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# Multi-PSF fusion in image restoration of range-gated systems

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ABSTRACT

For the task of image restoration, an accurate estimation of degrading PSF/kernel is the premise of recovering a visually superior image. The imaging process of range-gated imaging system in atmosphere associates with lots of factors, such as back scattering, background radiation, diffraction limit and the vibration of the platform. On one hand, due to the difficulty of constructing models for all factors, the kernels from physical-model based methods are not strictly accurate and practical. On the other hand, there are few strong edges in images, which brings significant errors to most of image-feature-based methods. Since different methods focus on different formation factors of the kernel, their results often complement each other. Therefore, we propose an approach which combines physical model with image features. With an fusion strategy using GCRF (Gaussian Conditional Random Fields) framework, we get a final kernel which is closer to the actual one. Aiming at the problem that ground-truth image is difficult to obtain, we then propose a semi data-driven fusion method in which different data sets are used to train fusion parameters. Finally, a semi blind restoration strategy based on EM (Expectation Maximization) and RL (Richardson-Lucy) algorithm is proposed. Our methods not only models how the lasers transfer in the atmosphere and imaging in the ICCD (Intensified CCD) plane, but also quantifies other unknown degraded factors using image-based methods, revealing how multiple kernel elements interact with each other. The experimental results demonstrate that our method achieves better performance than state-of-the-art restoration approaches.



## 1. Introduction

Range-gated imaging system has a wide range of applications in conditions lack of illumination, such as imaging and monitoring at night, remote surveillance and so on. Due to relative motions, backscattering, speckle noise and many other adverse factors, the image is seriously degraded, which leads to inevitable information loss. Updating hardware may be the most direct way to improve the performance of imaging system, while also maybe expensive. Another feasible way is to use image restoration technology to recover sharp images from the collected degraded images.

Image restoration is an important and challenging research topic. Although lots of techniques have been proposed to deal with this problem, they cannot be directly applied to range-gated imaging system due to the difficulty of estimating the PSF (Point Spread Function) of the system. Our research focuses on this topic. Shan et al. [1]'s work indicates that the more accurate the kernel is estimated, the better current restoration methods perform. Therefore, a more explicit handling of degraded PSF estimation error is critical for better restoration results. Once we get an accurate PSF, we can recover an sharp image by non-blind deconvolution methods, which are relatively mature.

Over the past decades, remarkable research efforts have been devoted to developing degraded kernel estimation methods. Cho and Lee [2] predict strong image structures from an estimated latent image, and use them instead of gray values to formulate the optimization function. With GPU implementation facilitates, their method is fast enough for practical application. Cho et al. [3] propose an approach to estimate the Random Transform of the degraded kernel using edges of the blurry image, and get the degraded kernel by Inverse Random Transform. In Fergus et al. [4]'s approach, a manual-specified process is required to supply an image region without saturation effects, and the kernel is estimated using a prior on image gradients in a coarse-to-fine framework. In this framework, the spatial domain prior on natural images leads to a capability to handle seriously blurred image. Instead of performing a MAP (Maximum A Posteriori) estimation, Goldstein and Fattal [5] try to estimate the power spectrum of the degraded kernel by a power-law of the natural image along with an spectral whitening formula, then recover the kernel by a phase retrieval method. Pan et al. [6] develop a L0-regularized

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intensity based method to obtain salient properties of the degraded image without any complex filtering strategies or additional selection processes, and use them to obtain a reliable degraded kernel. Shan et al. [1] introduce a unified probabilistic model which contains several novel terms of image prior. While each approach above has achieved significant success in their particular experiment dataset, none of them can get satisfying result in all cases. For our application, these approaches still have following defects:

(1) Most approaches are designed to deal with motion blur by camera shake, while image degradation in our range gated imaging system contains many other factors.
(2) A large part of these algorithms are based on strong edges, which may be difficult to extract in low-light condition.
(3) The priors for natural image are not suitable for illumination image.

Therefore, the existing PSF estimation method cannot be directly applied in our system. The PSFs estimated by different approaches sometimes differ widely, as they incorporate different priors in each individual frameworks. The bad news is that it's difficult to determine which one is optimal and there does not exist a generic solution for all degraded images. Mai and Liu [7] address that the PSFs from different approaches often complement each other and with a proper fusing strategy, combining multiple PSFs may lead to a more accurate one. Inspired by their work, we are eager to know whether making use of different priors of the system with appropriate merging strategies may bring an outstanding result. The answer is yes.

