



# ICML

International Conference  
On Machine Learning

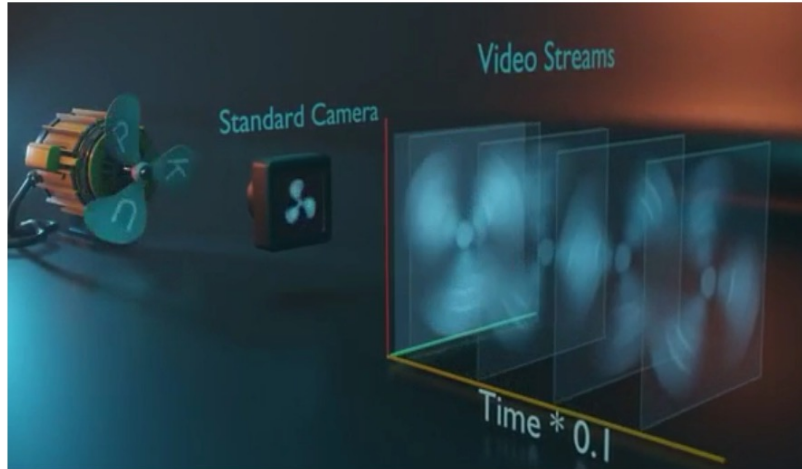


# Spike Camera Autofocus via Frequency-Domain Spectral-Centroid Migration

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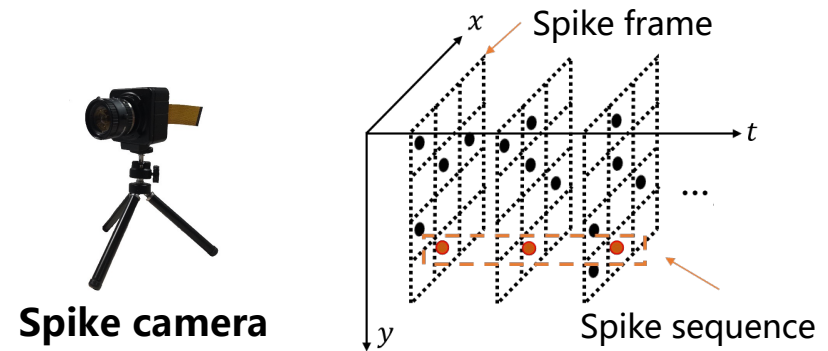
Code and dataset: [github.com/XIJIE-XIANG/CEN](https://github.com/XIJIE-XIANG/CEN)

# Spike camera



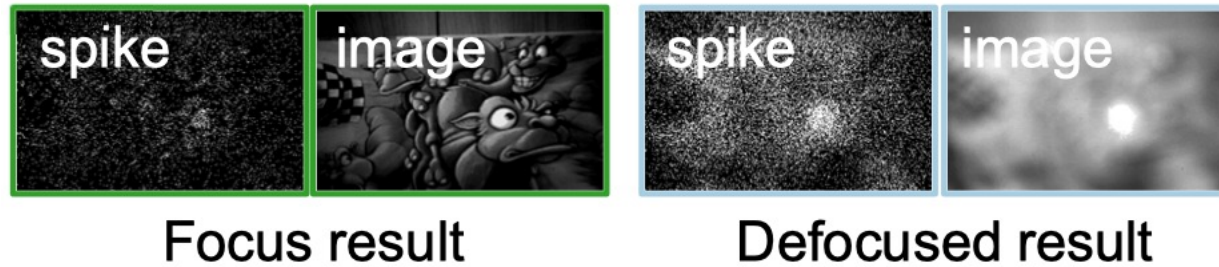
## Principle

- Integrate-and-fire sensing
- A spike is emitted when:  $\int I(t) dt \geq \theta$
- Spike frame: 0/1 matrix (40,000 fps)



