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Hierarchical image enhancement

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ABSTRACT

Image enhancement is an important technique in computer vision. In this paper, we propose a hierarchical image enhancement approach based on the structure layer and texture layer. In the structure layer, we propose a structure-based method based on GMM, which better exploits structure details with fewer noise. In the texture layer, we present a structure-filtering method to filter unwanted texture with keeping completeness of detected salient structure. Next, we introduce a structure constraint prior to integrate them, leading to an improved enhancement result. Extensive experiments demonstrate that the proposed approach achieves higher quality results than previous approaches.

1. Introduction

A popular applied procedure in low-level computer vision is contrast enhancement. Enhancement methods aim to enhance the significant image details with reducing unwanted noise. Because of the popularity of imaging devices, different images are captured under different configurations. For example, near infrared (NIR) images with a single channel recording infrared light reflected with 900–1500 nm spectrum length, generated by OWL320.[1] Due to the factors of the infrared imaging devices, background radiation and image environment, the quality of NIR images is limited. Accurate and reliable image enhancement techniques can help improve the quality of NIR images, also benefit numerous optics applications. Successful image enhancement algorithms facilitate object detection [1], image fusion [2], and surveillance [3].

With the prevalence of high-resolution infrared imaging sensors nowadays, image enhancement become more and more perceivable. NIR image is an important source information, the quality of NIR image is affected by many factors. Previous research has shown that properly handling these problems can design numerous methods related to image content. However, these methods may not perform well in some cases. Each method has its own specialty as well as limitation, there is no perfect solution yet to uniformly solve some challenging cases.

We in this paper propose a hierarchical model, to analyze image details from two layers of the input image, and then integrate them to infer the final enhancement map. Our hierarchical model decomposes the input image into two layers, structure layer and texture layer. For the structure layer, it is commonly observed that there exists rich structure information in this layer. Intuitively, an enhanced map usually has clear structure details instead of blurry noise. We then propose a structure-based method based on Gaussian Mixture Models (GMM) [4], which effectively makes the details of interest clear. Considering the texture layer with fine scene details, we present an effective structure-filtering method to remove the unwanted details. This method further reduces the unnecessary texture details, keeps the regions with large gradient.

Based on above two layers, we integrate them by introducing a structure constraint prior, producing a more accurate result. Experimental results on various NIR images demonstrate that the proposed method outperforms previous methods, and achieves high PSNR and SSIM values.

2. Related work

The image enhancement literature is huge and existing solutions have been designed based on different cues. In this section, we discuss the relevant ones.

A earlier global enhancement method, called histogram equalization (HE), is effectively applied in many vision tasks. Due its effectiveness, its variants [5–7] are designed to handle different cases, and perform better than HE method. In [8], Smolka et al. propose a new probabilistic method to enhance the image, which performs a random walk on the image lattice. Wang et al. [6] propose a contrast enhancement method by applying the plateau histogram equalization. In [9], Zeng et al. apply a top-hot morphological filtering for detail enhancement. In [10], Bai et al. exploit adaptive morphological clutter elimination, and propose an object

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[1] http://www.raptorphotonics.com/.

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1350-4495/

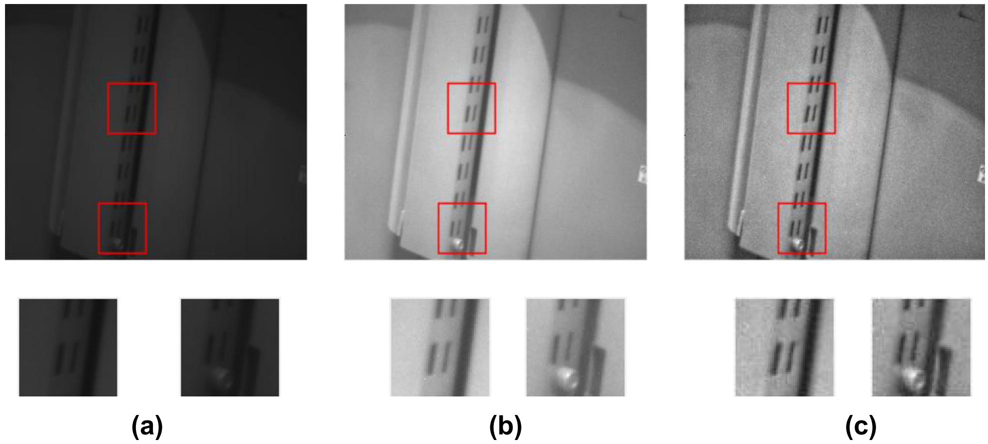

Fig. 1. (a) The input NIR image; (b) the initial structure layer map; (c) adding a structure-based method further makes the structure clear with fewer noise.

