Enhancement of LLLIs with improved BCP and matrix completion

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The problem of enhancement of low light level images (LLLIs) with the characteristics of extremely low brightness and low contrast is addressed. A coarse-to-fine framework to settle the problem is proposed. First, a point-wise linear relationship is constructed between an LLLI and its enhancement result, and a prior named bright channel prior (BCP) is introduced to guide the enhancement process. The BCP to avoid over enhancement is improved, and the idea of matrix completion to remove the outlier noises in the enhanced image is used. Experimental results on real images demonstrate that the method is effective for the enhancement of LLLIs.

Introduction: With the popularity of smart phones and cameras, people like to take photographs in various occasions, but it is difficult to obtain a pleasing picture in the situation of dim light, for instance during the night. Those photographs often have the characteristics of extremely low brightness and low contrast. However, it is a big waste to simply delete them because they carry rich information. Such images are usually called low light level images (LLLIs). Our task is to improve their visual quality for both human and automatic analysis application such as scene analysis, object detection and recognition and so on. To the best of our knowledge, few research have specially dealt with such LLLIs, and there has not been a satisfactory solution.

Although the problem is ill-posed and ambiguous, histogram equalisation (HE) [1] and contrast limited adaptive HE (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. The methods using multiple input images [3–5] can help improve the enhancement quality. However, the availability of multiple images on the same target is not common in practise.

More powerful methods usually apply learning-based techniques to transform a low contrast image to an enhanced one. Shan *et al.* [6] assumed linear mapping between pairs of patches from the input image and its enhanced version, and performed adjustments with a well-designed constrained regularisation on the transformation coefficients. The authors of [7–9] treated the inversion of an 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, whereas the latter lacks a rigorous formulation on the connection between a hazy image and an inverted LLLI.

In this Letter, we propose a learning-based coarse-to-fine approach for the enhancement of LLLIs. First, a point-wise mapping relationship between an LLLI and its well-illuminated version is constructed directly with a prior named bright channel prior (BCP). Then, we improve the BCP to obtain improvement. Finally, we adjust the estimations to remove outlier noises by matrix completion (MC). Experimental results on the practical images collected from the Internet demonstrate the effectiveness of our method.

The rest of this Letter is organised as follows. Section ‘Framework and method’ formulates the problem and details our method. Section ‘Experiments’ presents the experimental results and Section ‘Conclusions’ concludes this Letter.

Framework and method: We start from grey-scale images and formulate the enhancement problem of LLLIs in brief mathematical form

$$\boldsymbol{Y} = \boldsymbol{f}(\boldsymbol{X}) \tag{1}$$

where $\boldsymbol{Y}$ represents an LLLI, $\boldsymbol{X}$ is the enhancement result and $\boldsymbol{f}$ means the mechanism turning a pleasing looking image into an LLLI.

To reduce the uncertainty on function $\boldsymbol{f}$, we first make the assumption of Lambertian reflectance model [10] to decompose a pixel value of any image into two multiplicative components: illuminance value and reflectance value. The reflectance image is invariant under different lightings. If we assume that the relationship between illuminance images is point-wise linear, then we have

$$\boldsymbol{Y} = \boldsymbol{T} \circ \boldsymbol{X} \tag{2}$$

where $\boldsymbol{T}$ is the linear coefficients matrix and $\circ$ denotes the Hadamard point-wise product of two matrices.

For a colour image $\mathbf{Color}\boldsymbol{X}$, the bright channel is defined as

$$\mathbf{Color}\boldsymbol{X}^{\text{bright}}(s) = \max_{s' \in \Omega(s)} \{ \max_{c \in \{r,g,b\}} (\mathbf{Color}\boldsymbol{X}_c(s')) \} \tag{3}$$

where $\mathbf{Color}\boldsymbol{X}^{\text{bright}}(s)$ denotes the bright channel value at pixel s, $\Omega(s)$ is the local patch centring on s and $\mathbf{Color}\boldsymbol{X}_c$ is a colour channel of image $\mathbf{Color}\boldsymbol{X}$. It is our observation that most pixels' bright channels of a well-illuminated image approach high values, and we name the phenomenon BCP.

To validate the universality of BCP, we collected various types of images from Google and Flickr. To ensure the rationality of the images for statistics, we have manually removed images with poor brightness. Then, we chose 3000 images randomly for statistical validation. We obtain the statistics on the bright channel values of these images with patch size 10 × 10. The intensity histogram in Fig. 1 indicates that nearly 80% of pixels' bright channels tend to be 255.

