Learning to Discover Reflection Symmetry via Polar Matching Convolution
— *Supplemental Material* —

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1. Synthetic dataset (LDRS-synth)

In this section, we provide a step-by-step process of synthesizing the symmetry images and their axes in Fig. 1 and Alg. 1.

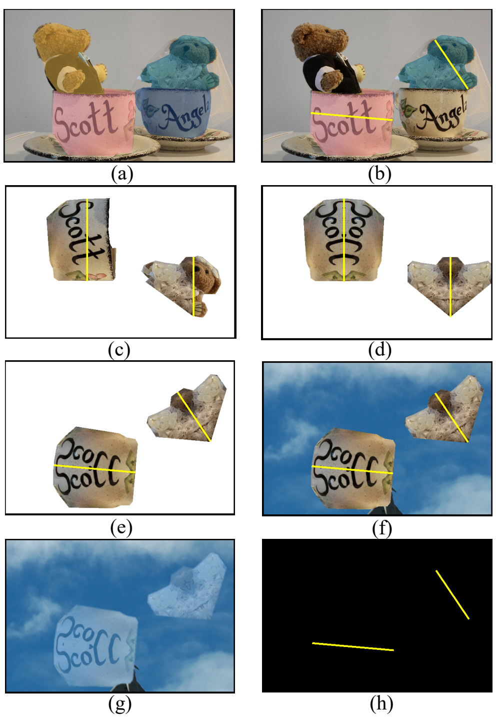

Figure 1. Synthesis process. (a) Given an image and its polygon annotations of instances from COCO, (b) we select some instances that show the maximum length of symmetries using depth-first-search (DFS) after synthesization. To construct symmetries in arbitrary angles (c) we rotate them in random degrees, (d) flip the left part of an vertical axis to the right and (e) rotate them back to the reverse direction with the same amount of angles. (f) Finally, we composite the foreground symmetries onto a randomly sampled background image from COCO. The alpha-blended version (g) and the axes heatmap (h) are used for training.

Algorithm 1: Synthesize Data from COCO [2]

Input : foreground and background images (I_{fg} and I_{bg}) and polygon instance annotations Ω_0 of I_{fg}
Output: heatmap of symmetry axis Y and blended image I_{sym}

Ψ_0: initial list of angles sampled within $[(0, \frac{1}{n}\pi), ..., (\frac{n-1}{n}\pi, \pi)]$ given $n = 2$
Ψ: selected list of angles from Ψ_0
L: randomly sampled list of vertical axes
Ω: selected list of annotations from Ω_0

$\Omega_0 \leftarrow$ SortInstancesByArea(Ω_0)
Ω, L, $\Psi \leftarrow$ EmptyLists
for $\omega_0 \in \Omega_0$ **do**
  for $\psi \in \Psi_0$ **do**
    $\omega \leftarrow$ RotatePolygon(ω_0, ψ)
    /* sample vertical symmetry axis l between 1/3 and 2/3 positions of the instance */
    $\omega \leftarrow$ FlipLeftPart(ω, vertical axis=l)
    $\omega \leftarrow$ RotatePolygon(ω, $-\psi$)
    Ω.append(ω), L.append(l), Ψ.append(ψ)
  end
end

/* Find the best combination that maximize the length of the symmetry axes by DFS*/
Ω, L, $\Psi \leftarrow$ BestSymmetryByDFS(Ω, L, Ψ)

/* Composite symmetry images with the same process that polygons are transformed. */
$I_{\text{symfg}} \leftarrow$ CompositeSymmetryFG(I_{fg}, Ω, L, Ψ)
$I_{\text{sym}} \leftarrow$ AlphaBlendwithBG(I_{symfg}, I_{bg}, Ω')

/* Composite symmetry axes by drawing and rotating vertical symmetric axes. */
$Y \leftarrow$ DrawRotateVerticalAxes(L, Ψ)
return Y, I_{sym}

*Equal contributions.

