Enhancement of Low Light Level Images with Regression Methods

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ABSTRACT

The enhancement of Low Light Level Images (LLLIs) is challenging, due to their poor brightness and low contrast. Traditional enhancement methods fail to perform satisfactorily when applying to LLLIs. In this paper, we formulate the LLLI enhancement as a regression problem: the regressor maps patches of input image to enhanced patches, and the regression function is estimated by learning from sample images. We implemented two efficient regression methods based on piecewise linear regression: locally linear regression and random forest (RF). Meanwhile, we designed a new split function considering reconstruction error for random forest method. Experimental results on an open dataset and practical LLLIs demonstrate the effectiveness of our methods. The RF regression method performs superiorly in both enhancement quality and computation efficiency.

Keywords: Low Light Level Image, regression, piecewise linear, random forest

1. INTRODUCTION

Low Light Level Images (LLLIs) have low brightness and low contrast, and their poor visual quality deteriorates remote sensing, object recognition and so forth. The objective of LLLI enhancement is to produce a visually pleasing image from a LLLI.

Although the problem is ill-posed and ambiguous, histogram equalization (HE)[1] and contrast limited adaptive histogram equalization (CLAHE)[2] have been used to generate the enhanced images. These methods are extremely fast but do not perform satisfactorily due to simple assumptions on image histograms.

Using multiple input images can help improve the enhancement quality. Zhuo et al.[3] achieved context enhancement with images captured by multiple sensors. Cai et al.[4] fused images of the same scene during day and night time for enhancement. Henrik et al.[5] and Bennett et al.[6] exploited image sequence to recover details as many as possible. However, the availability of multiple images on the same target is not common in practice.

More powerful methods usually apply learning based techniques to transform a low contrast image to an enhanced one. Shan et al.[7] assumed linear mapping between pairs of patches from the input image and its enhanced version, and performed adjustments with a well designed constrained regularization on the transformation coefficients. The authors of[8–10] treated the inversion of a LLLI as a hazy image, and made use of linear hazing model to obtain the result. However, the former does not perform stably on test images, while the latter lacks a rigorous formulation on the connection between a hazy image and an inverted LLLI.

In our work, we directly cast LLLI enhancement as a regression problem, and take piecewise linear regression to achieve good tradeoff between regression ability and computation efficiency. Locally linear regression is a choice to achieve this goal. Furthermore, we employ random forest[11–13] to alleviate the locally linear assumption. Random forest (RF) is a non-linear learner and runs extremely fast during learning and inference. While a tree is a piecewise linear regressor, the ensemble of multiple trees in RF improves the regression accuracy significantly. In the process of tree growing, we design the split objective function considering the reconstruction of enhanced images. Our experimental results demonstrate the effectiveness of the proposed methods. Particularly, random forest regression performs superiorly compared to previous representative methods.

The rest of this paper is organized as follows. Section II describes regression methods for LLLI enhancement. Section III presents the experimental results, and Section IV concludes the paper.

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2. APPROACH

Image (including LLLIs) enhancement can be viewed as a process that a patch in the input image is mapped to the corresponding patch in the enhanced image. Recently, regression methods have been successfully applied into the image enhancement problems, such as image denoising[14] and super resolution[15] . These methods cannot apply to LLLI enhancement directly, however. We propose to tackle LLLI enhancement using piecewise linear regression, with locally linear regression as a baseline.

2.1 Locally Linear Regression for LLLI Enhancement

We first tackle the LLLI enhancement as linear regression from LLLI's patches $\mathbf{y}_i$ to the ones $\mathbf{x}_i$ of the enhancement counterpart. To approximate nonlinear regression, we consider locally linear regression by adopting the divide-and-conquer strategy. Specifically, we propose to conduct k-means clustering operation on the raw patches of LLLIs from the image pairs dataset, and for each cluster a linear mapping matrix $\mathbf{W}$ is learned. For a cluster i, we compute the linear mapping matrix via

$$\mathbf{W}_i^* = \min_{\mathbf{W}_i} \left\| \mathbf{X}_i - \mathbf{W}_i \begin{pmatrix} \mathbf{Y}_i \\ \mathbf{1} \end{pmatrix} \right\|_F^2 + \lambda \left\| \mathbf{W}_i \right\|_F^2 , \tag{1}$$

where each column of $\mathbf{Y}_i$ is a raw patch in cluster i, $\mathbf{1}$ is a row vector with all values as 1, and λ is the regularization parameter.

Locally linear regression, though performs fairly well on LLLI enhancement, its performance depends on the cluster number K, which compromises the regression error and the running time. Besides, locally linear assumption should be relaxed in order to model the relationships of patch pairs more reasonably. Therefore, we use a tree classifier to replace clustering for acceleration and fuse multiple trees in random forest for enhancing the regression accuracy.

2.2 Random Forest for LLLI Enhancement

Random forest is an ensemble of random decision binary trees. Each tree T_j independently separates the data space into disjoint units, namely leaf nodes. The two key aspects of random forest modeling LLLI enhancement are the objective functions of leaf nodes and splitting functions of intermediate nodes. These two functions will be carefully designed to fulfill the requirements of LLLI enhancement.

