Optimizing Blocker Usage on NIF Using Image Analysis and Machine Learning

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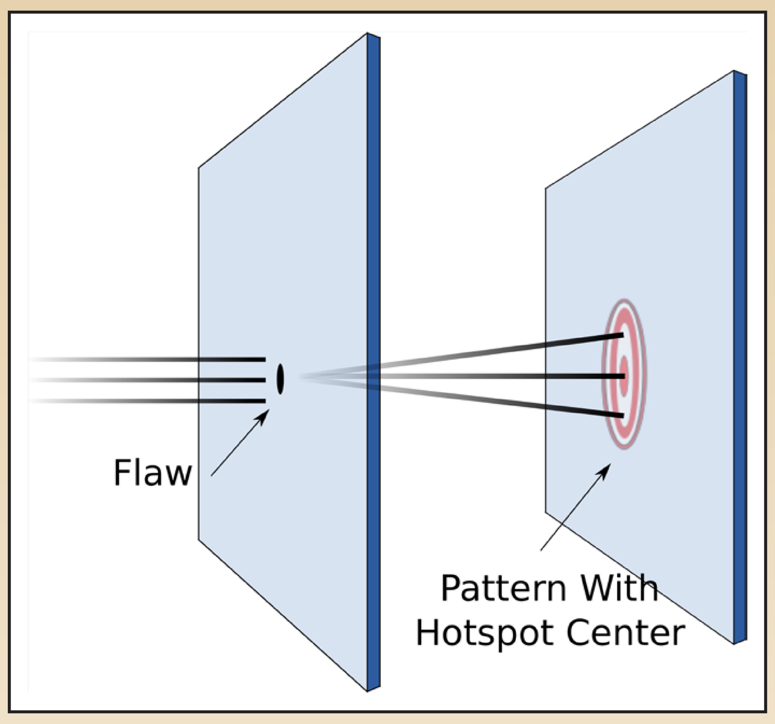
To optimize laser performance and minimize operating costs for high-energy laser shots it is necessary to locally shadow, or block, flaws from laser light exposure in the beamline optics. Blockers are important for temporarily shadowing a flaw on an optic until the optic can be removed and repaired. To meet this need, a combination of image analysis and machine learning techniques have been developed to accurately define the list of locations where blockers should be applied. The image analysis methods extract and measure evidence of candidate sites and their correlated downstream hot spots and this information is passed to machine learning algorithms which calculate the probability that candidates are flaws that require blocking. Results show that the machine learning helps to significantly reduce false alarms compared to the image analysis methods alone. Ten-fold cross validation of the refined training set shows about 99% of the 30,000 candidate sites are rejected, leaving only 1% (300) to be brought forward for review; about a sixth of those brought forward are false alarms compared to hundreds or thousands using image analysis alone. In practice, we see from 0 to 3 false alarms per image with over 98% true positive detection.

Optical Flaws Need to be Blocked. Flaws are Identified by Their Diffraction Pattern.

Flaws in laser optics diffract light passing through them, causing a diffraction pattern (or "hot spot") to appear on downstream optics.