# Spike camera autofocus

**Goal:** Find the best-focused position during a focus sweep from spike-camera measurements.



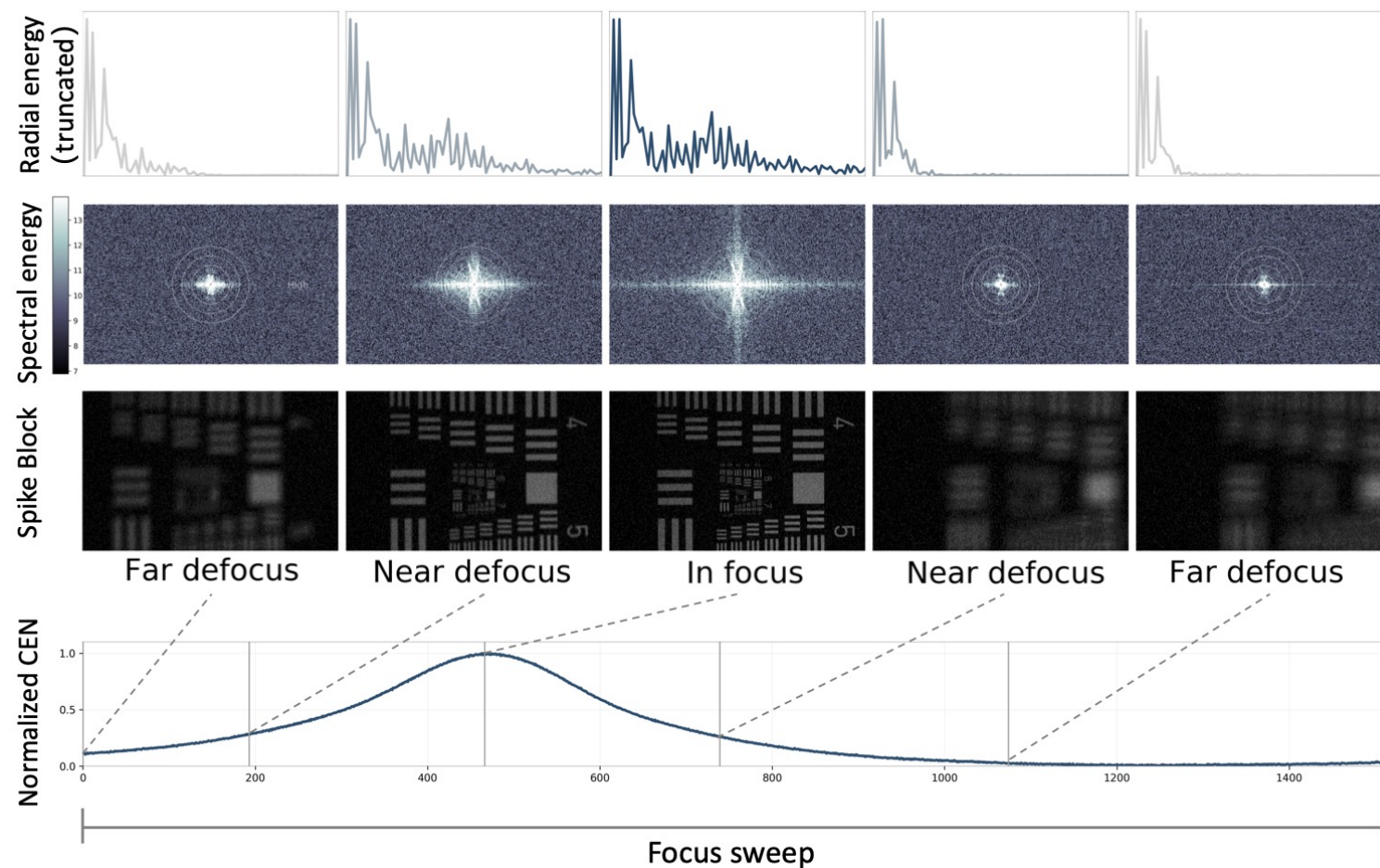
*Intensity-Robust Autofocus for Spike Camera, CVPR 2024.*

## Challenge

- Spike streams are sparse, binary, and noisy.
- The special data format makes image-based focus measures difficult to apply directly.
- Reconstructing images before autofocus sacrifices the high-speed advantage and still falls into conventional image-based autofocus.

**Key question:** What focus cue is directly observable from binary spike streams?

# Key Observation: Focus-Induced Spectral Migration



## Observation

- Focus: **high frequencies**
- Defocus: **low frequencies**
- Focus changes induce **spectral-energy migration**
- Energy moves **to higher frequencies** when approaching focus
- Energy moves **back to lower frequencies** after passing focus
- The resulting **spectral centroid curve peaks near focus**

A stable focus cue is therefore available in the frequency domain.

# CEN: Measuring Spectral Migration

How do we convert the frequency-domain observation into a focus score?

## Pipeline



## Core computation

1. Accumulate spike frames and **remove DC bias**

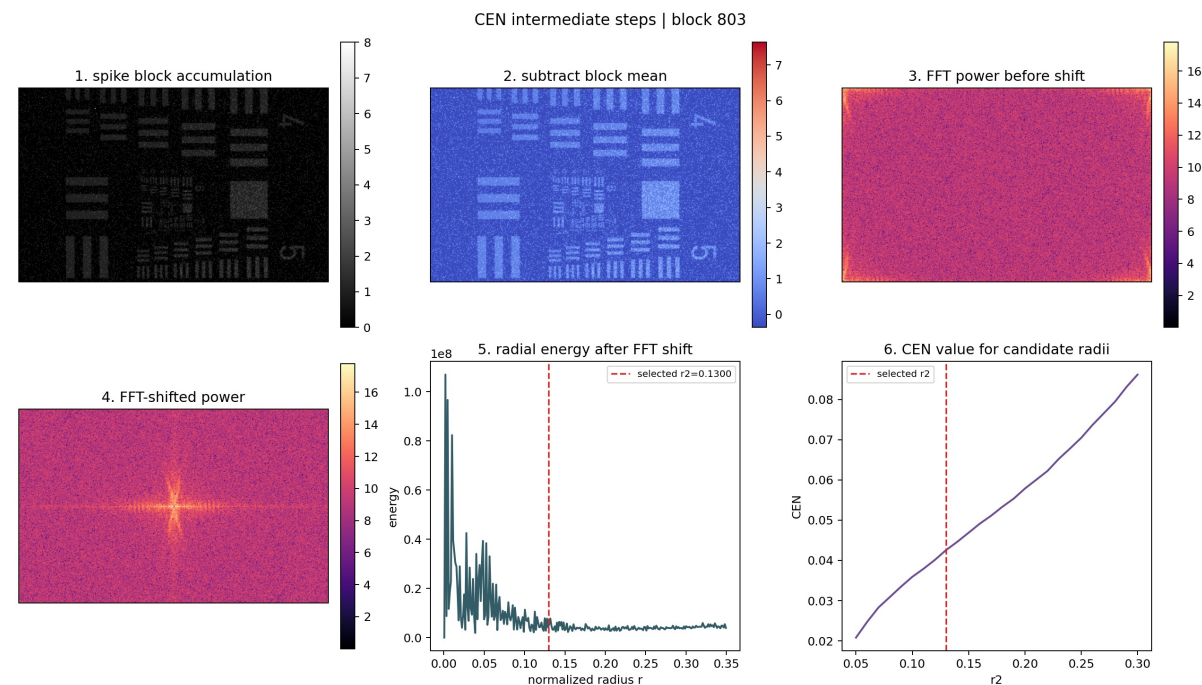
$$A_b = \sum_t S_t, \tilde{A}_b = A_b - \mu_b$$

