

Detecting Regions from Single Scale Edges

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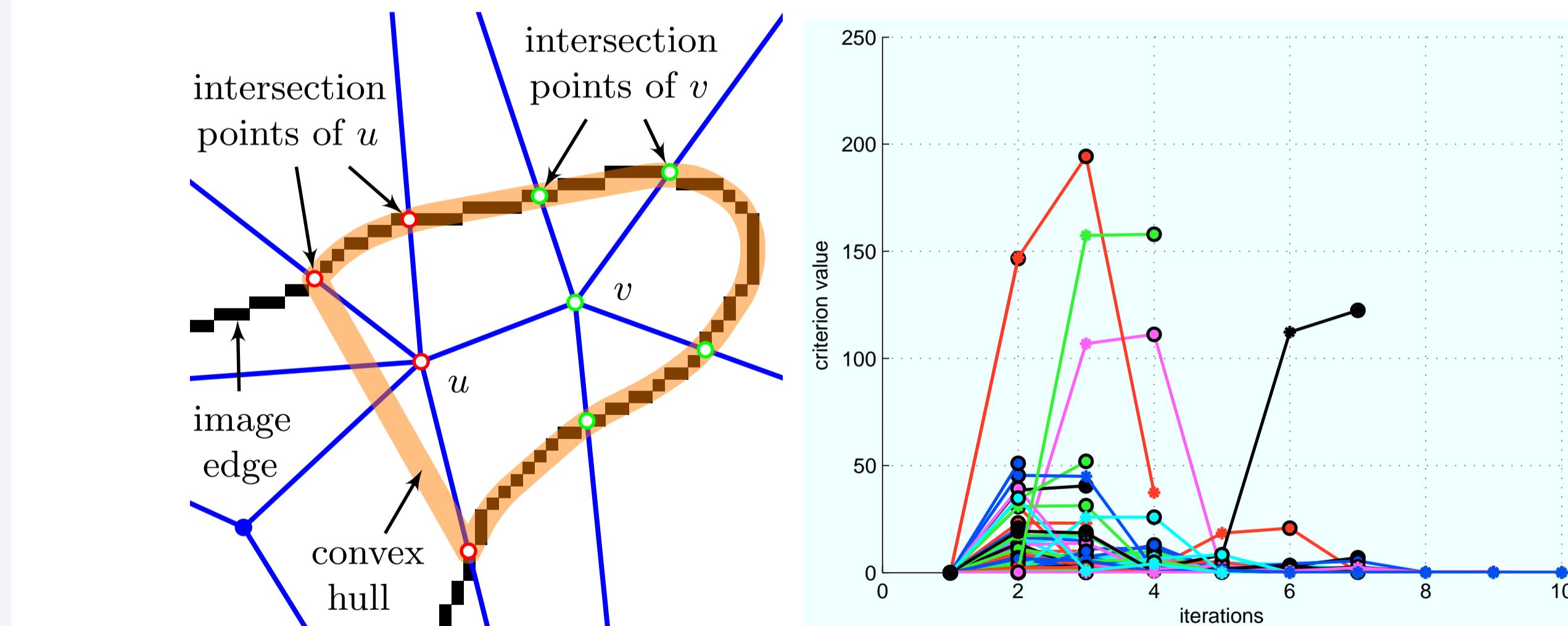
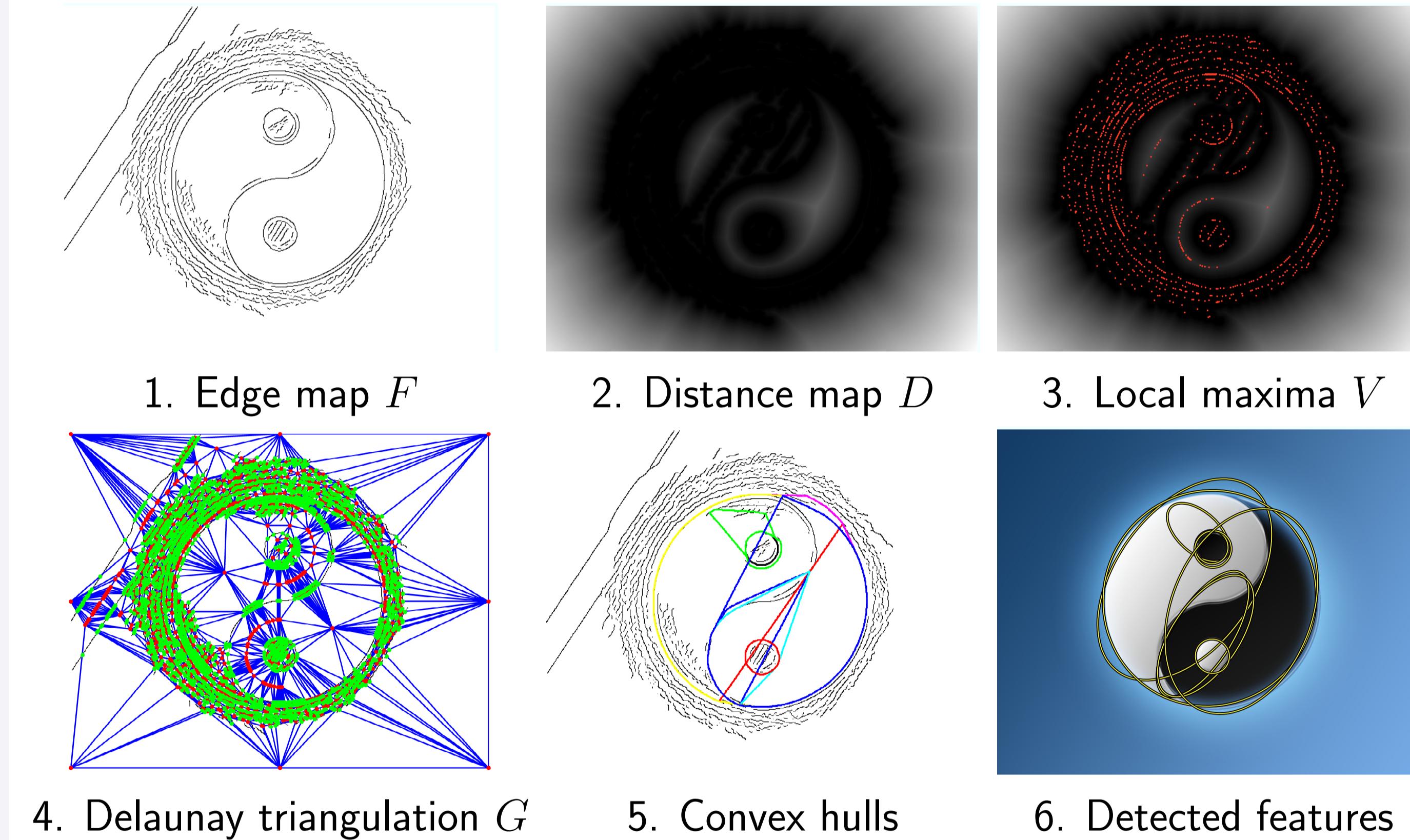