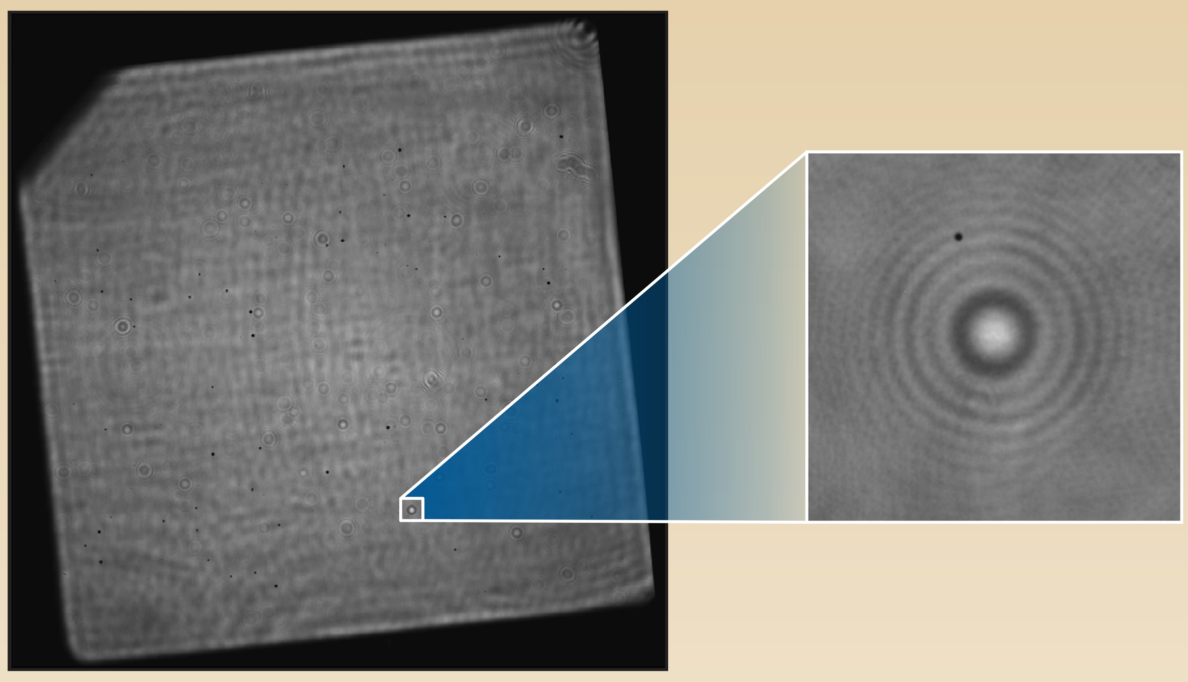
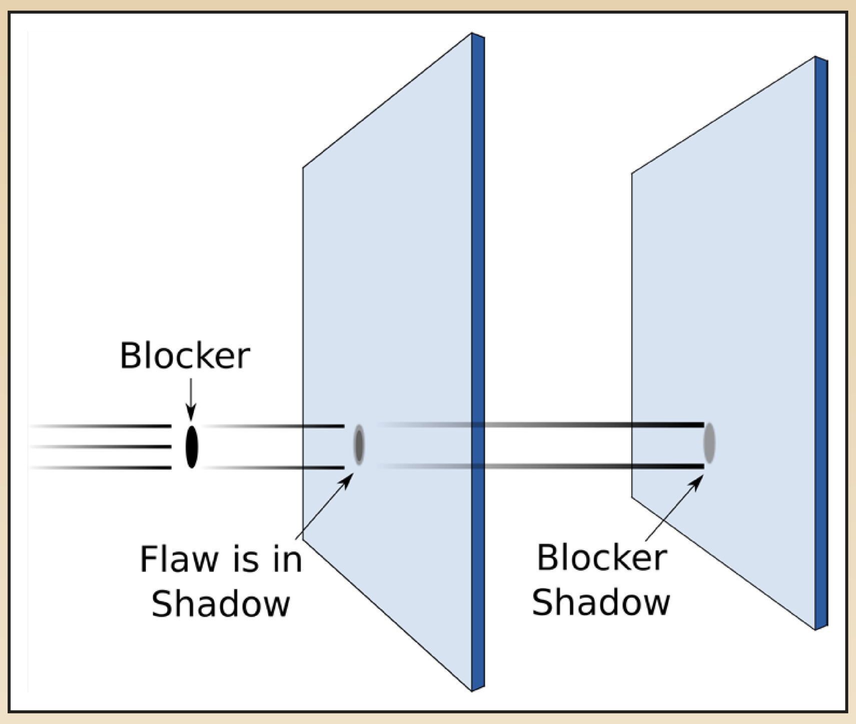


