Robust Symmetry Detection in Natural Images

Ching L. Teo and Cornelia Fermüller
University of Maryland Institute for Advanced Computer Studies
A.V. Williams Building, College Park, MD 20740
{cteo,fer}@umiacs.umd.edu

1. Approach

We propose a perceptually plausible mechanism for symmetry detection in natural images that consists of two steps: 1) A fast attentional step that creates a symmetry attention map followed by 2) a robust symmetry detection step that uses image edge statistics. The input is an image edge map, I_e, and the final output is a set of symmetry axes $\mathcal{A} = \{a_1, \ldots, a_S\}$ with $a_i = ((x_i, y_i), o_i)$ (centroid location and orientation) for the i^{th} symmetry axis.

1.1. Attention From Symmetry

Motivated by recent findings indicating that humans are attracted to symmetrical regions more easily than non-symmetric ones, our approach begins by computing a symmetry attention map that indicates where in the image is likely to contain symmetry. Given a image patch c containing $|\mathcal{Q}|$ edges, we create a histogram: $h_c(k) = \#\{\angle\mathcal{Q} \in \text{bin}(k)\}$ where $\text{bin}(k)$ denotes an orientation bin with $k \in [0, \pi]$ radians. We check for local symmetry per patch by selecting bins from opposing angles $h_o(\{k_1, \cdots, k_{o-1}\})$ and its symmetric counterpart $h'_o(\{k_O, \cdots, k_{o+1}\})$, via their χ^2 distance: $d_{\chi^2}(o) = \chi^2(h_o(\{k_1, \cdots, k_{o-1}\}), h'_o(\{k_O, \cdots, k_{o+1}\}))$ for the $o \in O$ orientation. Using the distance, we then compute the the symmetry *distance* per patch via: $d_{sym} = 1 - \text{argmin}_{o \in O}(d_{\chi^2}(o))/n$. We repeat this comparison over patches of different sizes and extract the maximum d_{sym} per patch over scales to yield the final symmetry attention map. To make the χ^2 comparisons fast in practice, we precompute the histograms over all O orientations via the method of Summed Area Tables (integral images).

1.2. Robust Symmetry Detection

Given the symmetry attention map, we apply a non-maxima suppression to obtain a set of fixation points $\mathcal{F} = \{f_1, \ldots, f_p\}$ that are associated with a potential symmetric object. To extract these regions accurately, we use the fixation-based segmentation method of Mishra et al. [3] to obtain a set of foreground segmentation $\mathcal{S} = \{s_1, \ldots, s_p\}$ that is used as input in this step. We want to obtain for each s_i with dimensions $|X| \times |Y|$ (width, height), the best symmetry axis $a_i = ((x_i, y_i), o_i), (x_i, y_i, o_i) \in (X, Y, O)$ parameterized by its centroid location and orientation. For efficiency, we show that by relaxing the geometric constraints of a real symmetry, we are able to decouple the search in 2D parameter space into two equivalent and fast 1D searches (orientation followed by translation). For each parameter, we estimate a probability distribution of edge orientations/counts and compare these distributions robustly via an efficient EMD-L1 [1] measure. This yields a final set of N axes $\mathcal{A}_s = \{a_1, \ldots, a_N\}$. We score each axis in $\mathcal{A}_s$ via a hough-voting scheme $L_s(\cdot)$ using symmetric SIFT keypoints of Loy and Eklundh [2] and obtain the final symmetry axis a_i that has the maximum score: $a_i = \text{argmax}\, L_s(\mathcal{A}_s)$.

2. Results

We demonstrate quantitatively the performance of our approach by comparing it with the state of the art symmetry detection approach of Loy and Eklundh [2] over several symmetry detection datasets with the same evaluation criterion suggested by [4]. In general, our approach tends to have the same precision as [2] at low-recalls but outperforms it at high-recalls. This improvement is due to the preselective symmetry attention stage that enables the second step of the approach to detect the strongest symmetries within the image. Additionally, as our method uses robust statistics that compares edges and orientations, it is also less sensitive to textureless regions which does not contain any discernible matching keypoints that [2] relies.

References

[1] H. Ling and K. Okada. An efficient earth mover's distance algorithm for robust histogram comparison. *PAMI*, 29(5):840–853, 2007.

[2] G. Loy and J.-O. Eklundh. Detecting symmetry and symmetric constellations of features. In *Computer Vision–ECCV 2006*, pages 508–521. Springer, 2006.

[3] A. Mishra, Y. Aloimonos, and C. Fermuller. Active segmentation for robotics. In *IROS 2009*, pages 3133–3139. IEEE, 2009.

[4] http://vision.cse.psu.edu/research/symComp13/index.shtml. Symmetry detection from real world images – a competition, 2013.