag{5}$$

Actually, each of the above two equations is a multi-task lasso problem. Many algorithms can address it efficiently, and we choose LARS [20] to have Θ_x and Θ_y.

Fixing Θ_x and Θ_y, the pursuit of updating dictionaries $\mathbf{D}_x$ and $\mathbf{D}_y$ will be completed as follows:

$$\min_{\mathbf{D}_x, \mathbf{D}_y} \|\mathbf{X} - \mathbf{D}_x\Theta_x\|_F^2 + \|\mathbf{Y} - \mathbf{D}_y\Theta_y\|_F^2$$
$$\text{s.t.}\|d_{x,i}\|_2 \leq 1, \|d_{y,i}\|_2 \leq 1, \forall i. \tag{6}$$

It is a quadratically constrained quadratic program problem and we take the similar strategy as [21] to solve it.

With the dictionaries and corresponding coefficients fixed, the linear mapping matrix $\mathbf{W}$ can be obtained:

$$\min_{\mathbf{W}} \|\Theta_x - \mathbf{W}\Theta_y\|_F^2 + (\lambda_w/\gamma) \|\mathbf{W}\|_F^2. \tag{7}$$

It is a ridge regression problem, and a closed form solution can be got.

C. Enhancement

After the training stage of our method, the dictionaries $\mathbf{D}_x$, $\mathbf{D}_y$ and the linear mapping matrix $\mathbf{W}$ have been ready. For a new LLLI $\mathbf{y}$, we can get the enhancement result $\mathbf{x}$ by solving the following optimization problem:

$$\min_{\mathbf{x}_i, \theta_{x,i}, \theta_{y,i}} \|\mathbf{x}_i - \mathbf{D}_x \theta_{x,i}\|_F^2 + \|\mathbf{y}_i - \mathbf{D}_y \theta_{y,i}\|_F^2 \\ + \gamma \|\theta_{x,i} - \mathbf{W}\theta_{y,i}\|_F^2 + \lambda(\|\theta_{x,i}\|_1 + \|\theta_{y,i}\|_1), \tag{8}$$

where $\mathbf{y}_i$ is a patch of $\mathbf{y}$ and $\mathbf{x}_i$ is the corresponding one of the result $\mathbf{x}$. The problem 8 can be addressed in the same way as problem 3 by alternatively solving $\theta_{x,i}$ and $\theta_{y,i}$. Then $\mathbf{x}_i$ is reconstructed via

$$\mathbf{x}_i = \mathbf{D}_x \theta_{x,i}. \tag{9}$$

In the final, we average all the estimations of overlapped patches together to construct the enhanced results.

D. Issues and Improvement

During the training preprocess, patches extracted from images should minus its mean value to compose the dataset $\mathbf{X}$ and $\mathbf{Y}$. At the test stage, the enhanced patches are reconstructed by adding the estimations of equation 9 and mean values. However, the mean value of a LLLI patch is far smaller than the one of its enhanced version. Therefore, the mean values of patches from enhanced results should not be the ones of raw image patches, and need careful estimations, too. Another issue lies in the limited effect of only one pair of dictionaries, for one associated linear mapping matrix is not enough to cover all variations of enhancement situations.

Algorithm 1 Learning algorithm of coupled dictionary

Input: Training datasets $\mathbf{Y}$ and $\mathbf{X}$ of patches from LLLIs and their well illuminated images, the initialization of $\mathbf{D}_x, \mathbf{D}_y, \mathbf{W}$, parameters $\gamma, \lambda, \lambda_w$, and the number of clusters K.
1: Cluster $\mathbf{Y}$ into K groups, $\mathbf{Y}^{(1)}, ..., \mathbf{Y}^{(K)}$, and clustering centers are $\mu^{(1)}, ..., \mu^{(K)}$;
2: $k = 1$;
3: **while** $k \leq K$ **do**
4:     **while** not converged **do**
5:         Fix other variables, update $\Theta_x^{(k)}, \Theta_y^{(k)}$ in (4) and (5);
6:         Fix other variables, update $\mathbf{D}_x^{(k)}, \mathbf{D}_y^{(k)}$ in (6);
7:         Fix other variables, solve $\mathbf{W}^{(k)}$ via (7);
8:     **end while**
9:     Solve α_k, β_k via Eq. (10);
10:    $k \leftarrow k + 1$;
11: **end while**
Output: $\mu^{(k)}, \mathbf{D}_x^{(k)}, \mathbf{D}_y^{(k)}, \mathbf{W}^{(k)}, \alpha_k, \beta_k, k = 1, 2...K$

