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Blind image restoration with sparse priori regularization for passive millimeter-wave images

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ABSTRACT

Passive millimeter wave imaging often suffers from issues such as low resolution, noise, and blurring. In this study, a blind image restoration method for the passive millimeter-wave images (PMMW) is proposed. The purpose of the proposed method is to simultaneously solve the point spread function (PSF) and restoration image. In this method, the data fidelity item is constructed based on Gaussian noise assuming, and the regularization item is constructed as the hyper-Laplace function $||x||^{0.6}$, which is fitted according to the high-resolution PMMW images. Moreover, a data-selected matrix is proposed to select the regions that are helpful for estimating the accurate PSF. The proposed method has been applied to simulated and real PMMW image experiments. Comparative results demonstrate that the proposed method significantly outperforms the state-of-the-art deblurring methods on both qualitative and quantitative assessments. The proposed method improves the resolution of the PMMW image and makes it more preferable for object recognition.

1. Introduction

Passive millimeter-wave images (PMMW) radiometer imaging systems [1–4] are being increasingly applied in several areas, such as environmental monitoring [5,6], aviation [7], and security [8,9]. The PMMW sensor forms interpretable imagery in the low-visibility conditions such as haze, fog, clouds, smoke, or sandstorms. Because of the high reflectivity on the metal and man-made objects, it can detect concealed weapons under clothing. However, owing to the diffraction limit and low signal level, the PMMW images often suffer from low-resolution and random noise (such as Fig. 1). In most cases, the blurring process is modeled as a convolution of the unknown sharp image $\boldsymbol{u}(x,y)$ with an unknown blur trace $\boldsymbol{k}(x,y)$ (called the point spread function, PSF) followed by corruption with an additive noise $\boldsymbol{n}(x,y)$. This results in an observed image $\boldsymbol{g}(x,y)$. A commonly used model for the image degradation process can be

$$\boldsymbol{g}(\boldsymbol{x}\cdot\boldsymbol{y}) = \boldsymbol{u}(\boldsymbol{x},\boldsymbol{y}) \otimes \boldsymbol{k}(\boldsymbol{x},\boldsymbol{y}) + \boldsymbol{n}(\boldsymbol{x},\boldsymbol{y}) \tag{1}$$

where the image observation system is limited to shift-invariant and linear systems.

Deconvolution is a mathematical technique to improve the PMMW image resolution. The methods can be further separated into two cases: non-blind deconvolution (NBD) [10–17], and blind deconvolution (BD) [18–22], In the NBD case, it is assumed that the blur kernel is known; the only remaining task is to estimate the latent PMMW image. Traditional methods such as Wiener filtering [10] and Richardson–Lucy (RL) deconvolution [11,12] were proposed decades ago; however, they are still widely used in several image restoration tasks today as they are simple and efficient. Alexander [13] et al. fit the gradient histogram of a natural image with the two-dimensional Lorentzian probability density function (TDL method) [15–17]. However, these methods tend to suffer from unpleasant ringing artifacts that appear near strong edges.

In the case of the BD methods, both the blur kernel and latent image are assumed to be unknown. Novel signal processing methods, such as positive-constrained [19], maximum entropy [21,23], sparse representation [24–26], and neural networks [27], have also been applied to the PMMW image restoration problem. Hong et al. [28] proposes a blind deconvolution method to recover PMMW image, and the estimated PSF approximates to a Gaussian function. In recent years, another framework was proposed in a two-step method, namely, first estimate the accurate PSF, and then utilize it to restore the PMMW image, such as P-deblurring filter method [29], universal deblurring algorithm [28], total variation-based blind deconvolution (TV-BD) method [30]. All these methods have restored the PMMW image successfully and have achieved desired

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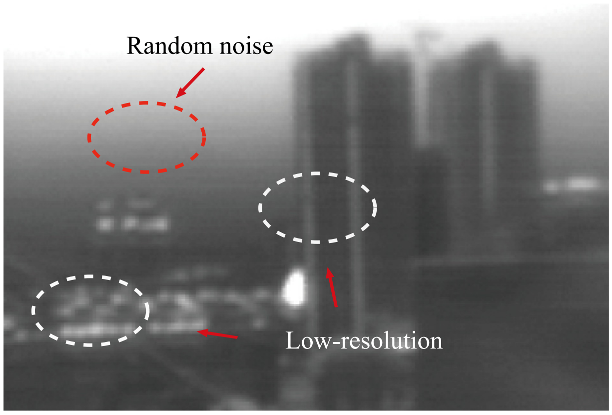

Fig. 1. PMMW image often suffers from low-resolution and random noise. It is captured by the PMMW imaging system (94 GHz, 360 mm aperture size, single channel scanning imaging, imaging distance of 1.5 km).

results. However, these methods are based on certain assumptions. Our study shows that current deconvolution methods perform sufficiently well if the blurry image contains no noise and the blur kernel contains no error.