2. Fourier transform, **FFT shift** and spectrum power

$$P_b(u, v) = |FFT_{shift}(F(\tilde{A}_b)(u, v))|^2$$

3. Compute **bounded** spectral centroid

$$CEN_r(b) = \sum_{\rho(u,v) \leq r} \rho(u, v) P_b(u, v) / (\sum_{\rho(u,v) \leq r} P_b(u, v) + \epsilon)$$



# Frequency-Bound Selection

## Structure-consistent response selection

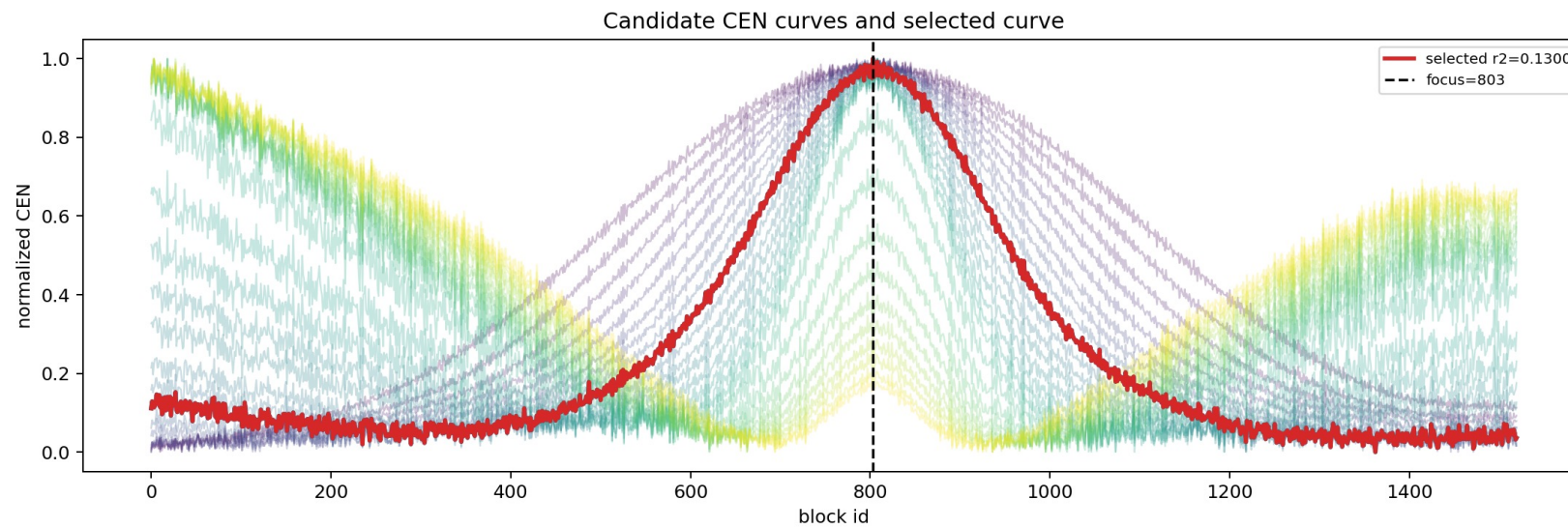
Different spectral bounds  $r$  generate different CEN curves.

$$y_r(b) = \frac{CEN_r(b) - \min_b CEN_r(b)}{\max_b CEN_r(b) - \min_b CEN_r(b) + \epsilon}$$

