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LASER DAMAGE IMAGE PRE-PROCESSING BASED ON TOTAL VARIATION

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Abstract

The inspection and tracking of laser-induced damages of optics play a significant role in high-power laser systems. Laser-induced defects or flaws on the surfaces of optics are presented in images acquired by specific charge coupled devices (CCDs), hence the identification of defects from laser damage images is essential. Despite a great effort we have made to improve the imaging results, the defect identification is a challenging task. The proposed research focuses on the pre-processing of laser damage images, which assists identifying optic defects. We formulate the image pre-processing as a total variation (TV) based image reconstruction problem, and further develop an alternating direction method of multipliers (ADMM) algorithm to solve it. The use of TV regularization makes the pre-processed image sharper by preserving the edges or boundaries more accurately. Experimental results demonstrate the effectiveness of this method.

INTRODUCTON

In high-power laser systems, because of reasons such as self-focusing, the laser-induced damage threshold of the optics that are irradiated by long periods of a high-power laser is lowered. The damage should be detected and tracked at the early stage of formation [1-2].

Currently, the inspection and tracking of laser-induced damages of optics play a significant role in high-power laser systems, and is also widely applied. NIF is the world's most energetic laser, delivering up to 2.0 MJ at 351 nm with its 192 beamlines. The Final Optics Damage Inspection (FODI) camera system is inserted in the centre of the NIF target chamber after a laser shot to acquire images of any or all of the final optics for all 192 beamlines [3]. The acquired images are processed using custom image processing and analysis software [4-5], referred to as the Optics Inspection (OI) package, to detect anomalies on the surface of the optics, with the intention of identifying and tracking laser-induced damage. The online inspection system technology for final optics damage was studied in order to build a final optics damage online inspection system for SG-Ⅲ prototype device [6].

However, damage analysis has been surprisingly difficult over the years. And many efforts have been made in this research area, which can be divided into two main categories, one is to develop the optic illumination techniques, and the other is to improve the damage image analysis and defect identification technology. Proper illumination of the optics to be imaged is critical for the successful performance of the final optics damage inspection. In [7], based on total internal reflection of flat optics, the light emitting from array LED was coupled into the large aperture optics, the edge illumination methods were employed to illuminate the optics. Further the method of timesharing illumination of large aperture optics was developed for damage imaging, and the model of signal noise ratio was developed for dark-field imaging mode. A technology of detecting laser-induced damage on optics, using line-scan imaging and dark-field imaging principle, is proposed in [8]. Defect inspection relies heavily on image processing. Optics inspection analysis is an essential component of the FODI system, whose main aim is to conduct automated image analysis, processing each image quickly and identifying candidate sites on each optic that may correspond to laser-induced damage [3]. During each inspection cycle up to 1000 images acquired by FODI are examined by OI to identify and track damage sites on the optics. The process of tracking growing damage sites on the surface of an optic can be made more effective by identifying and removing signals associated with debris or reflections. Considering the manual process to filter these false sites is daunting and time consuming. In [9], G. Abdulla etc. discuss the use of machine learning tools and data mining techniques to help with this task. To improve the inspection resolution of the FODI device in the ICF, an inspection method based on image mosaic was proposed [10]. Because of the tiny size of defects compared to the image, detection of the defects is a challenge. Moreover, the grey value of different image areas is different because of the uneven distribution of illumination. Considering these two factors, a robust defects detecting method based on Local Area Signal Strength (LASS) and 2-D histogram is theoretically and experimentally proposed in [11].

Laser-induced optics damage and image analysis process are described in the next section. Issues about the image preprocessing is further discussed in section Ⅲ, including the problem description, total variation (TV) based model, and the ADMM-based algorithm development. On this basis, section Ⅳ provides the results of preliminary experiments. Finally, we conclude this paper in section Ⅴ.

OPTICS DAMAGE AND IMAGE ANALYSIS

Currently, the laser flux in high-power laser systems is increasing more and more fast. Because of reasons such as self-focusing, laser-induced damages are likely to happen to the optics, and the laser-induced damage threshold of the optics that are irradiated by long periods of a high-power laser is lowered. Usually, laser-induced defects or flaws on the surfaces of optics are presented in images acquired by specific charge coupled devices (CCDs). Fig. 1 is an example

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of the imaging results of the optics acquired by the specific CCD. It is of a great importance to inspect and track these defects once they are initially produced, especially before they approach the specifically defined threshold, otherwise the optics would be damaged heavily and become non-repairable.