For each leaf node l_i^j of tree T_j, we take the same objective function as locally linear regression:

$$\min_{\mathbf{W}_{l_i^j}} \left\| \mathbf{X}_{l_i^j} - \mathbf{W}_{l_i^j} \begin{pmatrix} \mathbf{Y}_{l_i^j} \\ \mathbf{1} \end{pmatrix} \right\|_F^2 + \lambda \left\| \mathbf{W}_{l_i^j} \right\|_F^2 , \tag{2}$$

where each column of $\mathbf{Y}_{l_i^j}$ is an input raw patch in the leaf node l_i^j, and λ is the regularization parameter.

The structure of tree T_j is determined by the node splitting function with patch pairs $\mathbf{x}_i, \mathbf{y}_i$:

$$S(\mathbf{y}_i, \theta) = \begin{cases} 1, & \mathbf{y}_i[d] - \theta > 0; \\ 0, & \text{otherwise}, \end{cases} \tag{3}$$

where $\mathbf{y}_i[d]$ means randomly selecting one feature from $\mathbf{y}_i$, and θ is the threshold to control split. The typical procedure for finding a good value of θ in random forest is to sample a random set of parameter values and choose the best θ^* according to a pre-defined measure, for example, minimum of data variance. Considering that our task is to restore the enhancement patches, we design the evaluation measure as:

$$\begin{aligned} M(\mathbf{x}_i, \mathbf{y}_i) &= \min \sum_{t \in L,R} F(\mathbf{x}_i^t, \mathbf{y}_i^t); \\ F(\mathbf{x}_i^t, \mathbf{y}_i^t) &= \frac{N^t}{N} (\sum_i \left\| \mathbf{x}_i^t - \mathbf{W}_t \begin{pmatrix} \mathbf{y}_i^t \\ 1 \end{pmatrix} \right\|_F^2 + \lambda \left\| \mathbf{W}_t \right\|_F^2), \end{aligned} \tag{4}$$

where N is the total number of samples at current node, N^L and N^R are the numbers of samples allocated to the left and right subnode, respectively, $\mathbf{x}_i^t$ and $\mathbf{y}_i^t$ are the sample pairs allocated to the subnode t, and $\mathbf{W}_t$ can be estimated via Eq.

(2). For all internal nodes in T_j, splitting starts at the root node and continues in a greedy manner down the tree until a maximum depth D is reached. When splitting stops, a leaf node is created.

The inference or testing process of random forest is simple. The enhancement result of a single patch is the average of predictions of all the trees. For an input LLLI, we estimate the enhancement results of all extracted patches. If the extracted patches have overlap, we will get the means of overlap regions as the final values.

3. EXPERIMENTS

We evaluated the performance of our regression methods for single LLLI enhancement on an open dataset and test images downloaded from the Internet. We compare our methods with five typical methods: HE,[1] CLAHE,[2] learning based enhancement methods of Shan et al.,[7] Dong et al.[8] and Zhang et al.[10] These algorithms are implemented in Matlab with 3.20GHz Intel Core i5 Processor and 4GB RAM. The parameters in these methods are equal to the default values recommended by their authors. We scale the intensities of all images into [0, 1]. When processing color images, we transform them into the HSV color space and operate enhancement on the V channel.

3.1 Training Data and Experimental Setup

In practice, it's difficult to prepare a large quantity of image pairs composed of a LLLI and its bright version. We employ the image pairs provided by EMPA Media Technology. Each image pair is comprised by an image with a short exposure time to stand for a LLLI, and an image with a long exposure time to represent the reference of the enhanced style. We have converted the 48bit images in the EMPA dataset into 24bit images with size 400×400 by Photoshop. 10 image pairs were selected as training data, and 5 image pairs were for testing. From the training image pairs, 500,000 patch pairs were randomly extracted for training locally linear regression and RF.

In order to obtain more diverse training data, we also attempt to randomly synthesize image pairs from 200 images of the Berkeley segmentation dataset. Two functions are chosen to generate LLLI patches from the well illuminated ones: gamma correction and linear transformation (Note that we have scaled intensities of images into [0, 1]).

For each randomly selected patch $\hat{x}_i$, we sample the parameter γ from the distribution Uniform(L, U) and applied gamma correction to generate a LLLI patch. In our experiments, we set the parameter $L = 1$ and $U = 4$. The linear transformation is formulated as $\hat{y}_i = w\hat{x}_i$ and $w = t \cdot m + b$, where m is randomly sampled from distribution Uniform(0, 1), and we set $t = 1$, $b = 0.05$. We make use of two functions to generate 500,000 patch pairs separately, prepared to serve as training data.

We used the intensity values of raw patch as the features of regression, and the patch size was 5×5. The regularization parameters λ was set to 0.1. For locally linear regression, we set the cluster number K in linear regression to 50, which was shown to perform satisfactorily. The number of trees T and the maximum depth D of random forest were set as 10 and 5, respectively. During testing, we extracted patches from the input image with overlap of one pixel. All the parameters were set empirically, but we observed that moderate variations do not harm the visual quality of enhancement.