In this paper, we begin our investigation of the blind deconvolution problem by analyzing the true sparsity of the PMMW images according to the high-resolution PMMW images. To accomplish these results, our technique benefits from three main contributions. First, a data selection matrix is adopted to indicate the importance of the image data. Second, a new smoothness constraint is fitted to the high-resolution image, namely, sparse priori regularization. This constraint is highly effective in suppressing noise and preserving the PMMW image details. Our final contribution is an efficient optimization algorithm employing advanced optimization schemes and technique.

2. Sparse priori regularized image restoration

In this section, we introduce the regularized image restoration model and the sparse priori regularization model.

2.1. Regularized image restoration model

In the degradation model presented in Eq. (1), the image restoration is an ill-posed problem; hence, some prior information about the high-resolution image should be added to guarantee a stable and relative optimal solution. A popular and effective approach to this problem is to use the regularization-based least squares method, which has the following formulation,

$$\boldsymbol{E}(\boldsymbol{u},\boldsymbol{k}) = \min_{\boldsymbol{u},\boldsymbol{k}} \frac{1}{2}\|(\boldsymbol{u}\otimes\boldsymbol{k}-\boldsymbol{g})\|^2 + \alpha\boldsymbol{R}(|\nabla\boldsymbol{u}|) + \beta\boldsymbol{R}(|\nabla\boldsymbol{k}|) \tag{2}$$

where $\|(\boldsymbol{u}\otimes\boldsymbol{k}-\boldsymbol{g})\|^2$ is the data fidelity item, which stands for the fidelity between the degraded image and the original high resolution image, and $R(\cdot)$ is the regularization item, which gives a prior model of the high-resolution image $\boldsymbol{u}$ and PSF $\boldsymbol{k}$. The symbols α and β are the regularization coefficients that control the trade-off between the data fidelity and prior item.

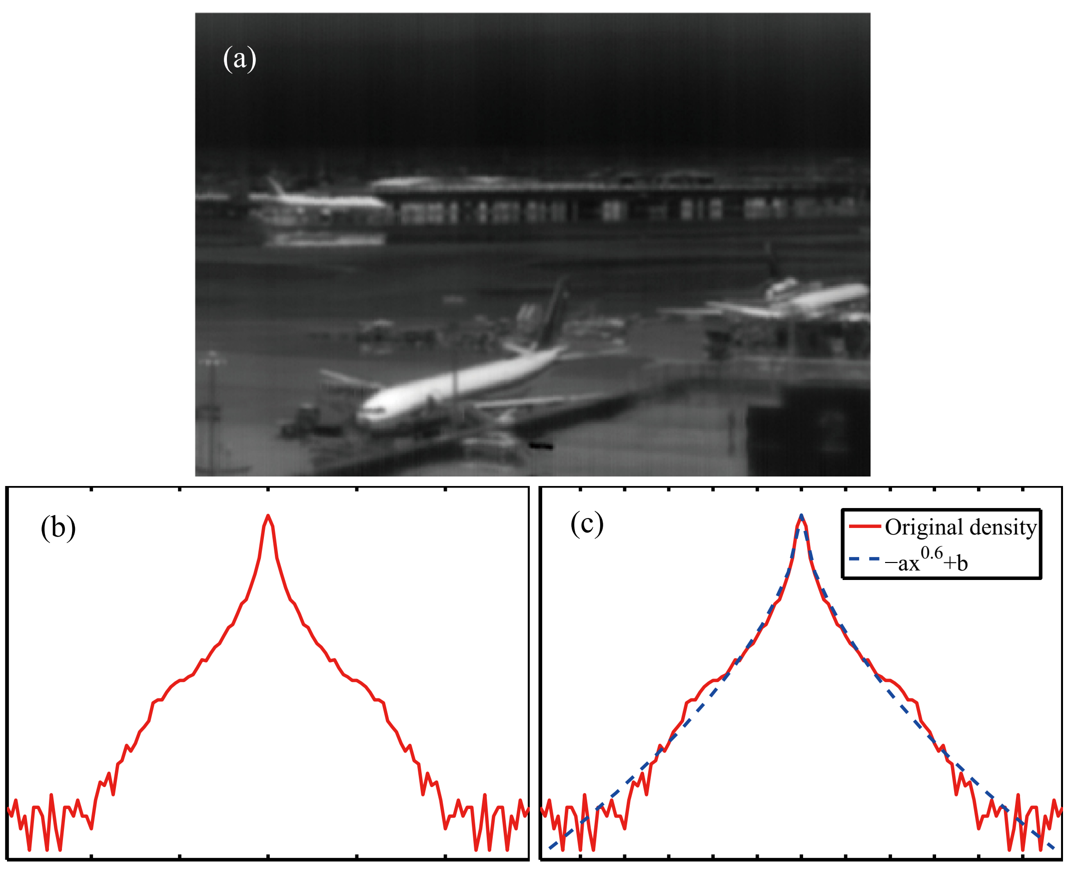

Fig. 2. Hyper-Laplace function is used to fit the gradients of the high-resolution PMMW images. (a) High-resolution PMMW images aperture sizes for the 94-GHz PMMW scanning system (b) we construct function to approximate the logarithmic density, as shown in red and blue.