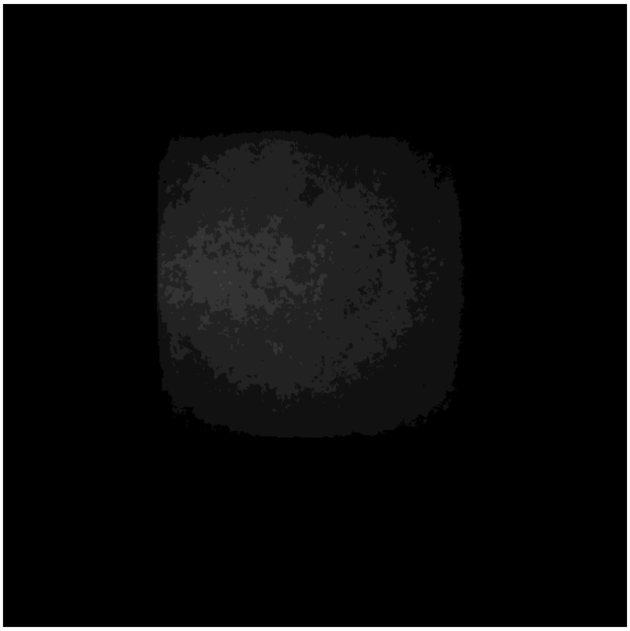

Figure 1: Example image acquired by the CCD.

Thus image analysis is a key task to inspect and track the optics defects. The analysis of laser damage images mainly consists of 3 steps:

1. Split the image to get the interested area, like the centre lighter squared area in Fig. 1.
2. Detect the defect or flaw points and their sizes presented in pixel.
3. Project the defect or flaw points in the damage image into the real optics, including their locations and spatial sizes.

Despite a great effort we have made to improve the imaging results, the defect identification is a challenging task. Reasons are multi folds. As mentioned in [11], the tiny size of defects compared to the image, and the fact that the grey value of different image areas is different because of the uneven distribution of illumination, are among the reasons. In [12], A. G. Basden etc. discuss the imaging principle of charge coupled device (CCD) and its major shortcoming. They point out that the major shortcoming of CCD is readout noise, i.e. the additional noise added by the on-chip output amplifier, where the charge of the detected photo-electrons is converted into an output voltage. Optics damage inspection system introduces a tiny part of the laser passing through the whole laser beam to reduce the energy, which means that the CCD captures few photo-electrons, leading to low-light-level images and bringing a big difficulty to identify the defect points.

Hence, this motivates us to raise one question: *Can we develop algorithms to pre-process these laser damage images acquired by CCDs, and to improve the identification of defect points?*

IMAGE PRE-PROCESSING

Problem Description

Given that the laser damage images we obtain from CCDs are generated with unknown signal pollutions, we regard the problem of image pre-processing as an image restoration problem, namely to reconstruct the image from blurry and noisy observations.

Without loss of generality, we assume that the underlying image is grayscale and has a square domain. Let $\bar{x}\in \mathbb{R}^{n^2}$ be an original $n\times n$ image, $K\in \mathbb{R}^{n^2\times n^2}$ be a blurring (or convolution) operator, $\omega\in \mathbb{R}^{n^2}$ be an additive noise, and $f\in \mathbb{R}^{n^2}$ be an observation which satisfies the relationship

$$f = K\bar{x} + \omega . \tag{1}$$

Given *K*, our objective is to recover $\bar{x}$ from *f*, which is known as deconvolution or deblurring.

It is well-known that recovering $\bar{x}$ from *f* by directly inverting Eq. (1) is unstable and produces useless results because the solution is highly sensitive to the noise ω. Researches about solving the above problem abound. In [13], the ellipsoid algorithm is proposed. Traditional regularization techniques include the Tikhonov-like regularization [14], the total variation (TV) regularization [15], both of which have been well studied in the literature, and others. Total variation (TV) regularization is popular in image reconstruction due to its edge-preserving property. However, the non-differentiability of TV makes the underlying optimization problems difficult to solve. In the past a few years, alternating minimization algorithms for recovering images from blurry and noisy observations with total variation (TV) regularization have been proposed and analysed [16-18].

Total Variation (TV) Based Model

To stabilize the recovery of $\bar{x}$, a common approach is to add a regularizer to certain data fidelity. The method of total variation (TV) regularization means that the regularizer is a total variation term. It has been shown both experimentally and theoretically to be suitable for preserving sharp edges. The discrete form of TV for a greyscale image $\bar{x}\in \mathbb{R}^{n^2}$ is given by

$$\mathrm{TV}(x) = \sum_{i=1}^{n^2} \left\| D_i x \right\|_2 , \tag{2}$$

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where for each i, $D_i x \in \mathbb{R}^2$ represents the first-order finite difference of x at pixel i in both horizontal and vertical directions, the quantity $\|D_i x\|_2$ is the variation of x at pixel i, and the summation in Eq. (2) is taken over all pixels, which explains the name of total variation (TV).

The fidelity term in is usually taken as a penalization on the difference between Kx and f measured in different norms. Here we choose the $l2$ norm.