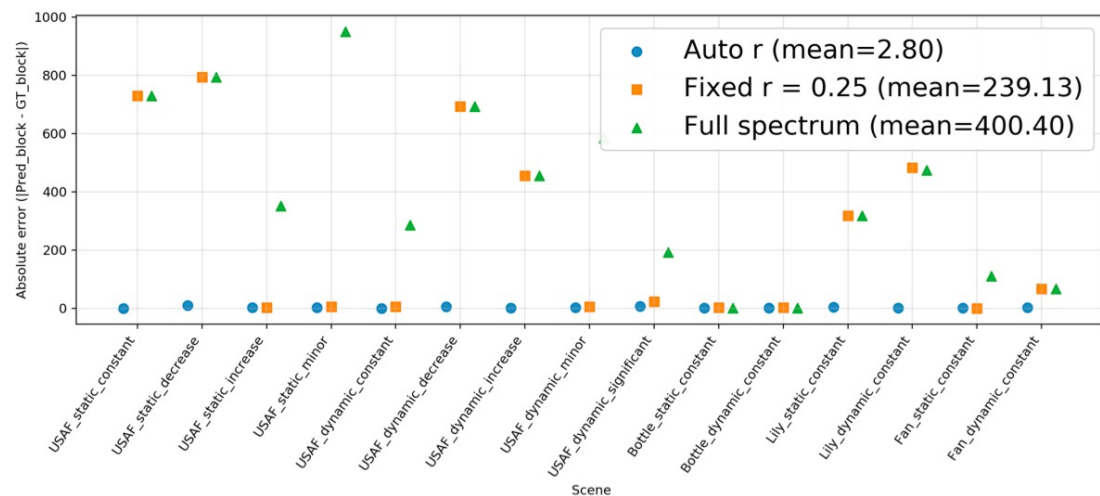
$$r^* = \arg \max_{r \in R} S(y_r)$$

$$S(y_r) = \alpha_{\text{prom}} S_{\text{prom}} + \alpha_{\text{curv}} S_{\text{curv}} - \alpha_{\text{width}} S_{\text{width}} - \alpha_{\text{plat}} S_{\text{plat}} - \alpha_{\text{edge}} S_{\text{edge}}$$

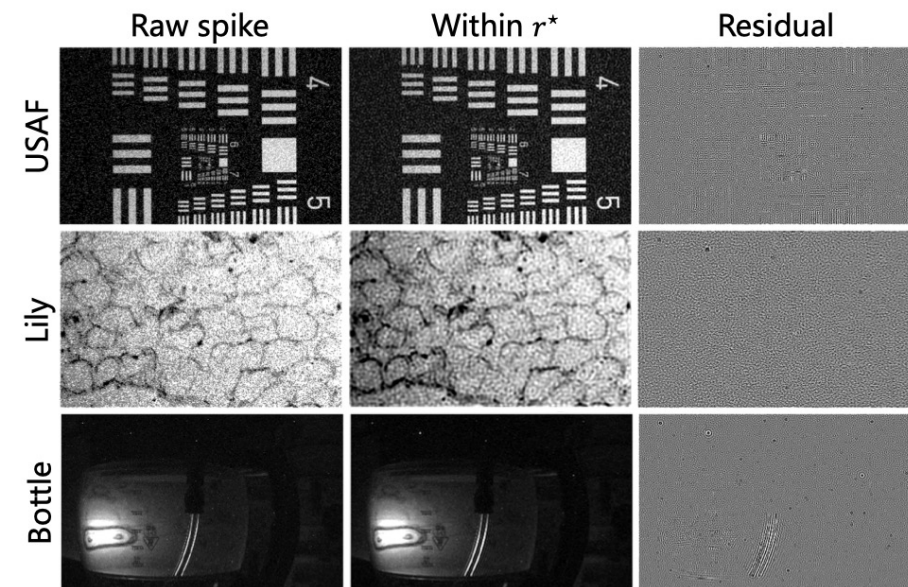
**Selection criteria:** prominent, localized, sharp, non-plateau, interior peak.



# Importance of Bounded parameter $r$



**Figure 5.** Ablation on the spectral radius  $r$ . We compare three settings: automatic radius selection (Auto- $r$ ), a fixed radius ( $r = 0.25$ ), and using the full spectrum. Each marker corresponds to one scene, and the y-axis reports the absolute block error. The legend shows the mean error over all scenes.



**Figure 6.** Effect of radius truncation in the frequency domain. Rows show representative scenes. From left to right: accumulated spike blocks, band-limited component within  $r^*$ , and high-frequency residual outside  $r^*$  dominated by noise-like patterns.

# Parameter ablation and sensitivity for focus curve selection

Table 7. Ablation of structural criteria used for focus curve selection.

| Variant         | prom | width | plateau | edge_pos | Err ↓ |
|-----------------|------|-------|---------|----------|-------|
| prom only       | ✓    |       |         |          | 56.47 |
| prom+width      | ✓    | ✓     |         |          | 33.40 |
| Full - prom     |      | ✓     | ✓       | ✓        | 35.27 |
| Full - edge_pos | ✓    | ✓     | ✓       |          | 33.07 |
| Full - plateau  | ✓    | ✓     |         | ✓        | 3.13  |
| Full - width    | ✓    |       | ✓       | ✓        | 3.07  |
| Full            | ✓    | ✓     | ✓       | ✓        | 2.80  |

Table 10. Parameter sensitivity analysis on real spike-camera sequences. Mean and median absolute error ranges are reported in block units.