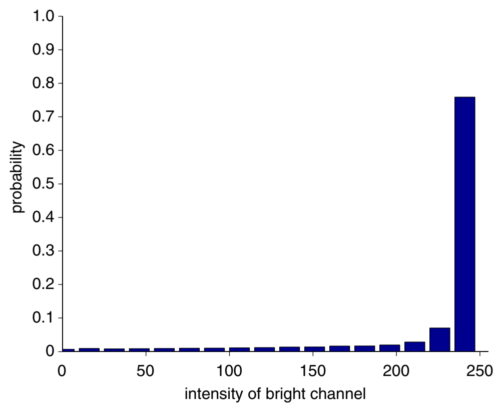

Fig. 1 *Statistics of bright channels (each bar stands for 16 intensity levels in direction of horizontal coordinate)*

$\max_{c \in \{r,g,b\}} (\mathbf{Color}\,\boldsymbol{X}_c)$ is the V channel value of image $\mathbf{Color}\boldsymbol{X}$ in the hue, saturation, value (HSV) colour space. As a result, grey-scale images $\boldsymbol{X}$ and $\boldsymbol{Y}$ should be the V channel values in the HSV colour space of their corresponding colour images. Taking max on in the local patch on (2), we can have the equation with constant T assumption and BCP (note the intensities of images in the V channel are in the interval [0,1])

$$\max_{s' \in \Omega(s)} (\boldsymbol{Y}(s')) = \boldsymbol{T}(s) \tag{4}$$

The statistics in Fig. 1 also show that not all bright channels of image $\boldsymbol{X}$ will have high values, which implies some of $\boldsymbol{T}(s)$ maybe incorrectly estimated. Therefore, we introduce a global linear function to adjust the value of $\boldsymbol{T}(s)$

$$\boldsymbol{T}^{\text{imp}}(s) = \alpha \cdot \boldsymbol{T}(s) + \beta \tag{5}$$

where $\boldsymbol{T}^{\text{imp}}(s)$ is the improved value of $\boldsymbol{T}(s)$, and α, β are the two parameters that will be learned from a dataset of image pairs. To make up the dataset, we choose 200 images of the Berkeley segmentation dataset to represent the enhancement images, and use these images to synthesise the LLLIs via gamma correction function with parameter γ from the distribution Uniform (1, 4). $N = 6000$ pairs of points $(x_i, \ y_i)$ from the image pairs are chosen randomly. We calculate the coefficients t_i of the points from LLLIs according to (4), and the coefficients $t_i^{\text{real}} = y_i^v / x_i^v$ via points pairs' intensities of the V channel. We estimate α and β with least-square regression. On the basis of the point pairs data, we obtain $\alpha = 0.8$, $\beta = 0.15$. Applying the two values into (5) and (2), we obtain $\boldsymbol{X}^{\text{imp}}$.

Although we have improved the estimation of linear coefficient T, there still exist some outliers in the previously enhanced result. We introduce a trust map $\boldsymbol{M}$ with threshold η to describe whether to trust the estimated result for each pixel. The pixel's enhanced result will become missing when its value is smaller than the threshold.

On the other hand, the fact that a natural image has the characteristic of low rank [11] can help to obtain more robust estimations of enhancement. Concretely, the result image $\boldsymbol{X}$ has low rank and the error $\boldsymbol{E}$ is sparse, and we solve the problem

$$\begin{aligned} \min_{X,E} \quad & \operatorname{rank}(\boldsymbol{X}) + \lambda \|\boldsymbol{M} \circ \boldsymbol{E}\|_0 \\ \text{s.t.} \quad & \boldsymbol{X} + \boldsymbol{E} = \boldsymbol{M} \circ \boldsymbol{X}^{\text{imp}} \end{aligned} \tag{6}$$

where λ is a regularisation parameter.

For the problem (6), we apply the augmented Lagrangian multiplier (ALM) method to obtain the solution efficiently. The Lagrangian function of the problem is

$$\begin{aligned} L(\boldsymbol{X},\ \boldsymbol{E},\ \boldsymbol{\Gamma},\ \mu) = {} & \|\boldsymbol{X}\|_* + \lambda \|\boldsymbol{M} \circ \boldsymbol{E}\|_1 \\ & + \langle \boldsymbol{\Gamma},\ \boldsymbol{M} \circ \boldsymbol{X}^{\text{imp}} - \boldsymbol{X} - \boldsymbol{E} \rangle + \frac{\mu}{2} \|\boldsymbol{M} \circ \boldsymbol{X}^{\text{imp}} - \boldsymbol{X} - \boldsymbol{E}\|_F^2 \end{aligned} \tag{7}$$

The detailed procedure is described in Algorithm 1.

Algorithm 1: The ALM algorithm for solving the problem

Require: $\boldsymbol{X}^{\text{imp}} \in \boldsymbol{R}^{m \times n}$, $\boldsymbol{M}$, λ.