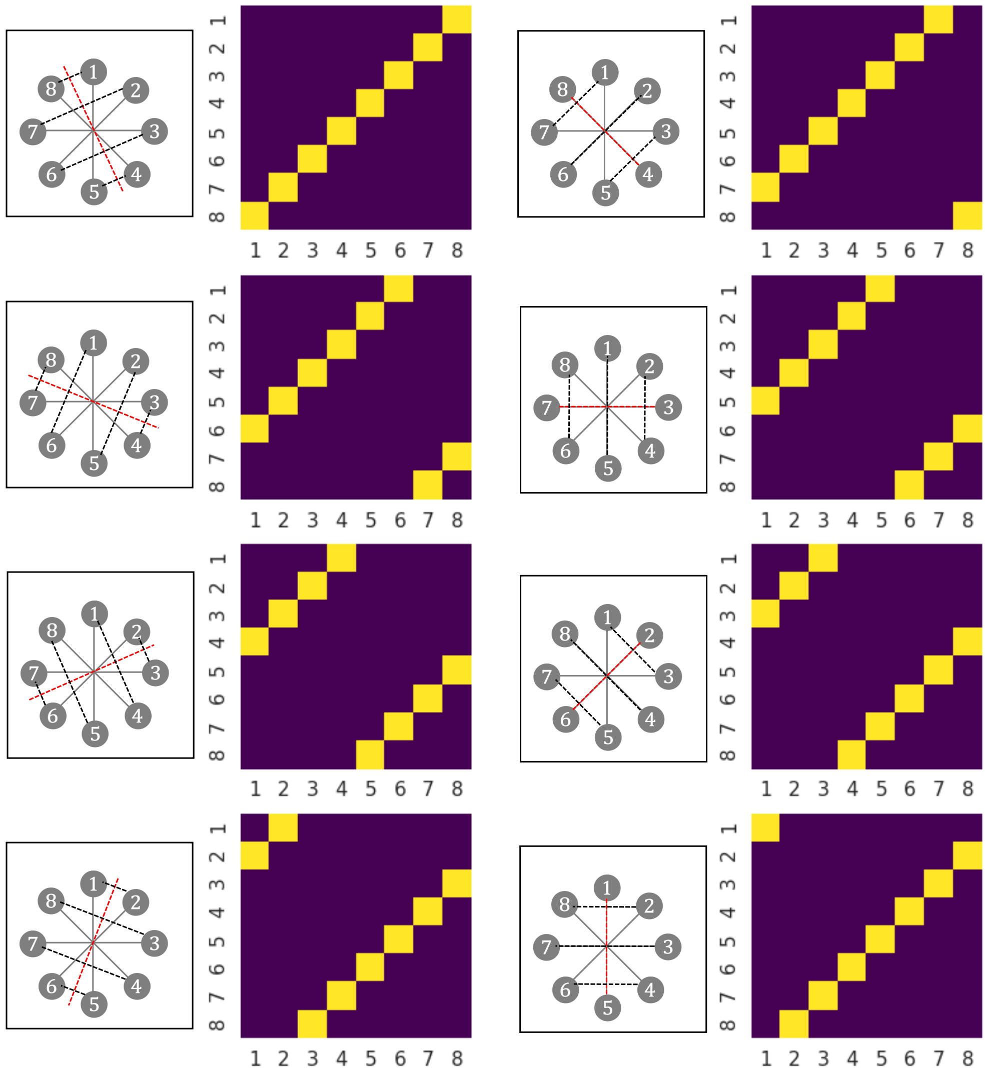

Figure 2. A visualization of the valid indices of the reflective matching kernel. Target axis (left) and corresponding kernel (right) are placed side to side. The kernel is binary where the bright yellow indicates *valid*.

2. Reflective matching kernel

We show that the *axis-aware* characteristic improves the kernel in Tab. 2 of the main paper. Although we illustrated the examples of the valid indices in the Fig.3 and Fig.4 of the main paper, we show the visualization of the valid indices for every candidate axes in Fig. 2. Note that N_{axi} candidate axes for the N_{axi} points have two cases: (1) axes crossing the points and (2) axes lying between the points.

train dataset			test dataset		
LDRS-*synth*	SDRW + LDRS	NYU	SDRW	LDRS	NYU
✓	✓		63.4	34.8	**62.1**
✓	✓	✓	**68.8**	**37.3**	-

Table 1. Experimental results on the training sets with/without NYU [1].

3. Experimental results on NYU dataset

Since NYU [1] does not distinguish the train and the test splits, we use them all for our training set in the main paper. To investigate the effectiveness of the NYU dataset, we conduct the experiments by separating them from our training sets (Tab. 1). Training with the NYU dataset offers improvements on F-score for the SDRW and the LDRS test datasets. When testing the NYU dataset, our method achieves the F1-score of 62.1%.

References

[1] M. Cicconet, V. Birodkar, M. Lund, M. Werman, and D. Geiger. A convolutional approach to reflection symmetry. http://arxiv.org/abs/1609.05257, 2016. New York. 2

[2] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *European conference on computer vision*, pages 740–755. Springer, 2014. 1