To handle the two issues, we take advantage of clustering to make our model more robust. We propose to conduct k-means clustering operation on the raw patches of LLLIs in the image pairs dataset. For each cluster, a pair of dictionaries and an associated linear mapping matrix will be learned. On the other hand, we assume that in each cluster a linear mapping relationship exists between the mean value $\bar{y}_i$ of a raw image patch and the one $\bar{x}_i$ of the corresponding enhanced style:

$$\min_{\alpha_k, \beta_k} \sum_{j=1}^{k_n} \|\bar{x}_j - (\alpha_k \bar{y}_j + \beta_k)\|^2, \tag{10}$$

where k_n is the number of samples in cluster k. Based on the previous descriptions, we summarize the learning and enhancement algorithm of the coupled dictionary in Algorithm 1 and Algorithm 2, respectively.

Algorithm 2 Enhancement algorithm of coupled dictionary

Input: $\mu^{(k)}, \mathbf{D}_x^{(k)}, \mathbf{D}_y^{(k)}, \mathbf{W}^{(k)}, \alpha_k, \beta_k, k = 1, 2...K$. Test image $\mathbf{y} \in \mathbf{R}^{m \times n}$;
1: Allocate $\mathbf{G} \in \mathbf{R}^{m \times n}, \mathbf{G} = \mathbf{0}, N = $ patches number of test image $\mathbf{y}, i = 0$;
2: **while** $i \leq N$ **do**
3:     Allocate the cluster index k of the patch y_i from the test image $\mathbf{y}$;
4:     Solve the mean value $\bar{x}_i$ of the enhanced patch via $\bar{x}_i = \alpha_k \bar{y}_i + \beta_k$;
5:     Obtain the coefficient vector $\theta_{x,i}$ via Eq. (8);
6:     Reconstruct $\hat{\mathbf{x}}_i$ via (9);
7:     Count the treated pixels $\mathbf{G}(y_i) = \mathbf{G}(y_i) + 1$;
8:     $i \leftarrow i + 1$;
9: **end while**
10: Average the dictionary decoding result $\tilde{\mathbf{x}} = \tilde{\mathbf{x}}./\mathbf{G}$;
11: The final enhancement result is solved via $\mathbf{x} = \tilde{\mathbf{x}} + \bar{\mathbf{x}}$;
Output: The enhancement result $\mathbf{x}$.

In addition to the above two issues, the computation time of the method is a serious issue. For an image with size 800*600, it takes nearly 40 minutes on PC to get the enhancement result. In order to speed up our method, we split the whole framework into three parts.

First, we take away the coupling item $\|\Theta_x - \mathbf{W}\Theta_y\|_F^2$ in the Eq. (2), and make use of the training dataset to get the $\mathbf{D}_x, \mathbf{D}_y$ quickly.

Second, after obtaining all pairs of the coefficients Θ_x and Θ_x, the mapping matrix $\mathbf{W}$ is solved directly by Eq. (7).

Third, in the enhancement process, there is no need to obtain the solution via iterative steps. After the coding of $\mathbf{y}_i$ with dictionary $\mathbf{D}_y$, $\mathbf{x}_i$ is achieved by $\mathbf{x}_i = \mathbf{D}_x \mathbf{W}\Theta_{y_i}$.

During the implementation of this simplified version, we also combine with clustering and the estimation on mean values of enhanced patches to address the previous two issues. As we

will see in the experiment section, our simplified method gets a much faster running speed than the whole framework, and also assures a pleasing visual quality.