Motivation & Approach

Detect blob-like regions of arbitrary shape from single scale edges.

- ▶ Detect edges using relaxed thresholds
- ▶ Compute binary distance transform
- ▶ Use Delaunay triangulation of local maxima to capture underlying structure
- ▶ Use various criteria to detect salient features

The algorithm



- ▶ Adjacent vertices u, v correspond to neighboring local maxima of D .
- ▶ If there is no edge fragment lying between u, v , then u and v are likely to lie within the same region or along a ridge.
- ▶ If there is an edge fragment, then the gradient at the intersection point will determine at which iteration u and v will be merged, which would be equivalent to removing the fragment.
- ▶ A change in the component evolution indicates a significant change in the topology.
- ▶ The spatial extent of a region is computed from the edge fragments surrounding the vertices of the component.

Feature detection

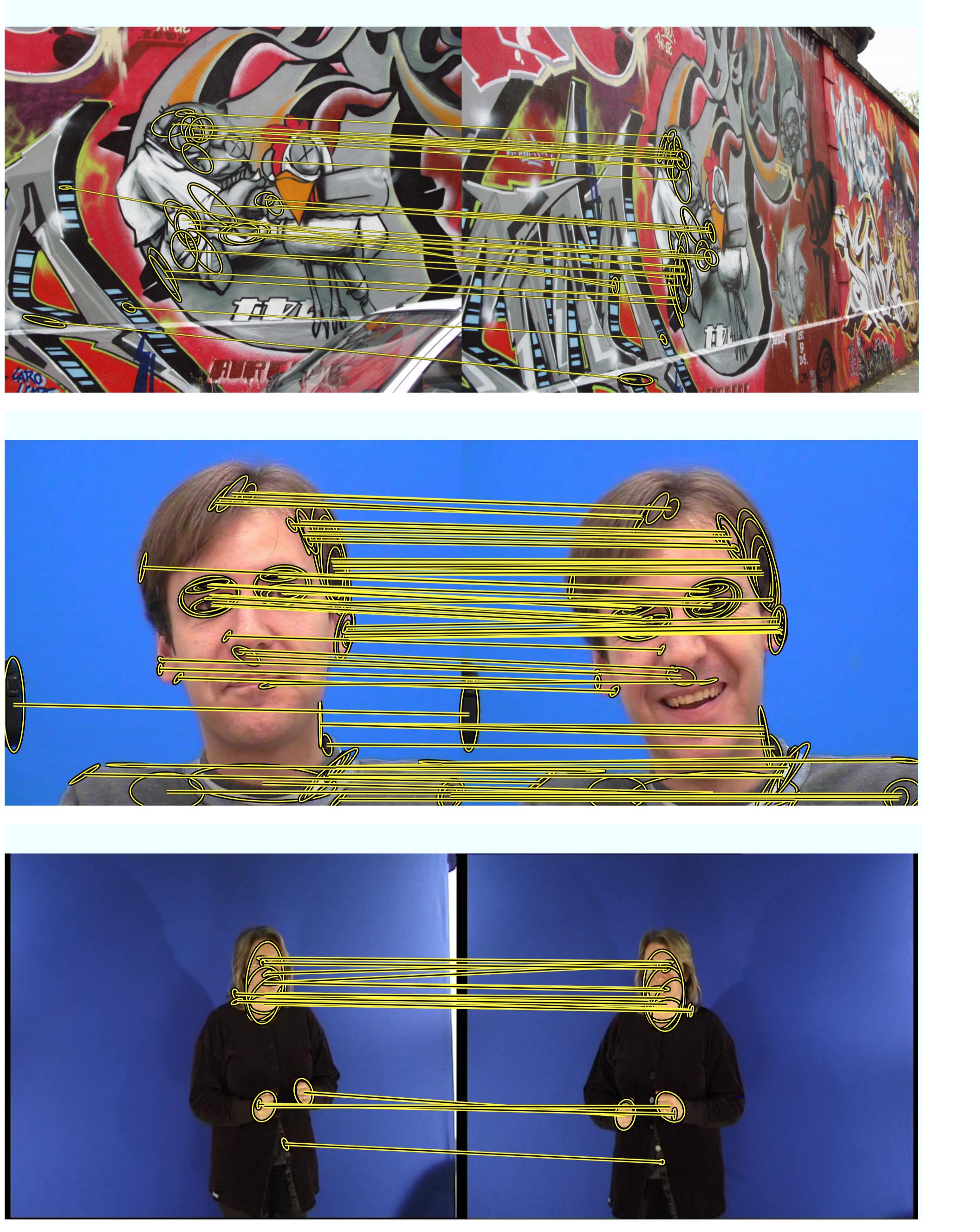
Algorithm 1 Distance Transform Detector

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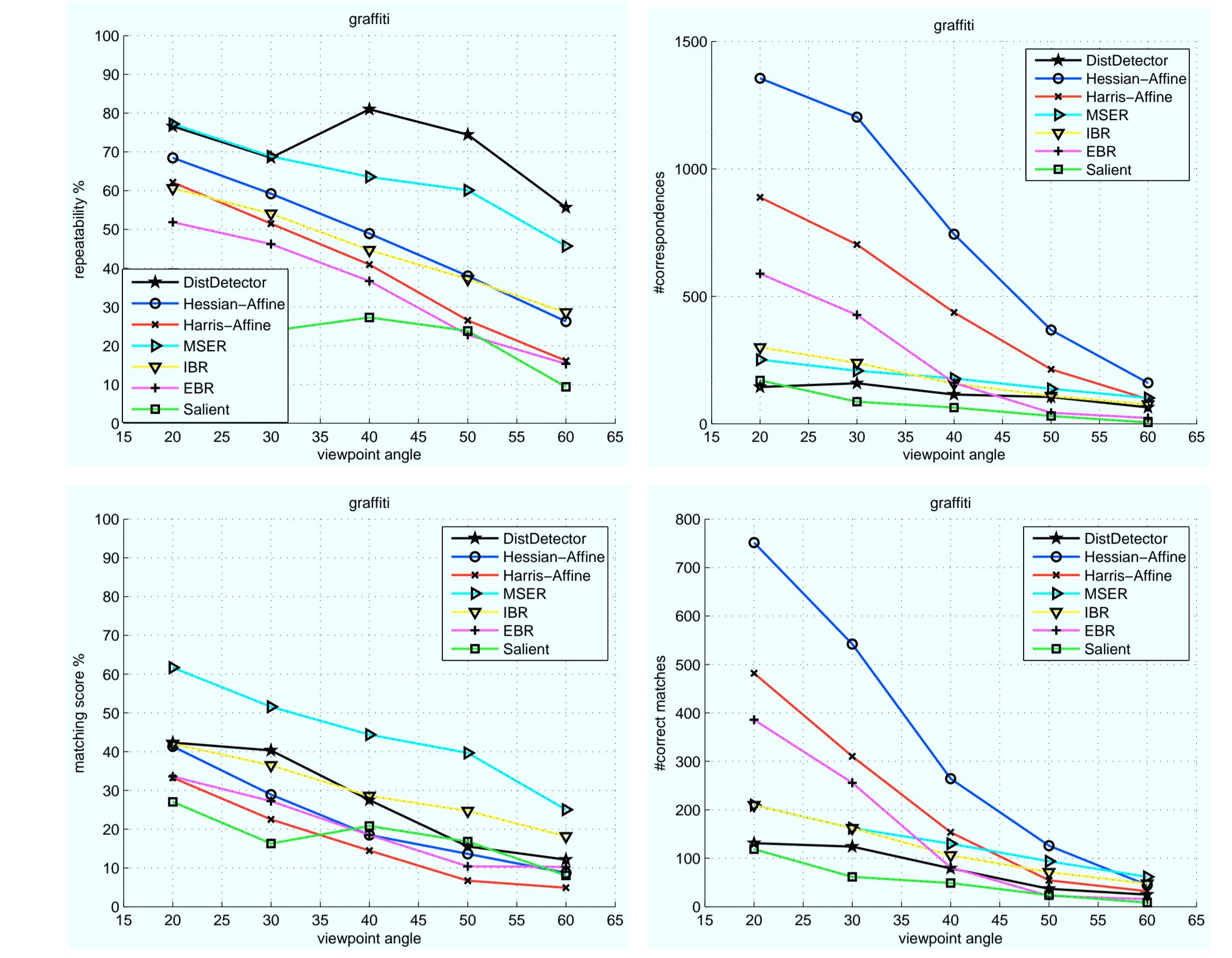
1: procedure DTD(image  $I$ , regions  $\mathcal{R}$ )
2:    $g \leftarrow \|\nabla G_\sigma * I\|$                                 ▷ gradient magnitude at scale  $\sigma$ 
