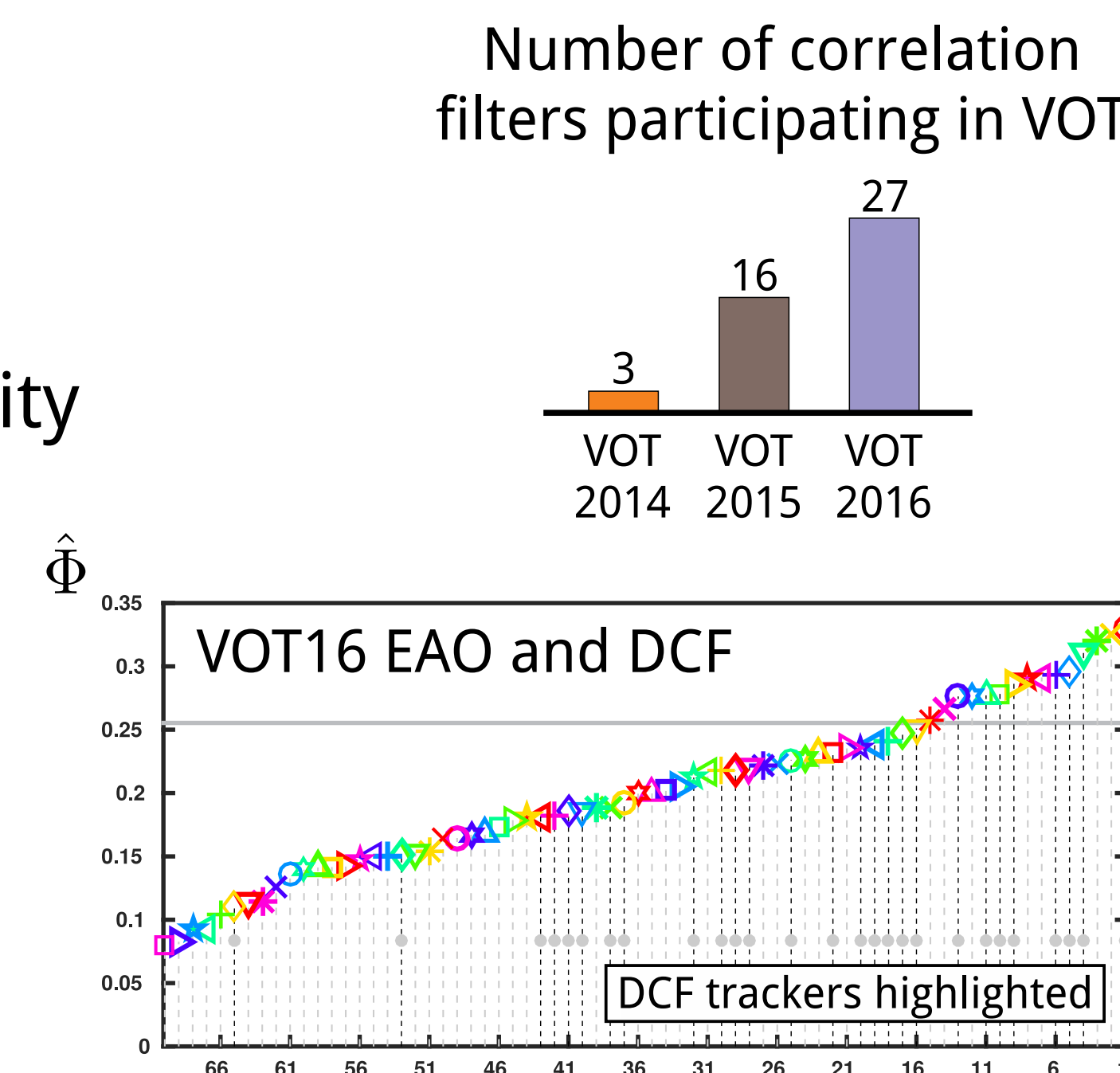
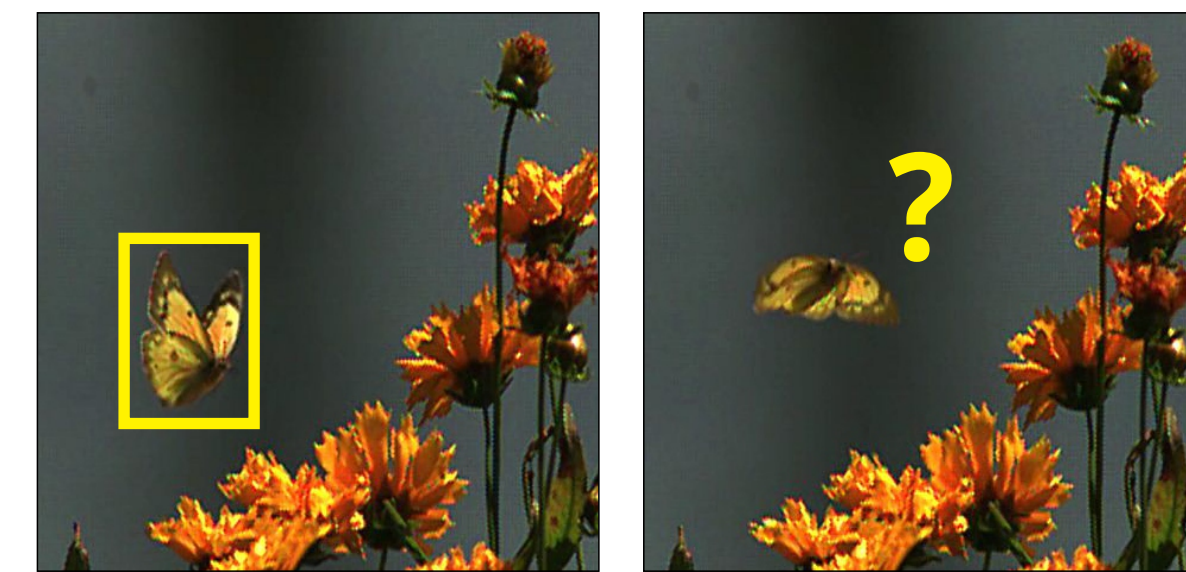
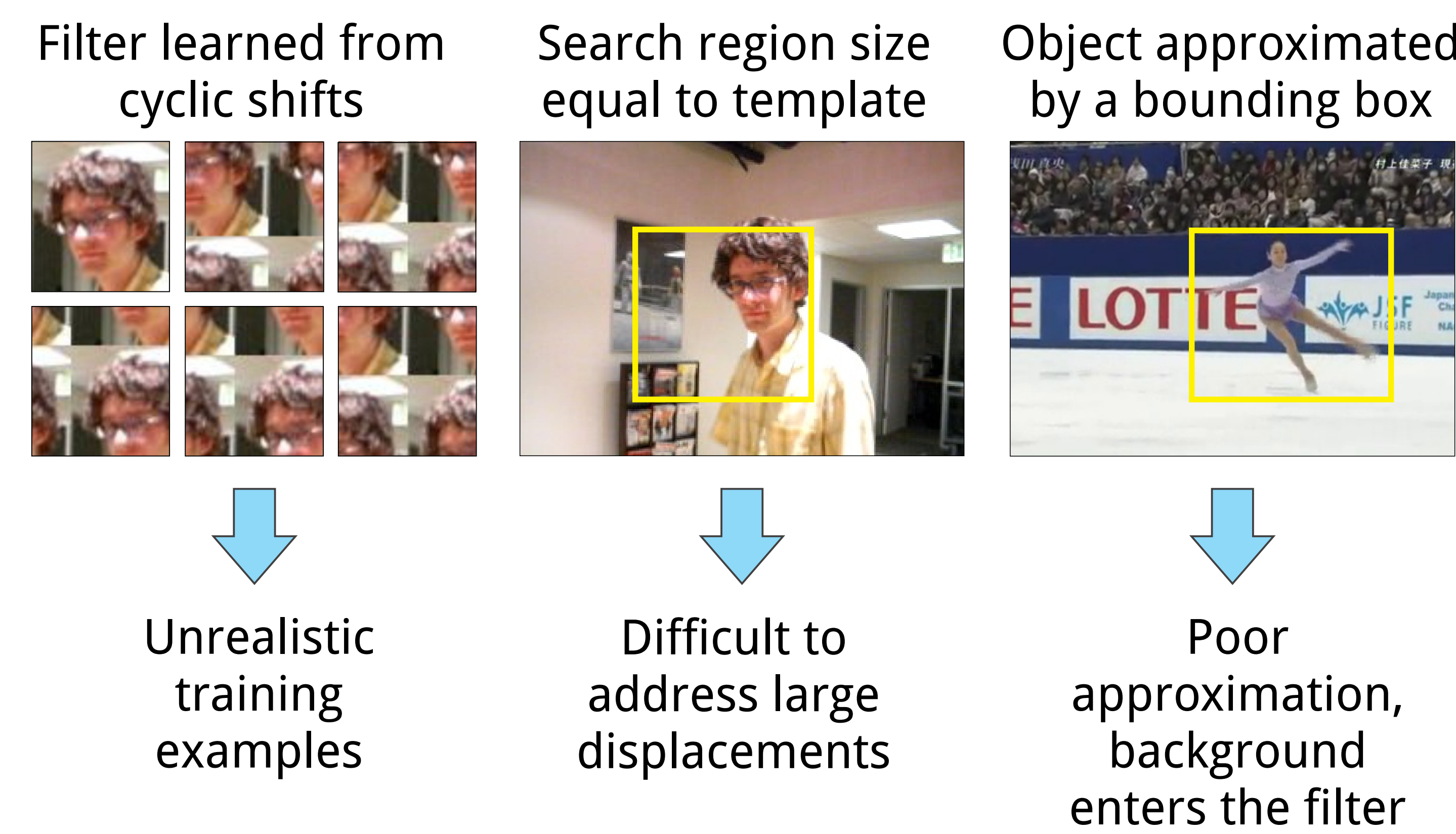


