Template Matching with Deformable Diversity Similarity

Itamar Talmi*    Roey Mechrez*    Lihi Zelnik-Manor

**Goal**
- Input: a template and a target image
- Output: the location of the template within the target image

**Challenges**
- Occlusions
- Complex deformations
- Out-of-plane rotation
- Background clutter

**Algorithm overview**
1. For each candidate window of the target image:
   1.1. Compute patch-based NNF
   1.2. Score the NNF using DDIS
2. Match = window with maximum score

**Similarity Definition**

\[
\text{DDIS} = \frac{1}{\#\text{patches}} \sum_{\text{window patches}} \frac{1}{r+1} \exp \left( 1 - \frac{\text{spatial distance}}{\text{template distance}} \right)
\]

\[
\text{spatial distance} = \| (x, y) - (\hat{x}, \hat{y}) \|
\]

\[
\text{template distance} = \# \text{window patches whose NN is } \hat{p}
\]

**Expected behavior – 1D Gaussian case**
Expected similarity between points sampled from two gaussian distributions:

\[
N(0,1) \quad \text{and} \quad N(\mu, \sigma), \ \mu, \sigma \in [0,1]
\]

**Comparison to BBS**
Don’t need bi-directional similarity (One Direction suffices)

**Summary**
1. NNF with high diversity and low deformation is a strong cue for similarity
2. Improve 5%-10% detection accuracy on the standard benchmark
3. Use one-direction search and dramatically improve runtime