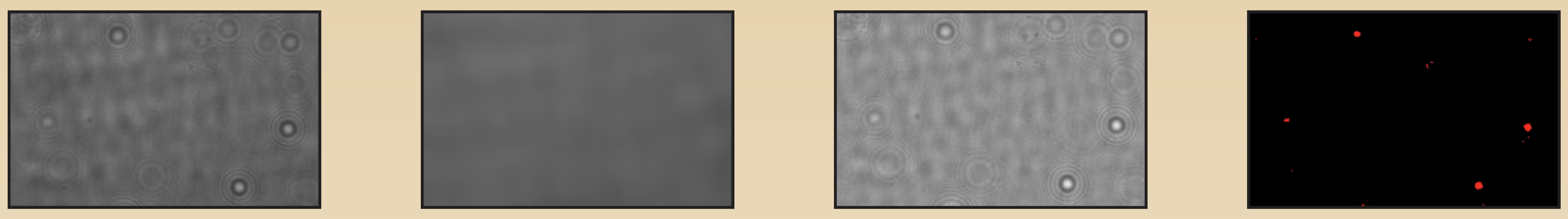
Image of a Wedge-Focus Lens (WFL), showing evidence of a flaw on an upstream optic

If we can identify hot spots we can place a blocker in front of the flaw.



To Locate Potential Hot Spots, First Find Peaks and Rings

To find bright peaks

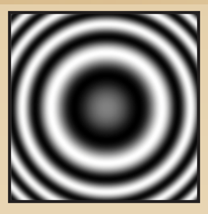


Given an image... → Create a locally-averaged image → Divide original image by the averaged image → Threshold at 1.2 (operationally-determined value)

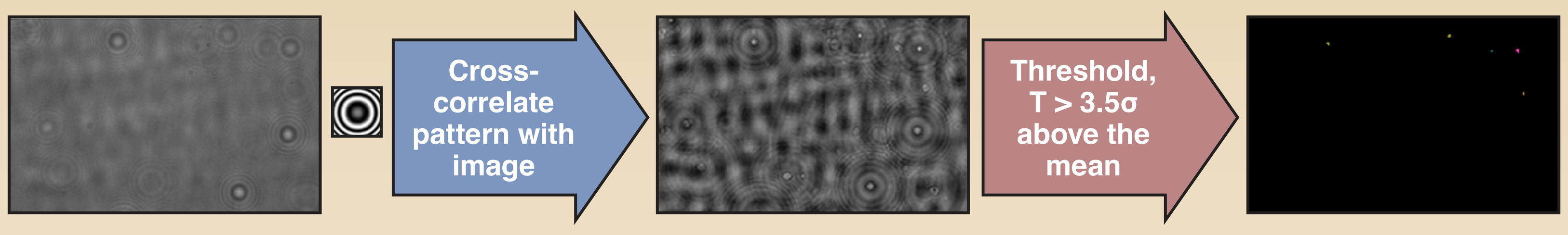
To find rings

Predict the ring pattern

$$I(r,R,z)=\frac{r^2+R\cdot J\left[1,\frac{2\pi rR}{\lambda\cdot z}\right]\left(R\cdot J\left[1,\frac{2\pi rR}{\lambda\cdot z}\right]-2r\sin\left[\frac{\pi r^2}{\lambda\cdot z}\right]\right)}{r^2}$$



z = distance from flaw to image plane, r = distance of image pixel from pattern center, R = defect radius, λ = light wavelength, J[1,x] = Bessel equation of the first kind

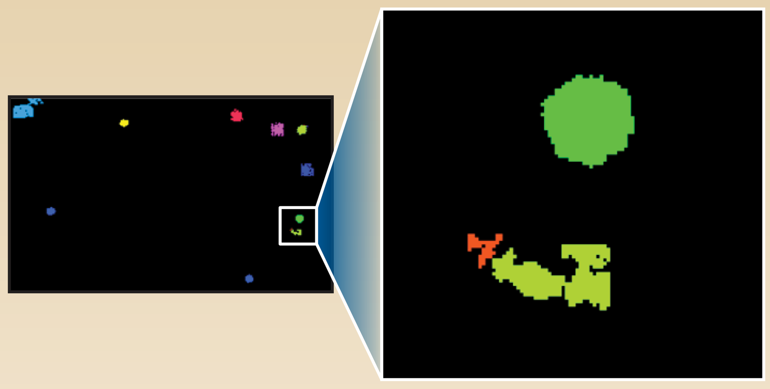


Each method finds a different set of potential sites, so we combine the results of each