| Parameter               | Values tested                             | Mean Err.  | Median Err. |
|-------------------------|-------------------------------------------|------------|-------------|
| $\alpha_{\text{prom}}$  | 0.55, 0.80, <b>1.10</b> , 1.40, 1.65      | 2.73–3.20  | 2.00–2.00   |
| $\alpha_{\text{curv}}$  | 0.10, 0.20, <b>0.35</b> , 0.50, 0.70      | 2.80–2.80  | 2.00–2.00   |
| $\alpha_{\text{width}}$ | 0.15, 0.30, <b>0.45</b> , 0.60, 0.75      | 2.73–3.13  | 2.00–2.00   |
| $\alpha_{\text{plat}}$  | 0.10, 0.20, <b>0.35</b> , 0.50, 0.70      | 2.73–2.93  | 2.00–2.00   |
| $\alpha_{\text{edge}}$  | 0.20, 0.40, <b>0.60</b> , 0.80, 1.00      | 2.80–33.07 | 2.00–2.00   |
| $\tau$                  | 0.005, 0.008, <b>0.012</b> , 0.016, 0.020 | 2.80–4.13  | 2.00–3.00   |
| $\gamma$                | 1.0, 1.5, <b>2.0</b> , 3.0, 4.0           | 2.80–2.80  | 2.00–2.00   |

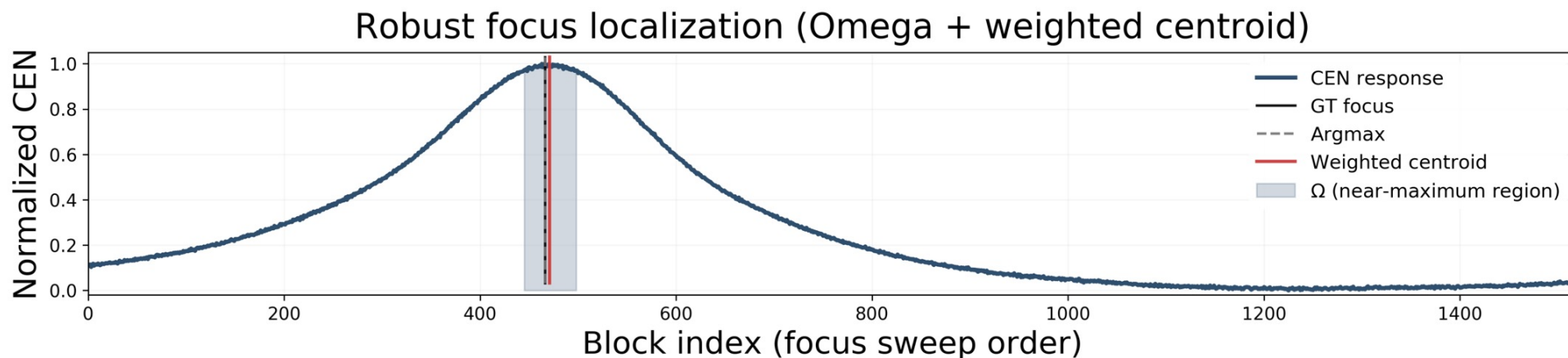
# Robust Focus Localization

Instead of directly using a single argmax, we localize focus within the near-maximum region:

$$\Omega = \{b \mid y_{r^*}(b) \geq (1 - \tau)y_{r^*}(p_0)\}, p_0 = \arg \max_b y_{r^*}(b)$$

$$\hat{b} = \text{round} \left( \frac{\sum_{b \in \Omega} b w_b}{\sum_{b \in \Omega} w_b + \epsilon} \right), w_b = (y_{r^*}(b))^\gamma$$

**Goal:** stabilize focus prediction under noisy or flat response peaks.



# Synchronous dataset experiment

*Table 1.* Focus estimation error on synthetic focus sweeps under moderate-light and low-light conditions. Error is reported in centimeters; lower is better.

| Method | Moderate-light |             |             |             | Low-light   |             |             |             |
|--------|----------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
|        | simu01         | simu02      | simu03      | Mean        | simu01      | simu02      | simu03      | Mean        |
| GRAD   | 0.37           | 0.00        | 0.63        | 0.33        | 4.00        | 4.00        | 6.30        | 4.80        |
| HF     | 0.37           | 0.37        | 0.00        | 0.24        | <b>0.37</b> | 0.37        | 5.00        | 1.90        |
| LAP    | 0.37           | 2.20        | 0.00        | 0.86        | 4.00        | 4.00        | 5.60        | 4.60        |
| MFDCT  | 0.37           | 0.37        | 0.00        | 0.24        | 4.00        | 4.00        | 5.60        | 4.60        |
| SD     | 0.37           | 0.37        | 0.00        | 0.24        | 12.00       | 2.20        | 6.30        | 6.90        |
| COUNT  | 4.00           | 4.00        | 0.63        | 2.90        | 12.00       | 6.60        | 2.50        | 7.20        |
| CEN    | <b>0.00</b>    | <b>0.00</b> | <b>0.00</b> | <b>0.00</b> | 2.90        | <b>0.37</b> | <b>0.63</b> | <b>1.30</b> |

