



# **Optimizing Blocker Usage on NIF using Image Analysis and Machine Learning**

**Presentation to  
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Image Analysis and Machine Learning identify hotspots of faraway flaws that require blocking

**Diffraction ring “signature” imaged 8m from the camera confirms the presence of a flaw 17m from the camera**

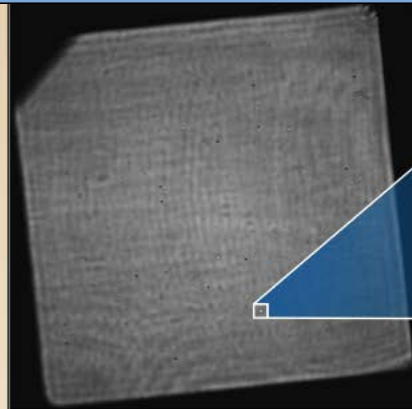
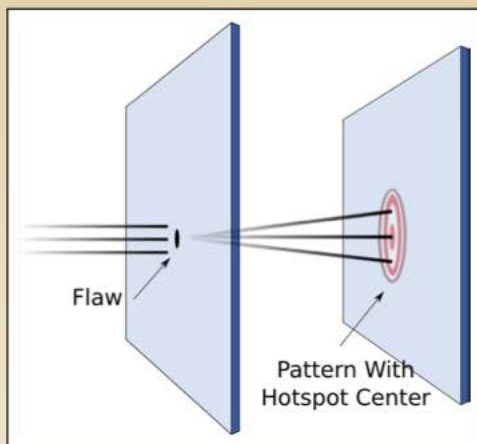
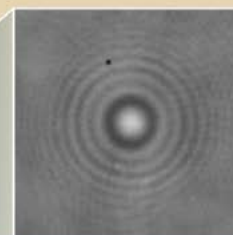
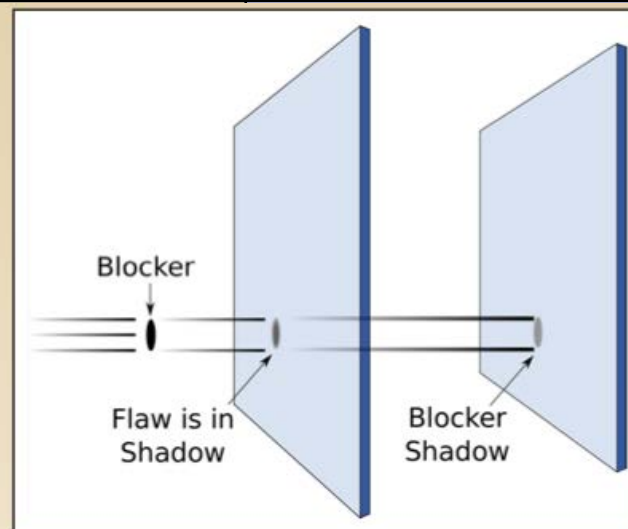


Image of a Wedge-Focus Lens (WFL), showing evidence of a flaw on an upstream optic



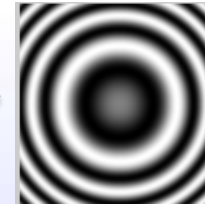
**Confirmed sites can be blocked to protect an optic until it is repaired**





## This wave interaction equation predicts the “signature” ring pattern for relevant sites

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



$z$  = distance from flaw to image plane (9.6 m)  
 $r$  = distance of image pixel from pattern center (110 um/pixel)  
 $R$  = defect radius (150 microns)  
 $\lambda$  = light wavelength (1053 nm)  
 $J[1,x]$  = Bessel equation of the first kind

The ideal template is used to find candidate locations for hotspots; candidates are measured and dozens of features extracted.

We used semi-supervised learning to create an ensemble of decision trees

10-fold cross validation: 99% false alarm rejection;  
98% True Positive detection

Machine learning distinguishes sites of interest from false alarms so the most relevant sites for blocking are brought forward