E. Postprocessing

Though coupled dictionary method can conspicuously improve the brightness and contrast of LLLIs, it also results in somewhat blurring effects. We make use of simple unsharp masking [6] to eliminate blurring, fast and effective. The unsharp masking is a process including the following steps: a mask is extracted by subtracting a blurred version of the input image from itself, and the result is generated by adding the mask back to the original image.

III. EXPERIMENTS

We employed the dataset provided by EMPA Media Technology[1] and 110 LLLIs collected from the Internet to evaluate the performance of algorithms quantitatively and qualitatively. When processing color images, we transform the inputs into the HSV color space and then apply the enhancement algorithms to the V channel.

We have conducted a series of comparison experiments on LLLIs to demonstrate the effectiveness of our method. We compared our method with five classical methods: HE [6], CLAHE [8], learning based enhancement method of Shan et al. [11], Dong et al.'s algorithm [12] and Zhang et al.'s algorithm [14]. The parameters in these methods were all set the default values recommended by their authors.

Our enhancement algorithm has six parameters: the patch size, the number of the atoms in two dictionary, the number of the clusters and three regularization parameters $\gamma, \lambda, \lambda_w$. We set the patch size 5×5 and cluster number was 10. The number of atoms in dictionary was 1024 for each cluster. The regularization parameters $\lambda, \lambda_w, \gamma$ were set to be 0.01, 0.1 and 0.1, respectively. These parameters were selected empirically for satisfactory performance, but moderate variations from these values do not affect the performance considerably.

To train our model, 500,000 patches were randomly extracted as the enhancement styles from 200 images of the Berkeley segmentation dataset [22], and the corresponding LLLIs' patches were synthesized by applying gamma correction function to previously chosen patches with parameter γ_* randomly sampled from the distribution Uniform(1, 3).

The first experiment was conducted on the images pairs from the EMPA dataset, and each image pair was comprised by a image with a short exposure time to stand for a LLLI and a image with a long exposure time to represent the reference of the enhanced version. For comparing the enhancement methods in ordinary scenario, we converted the 48bit images in the EMPA dataset into conventional 24bit images with size 400*400 by Photoshop. The reason is that we aim to compare

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[1]http://www.empamedia.ethz.ch/hdrdatabase/index.php

TABLE I: PSNR and SSIM comparisons of enhancement methods.

Image	Index	HE	CLAHE	Shan	Dong	Zhang	Proposed	Fast
FORTH1	PSNR(dB)	17.1	6.98	5.51	12	25	14	8.15
	SSIM	0.73	0.68	0.66	0.76	0.79	0.69	0.76
FORTH2	PSNR	10.18	4.61	10.13	7.89	5.8	7.8	4.77
	SSIM	0.65	0.53	0.73	0.72	0.65	0.63	0.56
Knossos3	PSNR	14.1	6.23	13.77	8.92	7.27	12.8	6.48
	SSIM	0.67	0.59	0.68	0.72	0.62	0.68	0.61
MonSaintMichel	PSNR	5.28	12.35	8.11	12.04	10.56	9.3	11.77
	SSIM	0.46	0.68	0.34	0.52	0.53	0.5	0.62
Museum	PSNR	8.5	9.13	4.06	6.97	11.59	9.7	13.92
	SSIM	0.62	0.79	0.63	0.79	0.89	0.84	0.89
Average	PSNR	11.03	7.86	8.32	9.56	12.04	10.72	9.02
	SSIM	0.67	0.65	0.61	0.7	0.7	0.67	0.69

the effectiveness of enhancement methods on general images. The results are illustrated in Fig. 1. From Fig. 1, we can observe that both our proposed method and the fast version achieved a good balance between global contrast and brightness, compared with the other five methods.

The peak signal-to-noise ratio (PSNR) and the Structural SIMilarity (SSIM) index [23] are employed to measure the enhancement quality. From Table I, it can be seen that our method and the fast version of our method ranked third and fifth on the average values of PSNR, and on the average values of SSIM they achieved the fourth and third place, respectively. Though HE and Zhang's method performed better at the quantitative index than our method, our method and the fast version of our method exhibited better visual quality.