The basic clue in our approach is to merge various individual PSFs into a more accurate one. We construct an imaging model and make use of imaging procedure instead of images to obtain a SPSF (system-based PSF). Then by using state-of-art kernel estimation methods based on different image features, we get some FeaPSFs (feature-based PSFs). These PSFs respectively contain different part of features in the imaging system, which are complementary and redundant with each other. With a fusion strategy based on GCRF framework, we joint these individual efforts into mutual work and get a final FuPSF (fusion PSF).

We develop a semi-data-driven training method using RTF (Regression Tree Field) framework to train the fusion parameters. The probability distribution models of inlier and outlier pixels are established. With EM and RL method we iteratively estimate latent image and update the FuPSF.

## 2. Imaging model

In range-gated imaging system, illumination and echo beam may be disturbed by factors such as atmospheric attenuation, background radiation and atmospheric aerosol backscattering, which dramatically degrade the performance of system. The model of range-gated image system is shown in Fig. 1.

Considering the factors in laser beam propagation path, the imaging model of the system is established to estimate SPSF. In gate opening time, factors affecting the imaging quality involve those following parts: target reflection, scattering, background radiation, speckle, atmospheric turbulence, diffraction limit and so on. Some factors carry the target information, while others cover the target information [8,9].

### 2.1. Reflected energy

Reflected energy is the part of laser energy that reaches the camera imaging surface through outbound atmospheric transmission, target reflection and inbound atmospheric transmission, which can be expressed as:

$$P_r = P_t \frac{A_\Delta}{R^2 \Omega_l} \frac{A_r}{R^2} T_a^2(R) \eta_t \eta_r \tag{1}$$

where $P_r$ donates reflected energy, $P_t$ donates emitting energy, $\eta_t$ donates the efficiency of emitting system, $\eta_r$ donates the efficiency of receiving system, $A_r$ donates the entrance pupil area of the receiving optical system, $A_\Delta$ donates effective covered area on target, $\Omega_l$ donates solid angle of laser beam.

### 2.2. Backscatter energy

The forward transmission light is scattered by the atmosphere, and a part of it enters the observation system against the optical axis, which masks the true image information, resulting in a decrease in contrast and resolution. This phenomenon is called backscattering, which is related to factors such as atmospheric scattering coefficient, scattering angle distribution, the distance between receiving optical system and laser, the divergence angle and the FOV (Field of Vision) of the optical system.

Let $l_o$ donate the distance between imaging system and the intersection of laser divergence angle and optical system angle, $l_m$ donate imaging distance, $E_p$ donate single pulse laser energy, then the backscattered energy can be expressed as:

$$E_{backscatter} = E_p \eta_t \eta_r A_r \frac{\sigma_e}{8\pi} \int_{l_o}^{l_m} \frac{\exp(-2\sigma_e l)}{l^2} dl \tag{2}$$

### 2.3. Background radiant energy

Background radiation energy means the energy of natural radiation light entering the optical system. In the gating opening time, the background radiation energy $E_b$ can be calculated as:

$$E_b = \frac{\rho_b}{\pi} L_\lambda \Delta\lambda \eta_r \Omega_r A_r \Delta\tau \tag{3}$$

where $L_\lambda$ donates background spectral radiation, $\Delta\lambda$ donates the bandwidth of the receiving optical system (which can be regarded as a bandpass filter), $\rho_b$ donates the average reflection coefficient of the background, $\Delta\tau$ donates single opening time of camera.

### 2.4. MTF of the atmospheric transmission

Since reflected and forward-scattered light contain useful target information, while back-scattered light overwhelms the information, we define the MTF (Modulation Transfer Function) of the atmospheric transmission as:

$$MTF_{atmosphere} = \frac{\pi}{4} F\left(\frac{E_d + E_f}{E_d + E_f + E_b}\right) \tag{4}$$

### 2.5. Diffraction limit

Due to the optical system aperture limitation, the diffraction limit of the imaging system [10] needs to be considered as a factor of image degradation. The MTF of diffraction is calculated as:

$$MTF_{diffraction} = \frac{2}{\pi}\left[\arccos\frac{f}{f_{co}} - \frac{f}{f_{co}}\sqrt{1-\left(\frac{f}{f_{co}}\right)^2}\right], \quad 0 < f < f_{co} \tag{5}$$

where $f$ donates the spatial frequency, and $f_{co}$ donates the cutoff frequency of the imaging plane.