# Real dataset experiment

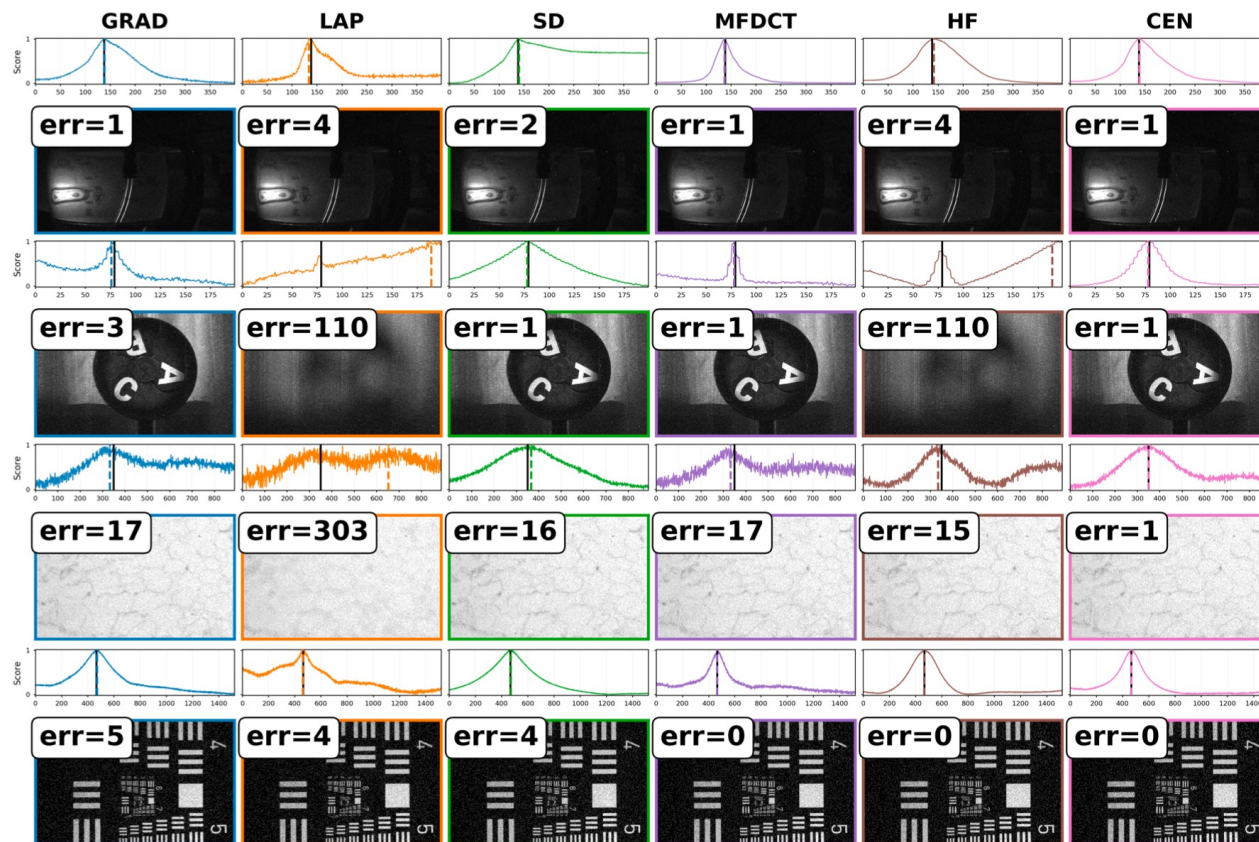


Figure 2. Qualitative comparison of autofocus responses and predicted focus blocks on representative spike-camera scenes. Each column corresponds to one method. For each scene (Bottle, Fan, Lily, USAF), the top subplot shows the normalized response curve over blocks with the ground-truth focus block indicated by a black vertical line and the method prediction indicated by a colored dashed line. The bottom subplot visualizes the accumulated block image at the predicted focus, and the block-level absolute error  $|\hat{b} - b^*|$  is annotated in the corner. Overall, CEN produces a sharper and better-aligned extremum and yields more accurate focus blocks across diverse scenes.

# Real dataset experiment

Table 2. Autofocus accuracy across representative spike-camera scenes. Mean AbsErr (RelErr, %) is reported; lower is better. Best and second-best results are shown in bold and underlined.

| Scene  | GRAD              | LAP               | SD                | COUNT         | MFDCT             | HF                 | CEN               |
|--------|-------------------|-------------------|-------------------|---------------|-------------------|--------------------|-------------------|
| Bottle | <b>1.00 (0.3)</b> | <u>2.00 (0.5)</u> | <b>1.00 (0.2)</b> | 129.50 (32.5) | <b>1.00 (0.3)</b> | 3.50 (0.9)         | <b>1.00 (0.3)</b> |
| Lily   | 20.50 (2.3)       | 298.00 (33.6)     | 12.00 (1.4)       | 427.50 (48.0) | 18.00 (2.0)       | <u>10.50 (1.2)</u> | <b>2.50 (0.3)</b> |
| Fan    | 4.50 (2.2)        | 88.50 (44.5)      | <u>2.50 (1.2)</u> | 79.50 (40.0)  | 3.50 (1.8)        | 88.50 (44.5)       | <b>2.00 (1.0)</b> |
| USAF   | 368.67 (24.3)     | 386.11 (25.4)     | <u>7.67 (0.5)</u> | 729.56 (48.0) | 500.89 (33.0)     | <b>3.33 (0.2)</b>  | <u>3.44 (0.2)</u> |
| MEAN   | 224.67 (15.2)     | 283.47 (25.7)     | <u>6.67 (0.7)</u> | 522.60 (44.9) | 303.53 (20.3)     | 15.67 (6.3)        | <b>2.80 (0.3)</b> |