We also validated our method on 110 LLLIs collected from the Internet via Google with keywords "low light level image", and this time we would have no reference images to compare with enhancement results. The comparisons on example images are exhibited in Fig. 2. Generally, our method greatly restored the details of the dark regions, and balanced well between the local contrast and overall brightness.

As for the running time, our method takes about 40 minutes for an 800*600 LLLI when implemented with 2.80GHz Intel Core2 Processor and 8.0GB RAM using Matlab. When processing the same size image, the fast version of our method takes only 6 seconds. From the two experiments we can see that the fast version also shows good performance on the enhancement results.

IV. CONCLUSION

In this paper, we have attempted to settle the enhancement of LLLIs with a coupled dictionary learning method. Experiments on an open dataset and images collected from the Internet clearly proved the effectiveness of our model. In the future, we will integrate prior knowledge on natural images into our model to improve the results, and parallel computing techniques will be exploited to speed up our algorithm.
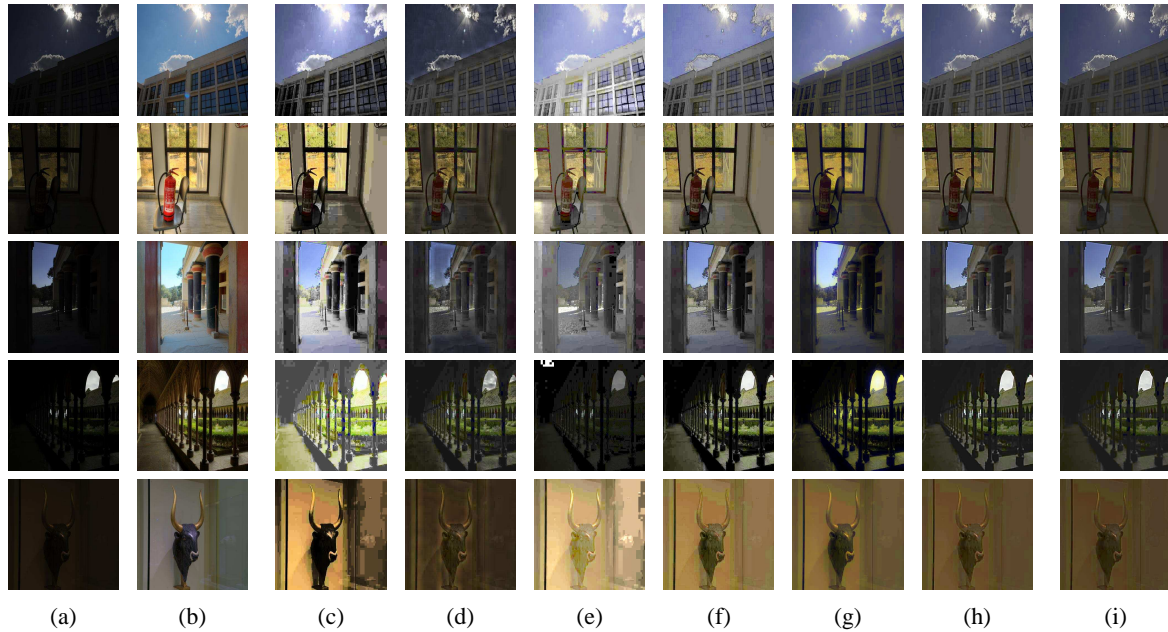
Fig. 1: Enhancement results of five images from top to bottom named "FORTH1", "FORTH2", "Knossors", "MonSaintMichel" and "Museum". From left to right: (a)Input. (b)Reference of enhancement results. (c-i) The enhancement results of HE, CLAHE, Shan's method, Dong's method, Zhang's method, our method and the fast version of our method. **Best viewed in ×6 sized color pdf file**