enhancement method. In [11], Bai et al. consider the importance of multi-scale information, and propose a multi-scale top-hot transform method to enhance the infrared images. Provenzi et al. [12] propose an effective enhancement method via local contrast. Carlos et al. [13] modify the energy transfer process, and present a method to effectively enhance the details of images. Thomas et al. [14] define image enhancement by increasing the resolution of image. In [15,16], some physical image operations are applied for infrared image enhancement, and obtain good performance. Zhang et al. [17] present a new gradient-domain-based visualization method for infrared image, and obtain good performance on some infrared images. Liu and Zhao [18] propose an effective method for detail enhancement and noise reduction of infrared images, which perform well based on guided image filter. Shanmugavadivu and Balasubramanian [19] analyze the histogram equalization method, and present a multi-objective histogram equalization model to enhance the image contrast. Although previous research works well, they does not perform well for NIR images. These methods are not well applied for different NIR image scenes.

Different from above-mentioned methods, we present a hierarchical method for image enhancement. Our hierarchical model exploits the strength of both structure layer and texture layer, and effectively enhances the important details with fewer noisy results.

3. Methodology

Natural images vary from scene to scene, thereby we directly capture image details from the input images. The image-capture process is modeled as two layers: structure layer and texture layer. We in this paper decompose the input image I into two layers [20], as follows:

$$I = I_S + I_T, \tag{1}$$

where I_S denotes the structure layer, which contains structure information from the input image, and I_T is the texture layer corresponding to the fine details. The structure layer contains the rich structure details of image, and is then enhanced using a structure-based method based on Gaussian Mixture Models (GMM) [4]. The texture layer is exploited to remove the unnecessary details from background regions using a structure-filtering method. Next, two layers are integrated to produce a more accurate enhanced map by introducing a structure constraint prior. In the following sections, we will describe the proposed method in detail.

3.1. Structure layer

The structure layer has rich structure details, which can represent the important information of the image. Inspired by [21], the structure layer I_S is obtained by minimizing the objective function as follows:

$$min \sum (I_{S_i} - I_i)^2 + \alpha |f'(I_{S_i})| \tag{2}$$

where i denotes the pixel index, $\alpha = 0.03$ represents the regulation parameter, f' denotes the gradient operator. This objective function is solved by [22]. As the structure information is required in Eq. (2), the structure details in such way don't always represent perfectly. For example, the holes are not clear and the image is not clear in Fig. 1(b).

According to above finding, our approach does not simply adopt Eq. (2), which performs poor results for NIR images. Considering the importance of structure information, we propose a structure-based method based on Gaussian Mixture Models (GMM) [4]. This prior can effectively encode region covariance and important pixels over patches. Thus, we rewrite Eq. (2) as follows:

$$min \sum (I_{S_i} - I_i)^2 + \alpha |f'(I_{S_i})| - \sum_i log(GMM(P_i I_{S_i})), \tag{3}$$

where $GMM(P_i I_{S_i}) = \sum_{j=1}^{N} e_j \aleph(P_i I_{S_i}; 0, D_j)$. P_i denotes the linear operator that extracts the ith patch from the structure layer I_{S_i}. D_j denote the covariance matrix of size 7×7, which is computed in [23]. $\aleph$ is a zero-mean 49-dimensional Gaussian distribution. The logarithm is to map these values to a suitable range. We directly in this work apply the GMM provided by [4], which contains 200 mixture components, and π_j is to weight the mixture components. As such, a structure-based method is applied to refine the structure information in this layer, resulting an improved structure layer I_S^e.

As shown in Fig. 1(c) , when a structure-based method is applied, the entire image is more clear and salient structure regions are highlighted uniformly (see the red[2] rectangle). We note that this method is more robust to deal with low contrast NIR image, the result of our method are more accurate, and more important details are preserved with adjusting the contrast of image uniformly.

[2] For interpretation of color in Figs. 1 and 2, the reader is referred to the web version of this article.