Then Analyze Each Potential Site and Collect Data

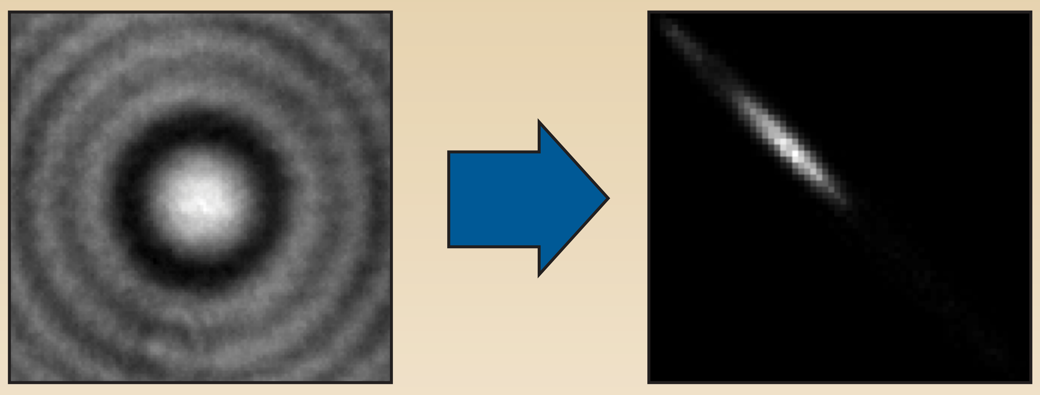
Fill each site using an adaptive fill algorithm, Measure the filled region properties

1. Use centroids of previously detected sites as seeds
2. Iteratively add neighboring pixels in nonincreasing order of intensity
3. Stop iterating when predefined threshold has been reached



Region:
- Area
- Axis Length
- Perimeter
- Solidity
- Extent
- Euler Number

Compute the co-occurrence matrix of the intensity region and measure



- Contrast
- Correlation
- Energy

Use Machine-Learning to Classify Sites

Tuning the thresholds and other analysis parameters above was not sufficient to adequately weed out false alarms without losing true positives. Instead, we set the parameters very generously, allowing many false positive detections and then applied machine learning techniques using the Avatar suite of machine learning tools (Chawla, et al.) to eliminate them:

1. Feature Extraction. All candidate sites found with the image analysis were recorded along with many measurements for each, such as: area, aspect ratio, size of the bounding box, solidity, Euler number, peak-to-mean, disk radius, radii ratio, fringe contrast and similarity to the ideal template.
2. Semi-supervised learning. To create a training set, over 30,000 measured candidates needed to be labeled with groundtruth. A small number of known real sites were labeled manually; all remaining candidates were labeled as false alarms without evaluation. Initial training of the classifier revealed the labeling errors. After correcting these and iterating a few times, the training set was refined and the classifier was correctly predicting real sites of interest, including some missed in manual inspections.

Evaluating the results with ten-fold cross validation of the refined training set showed 99% of the 30,000 detected candidate sites were rejected, leaving only 1% (300) to be brought forward for review; about a sixth of those brought forward were false alarms (primarily out-of-range, i.e. not of interest diffraction rings). Additional training may help reduce these as well. In practice, over 98% of true positives are brought forward and the generated report accurately reports trends and presents a list of sites to be blocked.

References

Barry Y. Chen ; Laura M. Kegelmeyer ; Judith A. Liebman ; J. Thaddeus Salmon ; Jack Tzeng ; David W. Paglieroni; Detection of laser optic defects using gradient direction matching. Proc. SPIE 6101, Laser Beam Control and Applications, 61011L (February 23, 2006); doi:10.1117/12.659867.

Laura Mascio Kegelmeyer ; Philip W. Fong ; Steven M. Glenn ; Judith A. Liebman; Local area signal-to-noise ratio (LASNR) algorithm for image segmentation. Proc. SPIE 6696, Applications of Digital Image Processing XXX, 66962H (September 24, 2007); doi:10.1117/12.732493.

Abdulla G, Kegelmeyer L, Liao Z, Carr W. "Effective and efficient optics inspection approach using machine learning algorithms." SPIE Laser Damage Conference, Boulder, CO. (Sept 2010)

N.V. Chawla, L.O. Hall, K.W. Bowyer, and W.P. Kegelmeyer. Learning ensembles from bites: A scalable and accurate approach. Journal of Machine Learning Research 5 (2004), 421-451.

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