3:    $F \leftarrow \text{EDGE MAP}(I)$ 
4:    $D \leftarrow \text{DISTANCE TRANSFORM}(F)$ 
5:    $V \leftarrow \text{LOCAL MAXIMA}(D)$ 
6:    $G \leftarrow \text{DELAUNAY TRIANGULATION}(V)$ 
7:    $\text{SORT}(E, w)$                                          ▷ sort edges by non-decreasing weight
8:    $t \leftarrow 0$ 
9:    $C \leftarrow V$ 
10:  for all  $e = (u, v) \in E(G)$  do
11:     $t \leftarrow t + 1$ 
12:    if  $w(e) \leq \min\{\rho(C^{t-1}(u)), \rho(C^{t-1}(v))\}$  then      ▷ check penalty
13:       $C^t \leftarrow \text{MERGE}(C^{t-1}(u), C^{t-1}(v))$           ▷ merge comp. of  $v$  into comp. of  $u$ 
14:       $\rho(C^t) \leftarrow w(e) + k/|C^t|$                          ▷ update penalty
15:    end if
16:  end for
17:   $\mathcal{R} \leftarrow \emptyset$ 
18:  for all  $C \in \mathcal{C}$  do
19:     $t \leftarrow \arg \max_s(\Delta\mu(C^s))$                       ▷ iteration where measure change is maximized
20:     $H \leftarrow \text{CONVEX HULL}(N(C^t))$                       ▷ neighborhood  $N(C)$  defined in (5)
21:     $R \leftarrow \text{FIT ELLIPSE}(H)$ 
22:     $\mathcal{R} \leftarrow \mathcal{R} \cup R$ 
23:  end for
24:  return  $\mathcal{R}$ 
25: end procedure