$\boldsymbol{D} = \boldsymbol{M} \circ \boldsymbol{X}^{\text{imp}}$;
$\boldsymbol{\Gamma}_0 = \operatorname{sgn}(\boldsymbol{D}) / \max\{\|\boldsymbol{D}\|_2,\ \|\boldsymbol{D}\|_\infty / \lambda\}$; $\boldsymbol{X}_0 = \boldsymbol{0}$; $\boldsymbol{E}_0 = \boldsymbol{0}$;
$\mu_0 > 0$; $\rho > 1$; $k = 0$;
while not converged **do**
    $\boldsymbol{A} = \boldsymbol{D} - \boldsymbol{E}_k + \mu_k^{-1} \boldsymbol{\Gamma}_k$;
    $(\boldsymbol{U},\ \boldsymbol{S},\ \boldsymbol{V}) = \operatorname{svd}(\boldsymbol{A})$;
    $\boldsymbol{X}_{k+1} = \boldsymbol{M} \circ \boldsymbol{U} \mathcal{S}_{\mu_k^{-1}}(\boldsymbol{S}) \boldsymbol{V} + (\boldsymbol{1}_m \boldsymbol{1}_n^{\mathrm{T}} - \boldsymbol{M}) \circ \boldsymbol{A}$;
    $\boldsymbol{E}_{k+1} = \mathcal{S}_{\lambda \mu_k^{-1}}(\boldsymbol{D} - \boldsymbol{X}_{k+1} + \mu_k^{-1} \boldsymbol{\Gamma}_k)$;
    $\boldsymbol{\Gamma}_{k+1} = \boldsymbol{\Gamma}_k + \mu_k (\boldsymbol{D} - \boldsymbol{X}_{k+1} - \boldsymbol{E}_{k+1})$;
    $\mu_{k+1} \leftarrow \rho \mu$;
    $k \leftarrow k + 1$;
end while

Ensure: $\boldsymbol{X}$, $\boldsymbol{E}$.

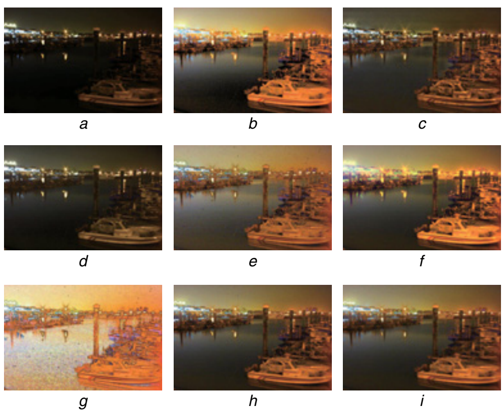

Fig. 2 *Example of results comparison. From left to right*

a Input image
b–i Enhancement results of HE, CLAHE, Shan *et al.*'s method, Dong *et al.*'s method, Zhang *et al.*'s method, our methods with BCP, improved BCP and mixture of improved BCP and low rank

During the iteration of ALM algorithm, the singular value shrinkage operator $\mathcal{S}_\epsilon$ is defined as

$$\mathcal{S}_\epsilon(\theta) = \begin{cases} \theta - \epsilon, & \text{if } \theta > \epsilon \\ \theta + \epsilon, & \text{if } \theta < -\epsilon \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

Experiments: We conducted a series of comparison experiments on LLLIs to demonstrate the effectiveness of our method. We set the parameter $\eta = 0.1$, $\lambda = 1.5$ and patch size as 3×3. Our method is compared with classical methods HE [1], CLAHE [2], learning-based tone mapping method of Shan *et al.* [6], Dong *et al.*'s algorithm [7] and Zhang *et al.*'s algorithm [9]. The parameters in these methods are all set the default values recommended by their authors. When processing colour images, we transform the inputs into the HSV colour space and then apply the enhancement algorithms to the V channel.

We validated our method on an image set of LLLIs collected from the Internet. The comparison on an example image is exhibited in Fig. 2. We observe that HE, Dong *et al.*'s method and Zhang *et al.*'s method cause the over enhancement effect, whereas Shan *et al.*'s algorithm and CLAHE lead to under enhancement results. Concretely, Shan *et al.*'s algorithm and CLAHE poorly recover the details of dark regions, and HE and Zhang *et al.*'s method perform badly in bright regions. Our method does well in detail recovery of dark regions and detail preserving of bright regions. In addition, Zhang *et al.*'s method and our method can handle the obvious outliers and noises, but our method obtains a better balance between brightness enhancement and details recovery than Zhang *et al.*'s.

Conclusions: In this Letter, we have proposed a learning-based method for the enhancement of LLLIs with the guide of a prior named BCP. To achieve better results, we have improved the BCP, and further used the idea of MC to remove the outliers of the previous estimations. Experiments on images collected from the Internet demonstrated the effectiveness of our method.

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One or more of the Figures in this Letter are available in colour online.

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