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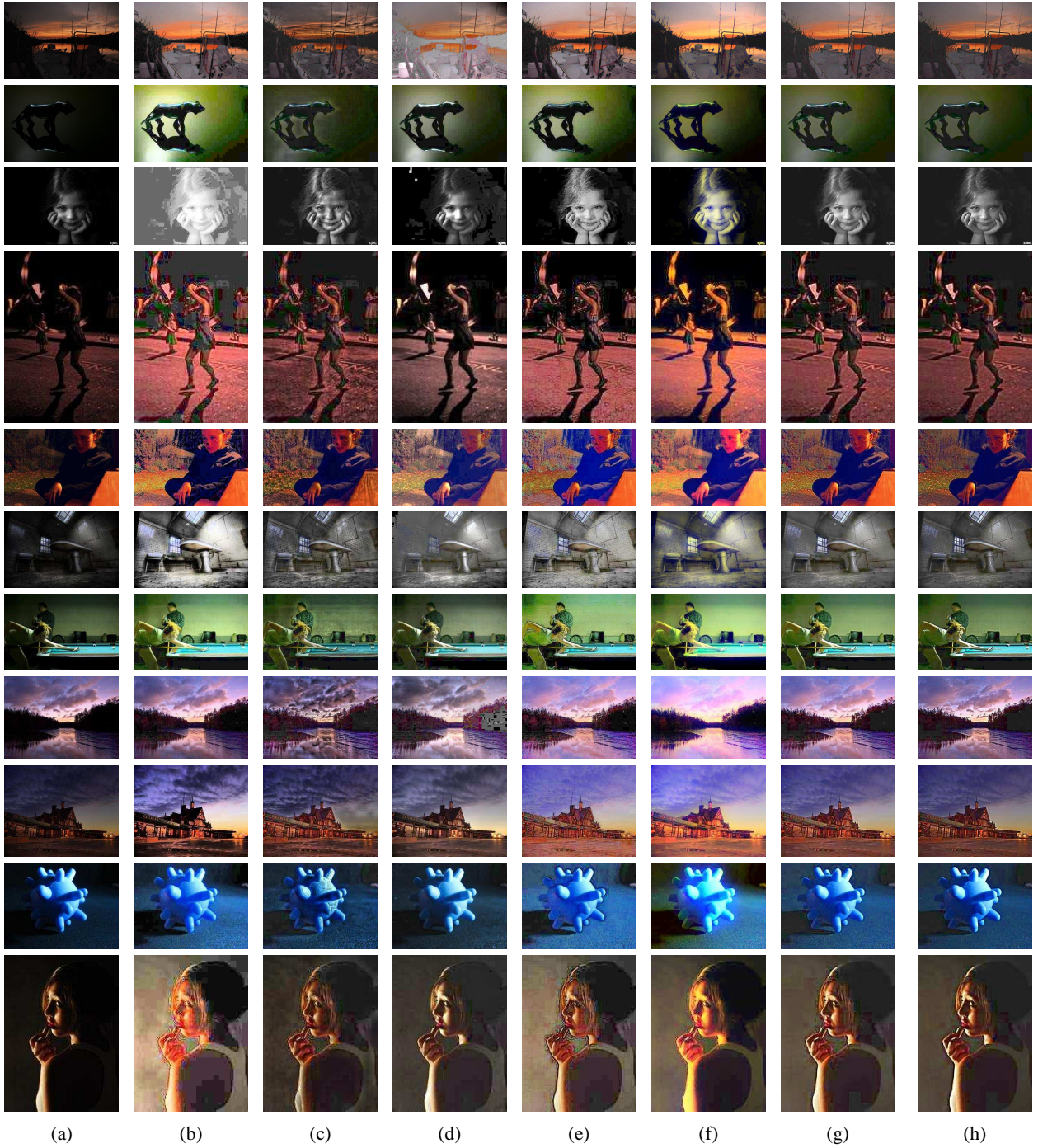
Fig. 2: Enhancement comparisons of 11 example images. From left to right: (a)Input. (b-h) The enhancement results of HE, CLAHE, Shan's method, Dong's method, Zhang's method, our method and the fast version of our method. **Best viewed in ×4 sized color pdf file**