Hence combining TV with $l2$ norm fidelity, we get the TV based image reconstruction model as following:

$$\min_x \sum_{i=1}^{n^2} \|D_i x\|_2 + \frac{\mu}{2}\|Kx - f\|_2^2 . \tag{3}$$

Applying ADMM to the TV Based Model

The problem of (3) can be transformed into an equivalent constrained problem of the following form:

$$\begin{aligned} &\min_{x,\mathbf{y}} \sum_i \|\mathbf{y}_i\| + \frac{\mu}{2}\|Kx - f\|_2^2 . \\ &\text{s.t. } \mathbf{y}_i = D_i x, \quad i = 1, \dots, n^2 \end{aligned} \tag{4}$$

In (4) the objective function is separable and the constraints are linear. Denote $y = (y_1; y_2) \in \mathbb{R}^{2n^2}$, where y_1 and y_2 are vectors of length n^2 satisfying $((y_1)_i; (y_2)_i) = \mathbf{y}_i \in \mathbb{R}^2$ for $i = 1, \cdots, n^2$.

Let $\Gamma_A(x, y, \lambda)$ be the augmented Lagrangian function of (4)

$$\begin{aligned} \Gamma_A(x, y, \lambda) = \sum_i (\|\mathbf{y}_i\| - \lambda_i^T(\mathbf{y}_i - D_i x) + \frac{\beta}{2}\|\mathbf{y}_i - D_i x\|_2^2) \\ + \frac{\mu}{2}\|Kx - f\|_2^2 . \end{aligned} \tag{5}$$

where each λ_i is a vector in $\mathbb{R}^2$ and $\lambda \in \mathbb{R}^{2n^2}$, similar to y, is a reordering of i, $i = 1, 2, \cdots, n^2$.

Started at $x = x^k$ and $\lambda = \lambda^k$, the alternating minimization idea applied to (4) yields the following iterative scheme:

- $y^{k+1} = \arg\min_y \Gamma_A(x^k, y, \lambda^k)$.
- $x^{k+1} = \arg\min_x \Gamma_A(x, y^{k+1}, \lambda^k)$.
- $\lambda^{k+1} = \lambda^k - \beta(y^{k+1} - Dx^{k+1})$.

Thus the process of image reconstruction is given below:

1. *Input f, K, $\mu > 0$, $\beta > 0$ and λ^0. Initialize $x = f$ and $\lambda = \lambda^0$.*
2. *Repeat the above iterative computations until converged.*

We terminated the iteration by relative change in x in all of our experiments, defined as

$$\frac{\|x^{k+1} - x^k\|}{\max\{\|x^k\|, 1\}} < \varepsilon . \tag{6}$$

where $\varepsilon > 0$ is a given tolerance.

EXPERIMENTAL RESULTS

We randomly choose one laser damage image obtained by the CCDs, as provided in Fig. 2. After splitting out the useful area, we conduct the image pre-processing according to the method developed in the former section.

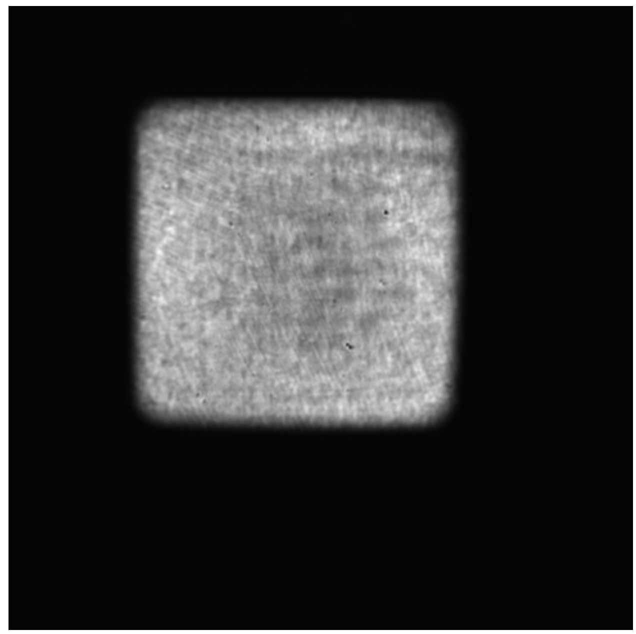

Figure 2: Original laser damage image.

After the image pre-processing, we utilize the traditional technology of defect inspection. Further we compare the results obtained by the method of this paper with those obtained directly with the original image, as provided in Table 1. We note that the pre-processed image makes both the false alarm rate and the missing rate of defect inspection dropped.

Table 1: Accuracy Comparison

Method	**False Alarm Rate**	**Missing Rate**
No pre-processing	30%	15%
With pre-processing	8 %	5%

CONCLUSION

We focus on the pre-processing of laser damage images in this paper, by formulating a total variation (TV) regularization based image reconstruction problem, and developing an alternating direction method of multipliers (ADMM) algorithm. The use of TV regularization makes the image

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pre-processed sharper by preserving the edges or boundaries more accurately, which shows a big potential to assist identifying optics defects and improve the inspection accuracy.

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