Summary
- **Problem:** occlusion detection and handling for visual tracking.
- **Contribution:** explicit occlusion detection by a single classifier, which is learnt based on likelihoods.
- Simple and active occlusion detection.
- Not perfect, but improving tracking performance significantly.
- Universal classifier for occlusion detection.

**Learning Occlusion with Likelihoods for Visual Tracking**

**Tracking with Occlusion Reasoning**

- **Tracking with an occlusion mask**
  - Problem: occlusion detection and handling for visual tracking.
  - Contribution: explicit occlusion detection by a single classifier, which is learnt based on likelihoods.
  - Observation likelihoods only by unoccluded parts:
    \[ \ell(y_i) = \exp\left( -\frac{1}{2} \| \tilde{y}_i - \tilde{T} \tilde{a}_i \|^2 \right) \]
  - Tracking results:
    \[ t^* = \arg \max_y \ell(y_i), \quad y^* = y^*_i \]

**Occlusion reasoning by classification**

- Reconstruction of \( y^* \)
- Patch-likelihoods
- Occlusion mask update

**L_1 Minimization Tracking**

- **Particle filter + sparse representation** [1]
  - Dictionary = target templates + trivial templates
  - Observation based on sparse representation
    \[ y = [T \ 1 - T] \cdot \begin{bmatrix} e_{x_1} \\ e_{x_2} \end{bmatrix} = Bc, \text{subject to} \ c \geq 0. \]
  - Observation likelihoods of samples:
    \[ \ell(y_i) = \exp\left( -\frac{1}{2} \| y_i - T a_i \|^2 \right) \]
  - Training dataset
    \[ (t_{ij}, h^2_{ij}(y)) \]
  - Learning a linear SVM in off-line

**Experiments**

- **Simulation**
  - \( L_1 \) minimization tracking + groundtruth
  - Decent occlusion reasoning improved tracking performance significantly.

**Tracking with Full Occlusion**

- **Tracking results:** L1TOR (Ours) L1T [1] IVT [2] groundtruth

**Our occlusion reasoning + IVT [2]**

The quantitative comparisons of 4 occlusion reasoning algorithms over time:
- ORR – random guessing
- ORM – one cell likelihood
- ORC – more conservative ORM