3.2 Results and Discussions

As mentioned above, we take advantage of two datasets to evaluate the performance of algorithms quantitatively and qualitatively. The two datasets contain 5 image pairs from EMPA dataset and 110 LLLIs downloaded from the Internet via Google with keywords ”low light level image”.

The first experiment was conducted on the 5 images pairs from the EMPA dataset. Each image pair involves a LLLI and a reference image of the enhanced version. The peak signal-to-noise ratio (PSNR) and the Structural SIMilarity (SSIM) index are used to measure the enhancement quality.

In the quantitative assessment, we take the results of regression methods with linearly synthesized training data for comparison, because they have produced better visual quality than the methods with real and gamma correction synthesized data. From Table 1, it can be seen that LLR and RF rank fourth and third on the average values of PSNR, and on the average values of SSIM they achieve the second and first place, respectively.

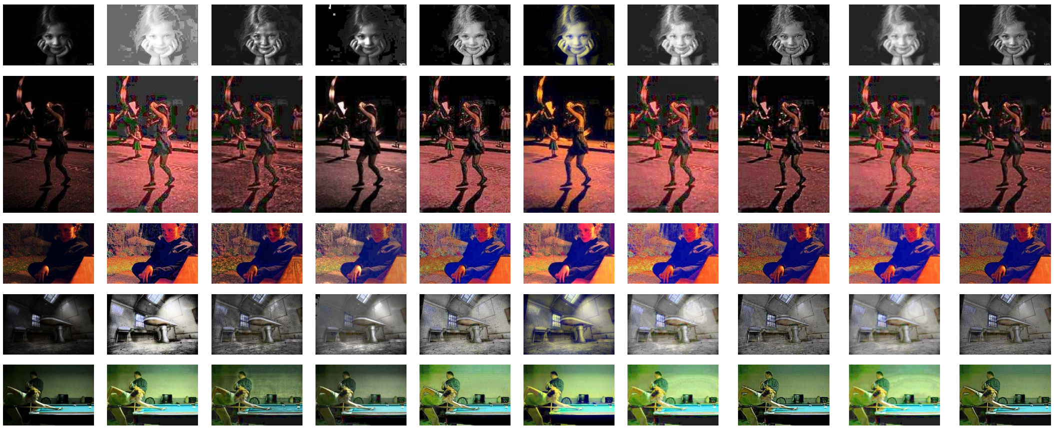
To compare the enhancement effects on general scenario, we validated our methods on 110 LLLIs collected from the Internet. This time we have no reference enhancement results. The comparisons on example images are shown in Fig. 1. Generally, our methods greatly reveal the details of the dark regions, and balance well between contrast and overall

Table 1: PSNR and SSIM comparisons.

Image	Index	HE	CLAHE	Shan	Dong	Zhang	LLR	RF
FORTH1	PSNR(dB)	17.1	6.98	5.51	12	25	10.25	10.87
	SSIM	0.73	0.68	0.66	0.76	0.79	0.78	0.81
FORTH2	PSNR	10.18	4.61	10.13	7.89	5.8	5.78	5.89
	SSIM	0.65	0.53	0.73	0.72	0.65	0.66	0.69
Knossos	PSNR	14.1	6.23	13.77	8.92	7.27	7.26	7.39
	SSIM	0.67	0.59	0.68	0.72	0.62	0.68	0.7
MonSaintMichel	PSNR	5.28	12.35	8.11	12.04	10.64	9.3	11.5
	SSIM	0.46	0.68	0.34	0.52	0.53	0.56	0.65
Museum	PSNR	8.5	9.13	4.06	6.97	11.59	15.77	13.04
	SSIM	0.62	0.79	0.63	0.79	0.89	0.87	0.87
Average	PSNR	11.03	7.86	8.32	9.56	12.04	9.67	9.74
	SSIM	0.67	0.65	0.61	0.7	0.7	0.7	0.75

brightness. At the same time, we can see that the RF method achieve a more natural contrast than the LLR method. Besides, the LLR method brings artifacts to some extent. By contrast, the RF method presents a more satisfactory visual effect.

During testing, it takes 1.5s to enhance an 800$\times$600 LLLI for our LLR method, while the RF method takes 1s.



(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 1: Enhancement results of seven example images. From left to right: (a) input image; (b-j) The enhancement results of HE, CLAHE, Shan's method, Dong's method, Zhang's method, our proposed locally linear regression method with real training data and with linearly synthesized data, and our proposed random forest method with real training data and linearly synthesized data. **Best viewed in $\times$6 sized color pdf file**

4. CONCLUSION

In this paper, we propose to settle the enhancement of LLLIs with regression methods. We introduce locally linear regression and random forest based regression, and give their detailed formulation for implementing LLLI enhancement. The experiments have demonstrated the effectiveness of our methods. At the same time, we have found the usefulness of synthesized training data to improve the performance of our methods. In the future, we will solve the enhancement of LLLIs with noises.

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