Table 3. Additional comparison with reconstruction-based image autofocus baselines. Mean AbsErr (RelErr, %) is reported; lower is better. The left block uses direct count-normalized reconstruction, while the right block uses TFI reconstruction. Best and second-best results in each row are shown in bold and underlined, respectively.

| Scene  | Count-normalized reconstruction |               |               |               | TFI reconstruction |                      |               |                     | CEN               |
|--------|---------------------------------|---------------|---------------|---------------|--------------------|----------------------|---------------|---------------------|-------------------|
|        | GRAD                            | LAP           | RDF           | DRDF          | GRAD               | LAP                  | RDF           | DRDF                |                   |
| Bottle | <b>0.50 (0.3)</b>               | 1.50 (1.0)    | 2.00 (1.4)    | 2.00 (1.4)    | <u>1.00 (0.7)</u>  | <u>1.00 (0.7)</u>    | 4.50 (3.0)    | 3.50 (2.3)          | <u>1.00 (0.7)</u> |
| Lily   | 13.50 (3.8)                     | 330.50 (92.7) | 14.50 (4.1)   | 17.00 (4.7)   | <u>34.50 (9.6)</u> | <u>340.00 (95.0)</u> | 150.00 (42.8) | <u>11.50 (3.3)</u>  | <b>2.50 (0.7)</b> |
| Fan    | <u>3.50 (3.1)</u>               | 88.50 (89.5)  | 4.50 (4.4)    | 52.00 (43.3)  | 89.50 (87.0)       | 89.50 (87.0)         | 91.00 (92.0)  | <u>91.00 (92.0)</u> | <b>2.00 (1.9)</b> |
| USAF   | <u>43.11 (6.7)</u>              | 550.11 (91.6) | 308.78 (50.2) | 447.11 (70.2) | 95.22 (14.1)       | 138.78 (19.6)        | 85.56 (12.7)  | 85.56 (12.7)        | <b>3.44 (0.5)</b> |
| MEAN   | <u>28.20 (5.0)</u>              | 386.13 (79.4) | 188.07 (31.4) | 277.73 (48.7) | 73.80 (21.4)       | 140.67 (36.1)        | 84.07 (26.0)  | 65.47 (20.7)        | <b>2.80 (0.8)</b> |

# Robustness under Motion and Illumination Variations

Table 5. Autofocus accuracy (AbsErr (RelErr) ↓) under static and dynamic scenes.

| Motion Type | GRAD           | LAP            | SD                 | COUNT          | MFDCT          | HF            | CEN                |
|-------------|----------------|----------------|--------------------|----------------|----------------|---------------|--------------------|
| Static      | 391.00 (23.26) | 183.71 (30.43) | 3.00 (0.39)        | 541.71 (46.34) | 356.86 (32.30) | 33.86 (15.46) | <b>3.14 (0.33)</b> |
| Dynamic     | 201.63 (13.70) | 245.13 (21.61) | <u>9.50 (0.94)</u> | 505.88 (43.72) | 256.88 (16.25) | 12.25 (4.62)  | <b>2.50 (0.36)</b> |

Table 6. Autofocus accuracy (AbsErr (RelErr) ↓) under different illumination variation patterns during focus sweeping.

| Illumination | GRAD           | LAP            | SD                 | COUNT          | MFDCT          | HF                 | CEN                |
|--------------|----------------|----------------|--------------------|----------------|----------------|--------------------|--------------------|
| Constant     | 98.38 (7.55)   | 188.38 (29.32) | 4.38 (0.79)        | 327.00 (41.23) | 96.88 (7.03)   | 25.75 (11.66)      | <b>1.50 (0.40)</b> |
| Decrease     | 242.00 (15.90) | 743.00 (48.90) | <b>6.50 (0.40)</b> | 624.00 (41.10) | 620.00 (40.80) | 7.00 (0.45)        | 7.50 (0.50)        |
| Increase     | 21.50 (1.40)   | 403.00 (26.55) | <b>1.50 (0.10)</b> | 881.00 (58.00) | 239.00 (15.75) | 3.00 (0.20)        | <b>1.50 (0.10)</b> |
| Minor        | 753.50 (49.60) | 147.50 (9.70)  | 4.00 (0.25)        | 754.50 (49.70) | 758.50 (49.95) | <b>0.50 (0.05)</b> | 2.50 (0.20)        |
| Significant  | 549.00 (36.10) | 154.00 (10.10) | 37.00 (2.40)       | 696.00 (45.80) | 543.00 (35.70) | 8.00 (0.50)        | <b>7.00 (0.50)</b> |