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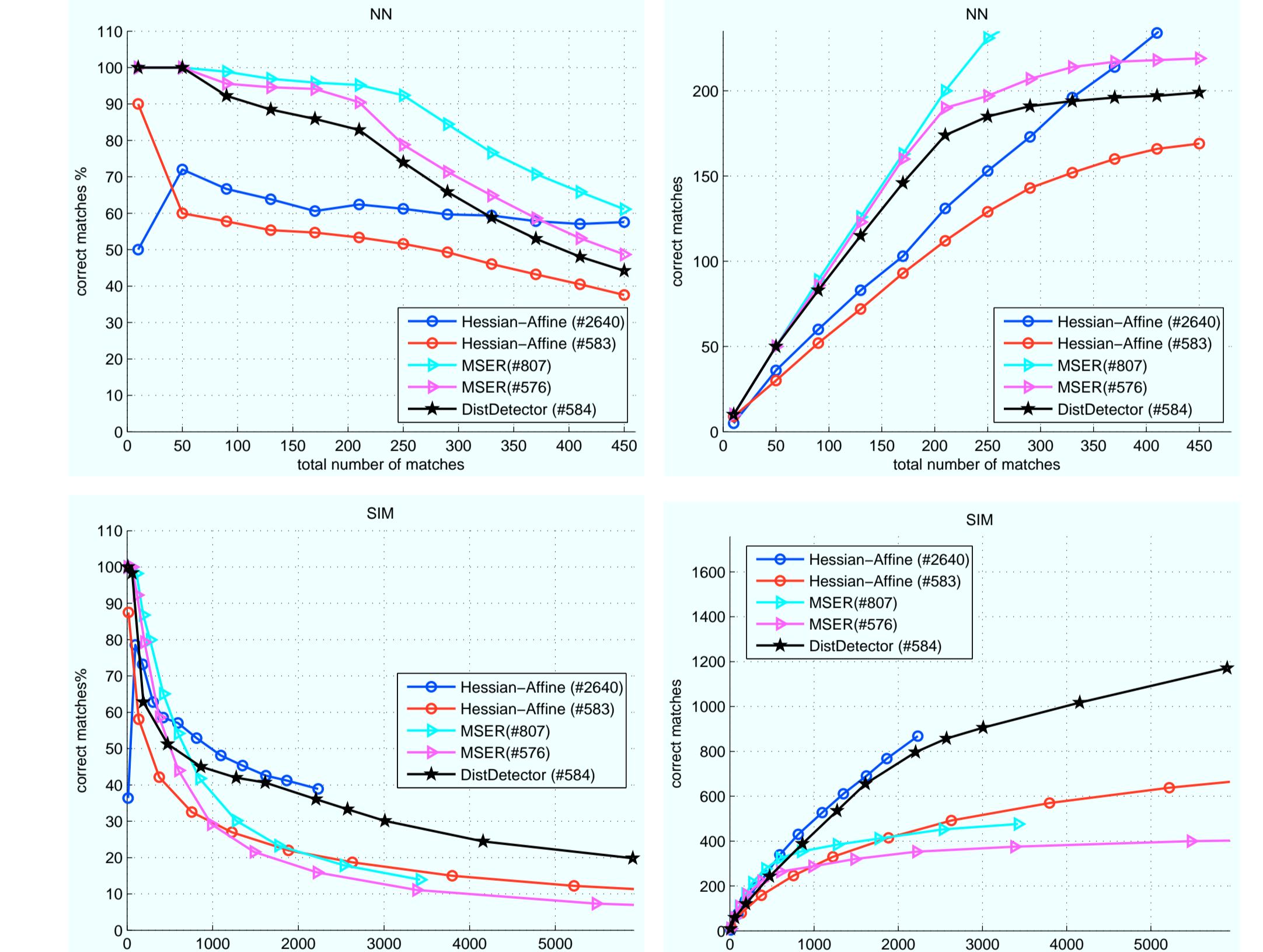
Results



Performance



Achieves a good trade-off between performance and number of features.



Performs quite well for a small number of total matches and ranks second after the MSER for the NN strategy. Outperforms both Hessian-Affine and MSER for approximately the same number of detected features under the similarity threshold strategy.

Conclusions

- ▶ A novel feature detector based on single-scale edges.
- ▶ Compares well to state-of-the-art detectors and produces a compact set of interpretable and repeatable features.
- ▶ Potential application to wide-baseline matching and feature detection in sequences involving human activity.
- ▶ Straightforward extension to spatiotemporal data.