Energy-based Iterative Calibration of Parametric Point Spread Functions for Curvilinear Pattern Prediction

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ILT curvilinear (CL) patterns are highly irregular and complex. To obtain accurate post-exposure patterns for proximity effect correction (PEC) and defect inspection, precise pattern prediction (PP) simulation is essential. For reliable PP simulation and to enable convenient parameter tuning to match experimental results, a parametric point spread function (PPSF), calibrated from the absorbed energy distribution (AED) obtained via Monte-carlo (MC) scattering simulations, is commonly employed. However, conventional calibration methods rely on curve fitting (CF) to adjust the parameters of the PPSF to match the AED energy profiles. It has been observed that the PPSF obtained through CF alone does not provide sufficient accuracy in pattern prediction (PP), particularly for curvilinear (CL) patterns[1]. To address this limitation, we propose an energy-fitting-based method that iteratively calibrates the PPSF parameters by minimizing the error in the energy image. As illustrated in the flowchart in Fig. 1(a), energy images are generated by convolving candidate PPSFs with the test pattern. The predicted contours are then extracted and compared with the contours derived from the AED energy image. When the edge placement error (EPE) of a given model converges, that model is selected as the final calibration result. Figure 1(b) illustrates the complete optimization workflow of the proposed energy-fitting method. In Fig. 1(b1), multiple PPSF forms (e.g., EEE, GEE, and EG+L) are convolved with the target layout to perform pattern prediction and generate corresponding energy images. In Fig. 1(b2), the energy images produced by the PPSF are compared with the AED energy image, and the optimizer minimizes the energy deposition error using four merit functions (e.g., NMSE, MSE, MAE, and MER) as defined in Fig. 2. In Fig. 1(b3), the optimized parameters are fed back to update the PPSF. This procedure is iteratively repeated, and the optimized PPSF corresponding to each merit function is obtained for subsequent evaluation. Figure 3(a) illustrates the contour extraction under different exposure thresholds. To evaluate the accuracy and reliability of the fitting results, the EPE of the PP contours was assessed at the nominal threshold as well as under ±5% threshold variations. As shown in Fig. 3(b), the mean EPE (EPE_{mean}) is compared across different PPSF forms and threshold conditions, where the solid and dashed bars represent the proposed energy-fitting method and the conventional CF approach, respectively. The results indicate that the proposed energy-fitting method consistently achieves lower EPE_{mean} not only at the nominal threshold but also across the perturbed threshold levels. This performance demonstrates that the fitted PPSFs more accurately capture the complete energy-field distribution. Consequently, the proposed method exhibits improved physical fidelity and enhanced robustness against threshold-related process variations. Figure 4 presents two representative test patterns: (a) CL pattern 1 (CL 1) and (b) CL pattern 2 (CL 2). The contour overlays demonstrate that the results obtained using the proposed energy-fitting method are consistently closer to the target contours, indicating a significant improvement in PP accuracy compared with the conventional CF approach. Table I summarizes the quantitative comparison of PP performance indices, including NMSE and EPE_{mean}, for two CL patterns and one line-and-space (L&S) pattern. Compared with the conventional CF method, both NMSE and EPE_{mean} achieved by the proposed energy-fitting method are substantially reduced across all evaluated patterns. Specifically, the EPE_{mean} is reduced by up to 66% for CL patterns and 59% for the L&S pattern, confirming that optimizing PPSF parameters to accurately match energy-deposition behavior leads to higher-fidelity pattern prediction. Overall, the proposed energy-fitting method enables accurate PPSF calibration by effectively bridging the gap between energy modeling and CL pattern prediction.

[1] P. Ryan, et al. "Adopting curvilinear shapes for production ILT: challenges and opportunities," in *Proc.SPIE*, 2019, vol. 11148, p. 111480T

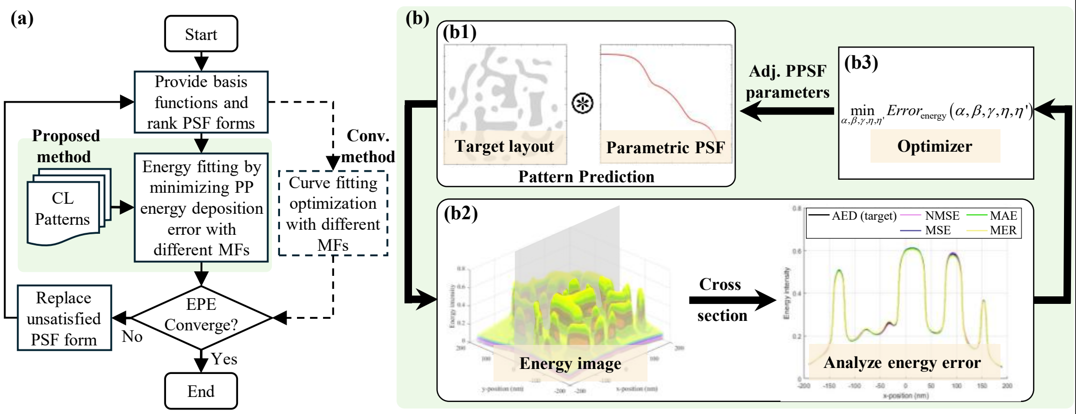

Fig. 1 (a) Comparison between the conventional CF-based PPSF calibration flow and the proposed energy-fitting-based calibration framework. (b) Workflow of the proposed energy-fitting method: (b1) pattern prediction and energy image generation using candidate PPSFs; (b2) energy image-domain error evaluation using multiple MFs; (b3) PPSF parameters update through iterative optimization.