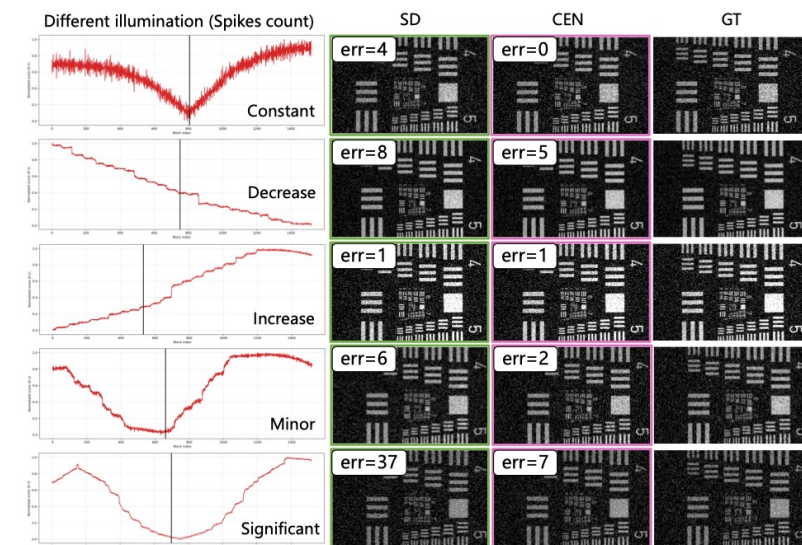


Figure 4. Autofocus comparison under different illumination changes. Each row shows one illumination pattern (constant, decrease, increase, minor, significant). From left to right: spike count curve, SD result, CEN result, and GT. Absolute block error is shown in the upper-left of each estimated focus image.

# Limitations and failure cases

1. CEN works when focus variation produces a stable spectral migration pattern. It may fail when the cue is corrupted or missing.

- **Severe noise:** response tail may be dominated by noise
- **Insufficient spikes:** near-zero illumination makes the focus cue unobservable

2. Edge deployment and computational cost

- CEN requires repeated block-wise 2D FFTs, complexity:  $O(N \log N)$
- Latency and energy cost under strict edge constraints still need verification

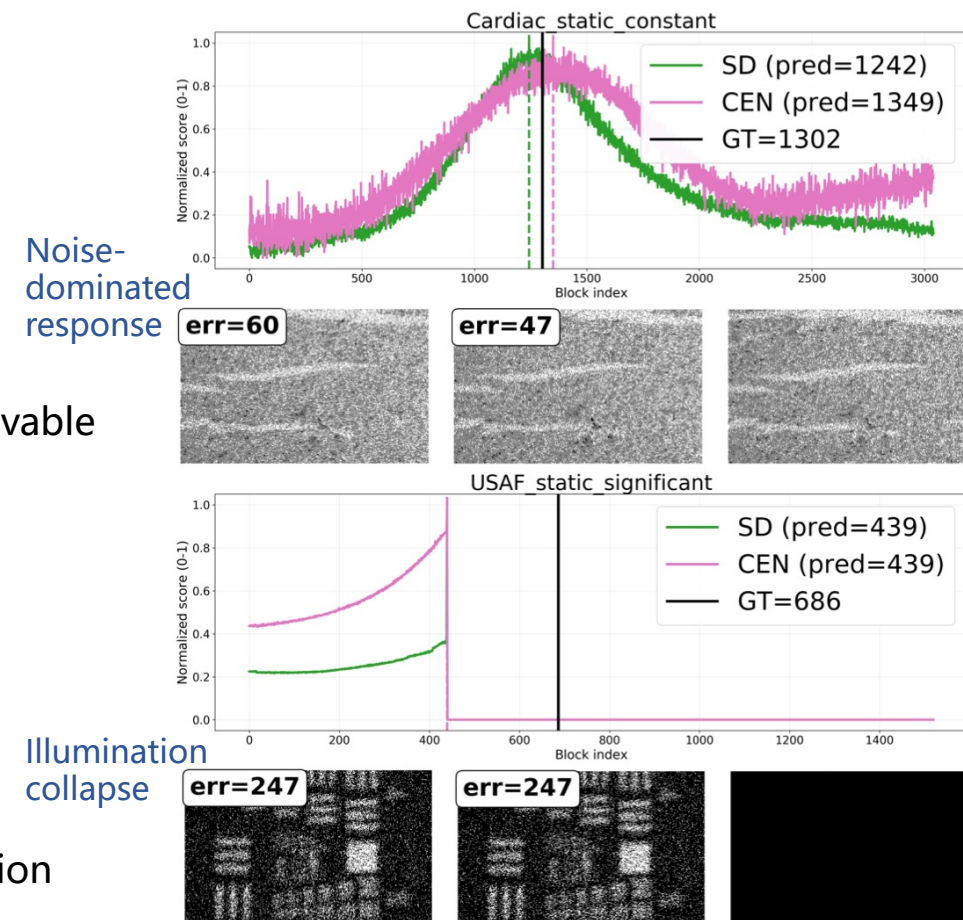


Figure 8. Representative failure cases. Top: an extremely noisy scene where noise dominates the response tail after the GT focus position. Bottom: the USAF static significant scene, where illumination drops to near zero and no spikes are generated at the GT focus. For each case, response curves of SD and CEN are shown together with the GT, and the accumulated spike blocks at the predicted focus are visualized with absolute block error indicated.

*Thank you !*