Merit functions

E_{AED}: energy of AED. E_{PPSF}: energy of PPSFs.

$$\text{MAE MF} = \max \left\| E_{\mathrm{PPSF}} - E_{\mathrm{AED}} \right\|$$

$$\text{MER MF} = \max \frac{\left\| E_{\mathrm{PPSF}} - E_{\mathrm{AED}} \right\|}{\left\| E_{\mathrm{AED}} \right\|}$$

$$\text{NMSE MF} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} \left\| E_{\mathrm{PPSF}} - E_{\mathrm{AED}} \right\|^2}{\sum_{i=1}^{M}\sum_{j=1}^{N} \left\| E_{\mathrm{AED}} \right\|^2}$$

$$\text{MSE MF} = \frac{1}{M \times N} \times \sum_{i=1}^{M}\sum_{j=1}^{N} \left\| E_{\mathrm{PPSF}} - E_{\mathrm{AED}} \right\|^2$$

Fig. 2 MFs used to evaluate energy image-domain fitting quality between PPSF-predicted energy images and the MC-derived AED.

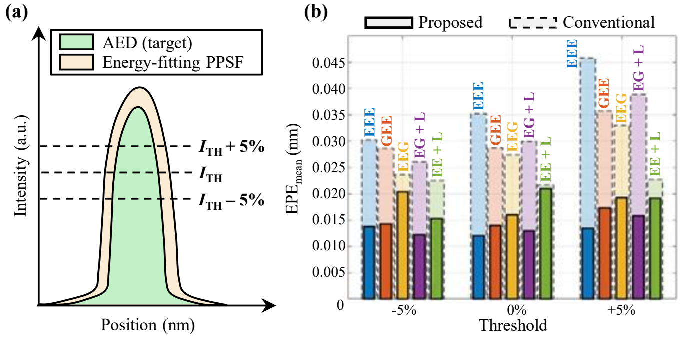

Fig. 3 (a) Contour extraction under the nominal threshold and ±5% threshold variations. (b) Comparison of $\mathrm{EPE_{mean}}$ for different PPSF forms and threshold conditions. Solid bars denote the proposed energy-fitting method, while dashed bars denote the conventional CF method.

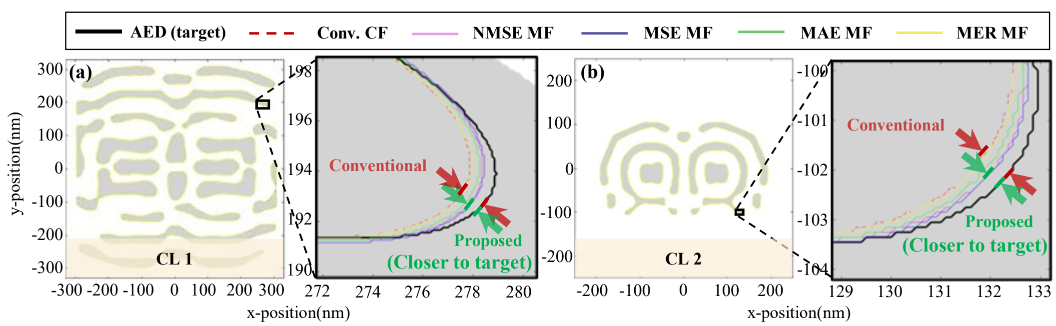

Fig. 4 Contour comparison results for curvilinear test patterns: (a) CL 1 and (b) CL 2. The proposed energy-fitting method yields contours closer to the target geometry than the conventional CF approach.

Table I Comparison of PP performance between the conventional CF method and the proposed energy-fitting PPSF calibration, evaluated using NMSE and $\mathrm{EPE_{mean}}$.

Pattern type	PPSF form	Conventional method (Curve-fitting) NMSE(%)	Conventional method (Curve-fitting) $\mathrm{EPE_{mean}}$(nm)	Proposed method (Energy-fitting) NMSE(%)	Proposed method (Energy-fitting) $\mathrm{EPE_{mean}}$(nm)	Improvement (Conventional vs. Proposed) NMSE	Improvement (Conventional vs. Proposed) $\mathrm{EPE_{mean}}$
CL 1 / CL 2 / L&S	EEE	0.395 / 0.596 / 0.383	0.043 / 0.035 / 0.060	0.280 / 0.214 / 0.232	0.031 / 0.012 / 0.035	29% / 64% / 39%	28% / 66% / 42%
	EEG	0.445 / 0.468 / 0.348	0.048 / 0.027 / 0.053	0.329 / 0.351 / 0.220	0.036 / 0.020 / 0.033	26% / 25% / 37%	25% / 26% / 38%
	GEE	0.449 / 0.483 / 0.501	0.050 / 0.029 / 0.080	0.324 / 0.248 / 0.360	0.036 / 0.015 / 0.056	28% / 49% / 28%	28% / 48% / 30%
	GG + L	0.334 / 0.833 / 0.207	0.038 / 0.051 / 0.034	0.280 / 0.383 / 0.093	0.030 / 0.022 / 0.014	16% / 54% / 55%	21% / 57% / 59%
	GE + L	0.694 / 1.387 / 0.317	0.082 / 0.088 / 0.054	0.599 / 0.633 / 0.317	0.068 / 0.038 / 0.054	14% / 54% / 0%	17% / 57% / 0%
	EG + L	0.217 / 0.505 / 0.107	0.024 / 0.030 / 0.017	0.217 / 0.222 / 0.078	0.024 / 0.013 / 0.012	0% / 56% / 27%	0% / 57% / 29%

Accuracy improved