1. Short-term Visual Object Tracking

- Frame 1: target bbox specified
- Frame t+1: localize the target and update the model
- Correlation filters gaining popularity



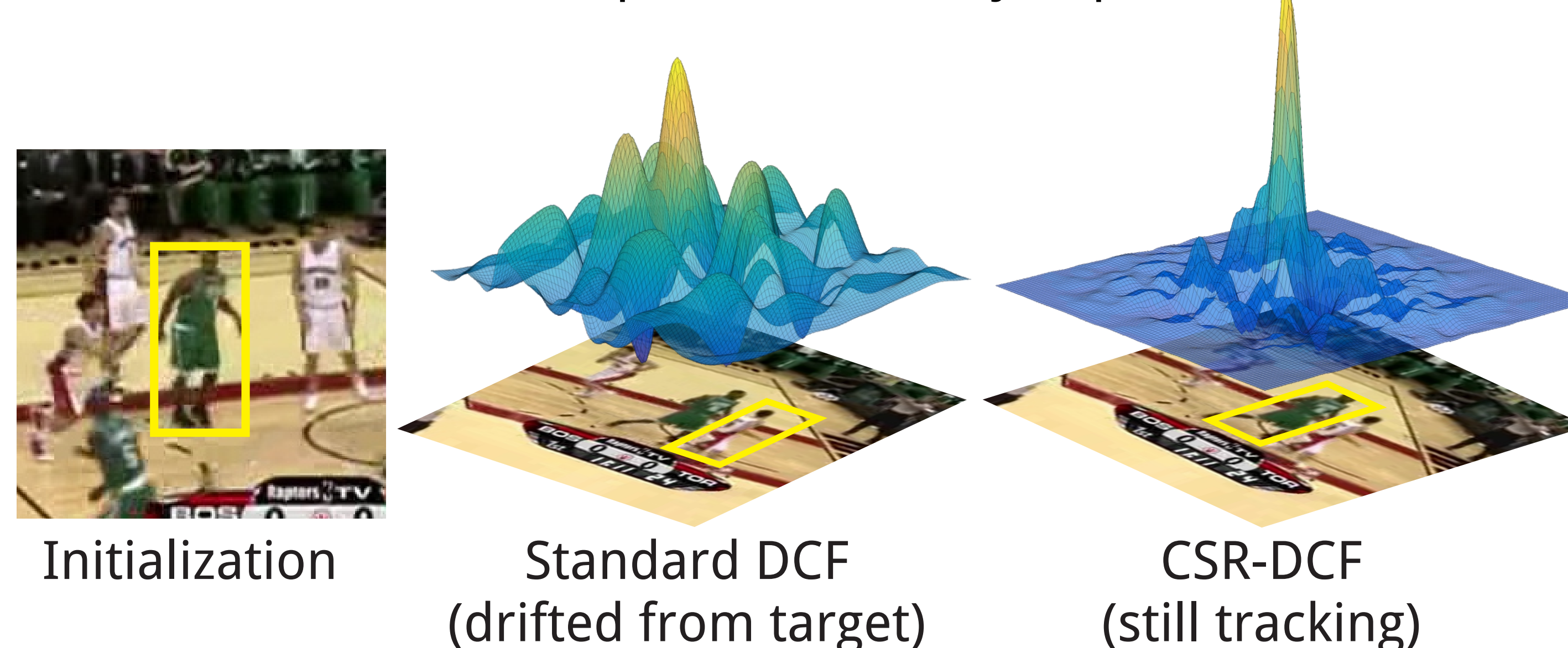
2. Correlation Filter Drawbacks: Search Region



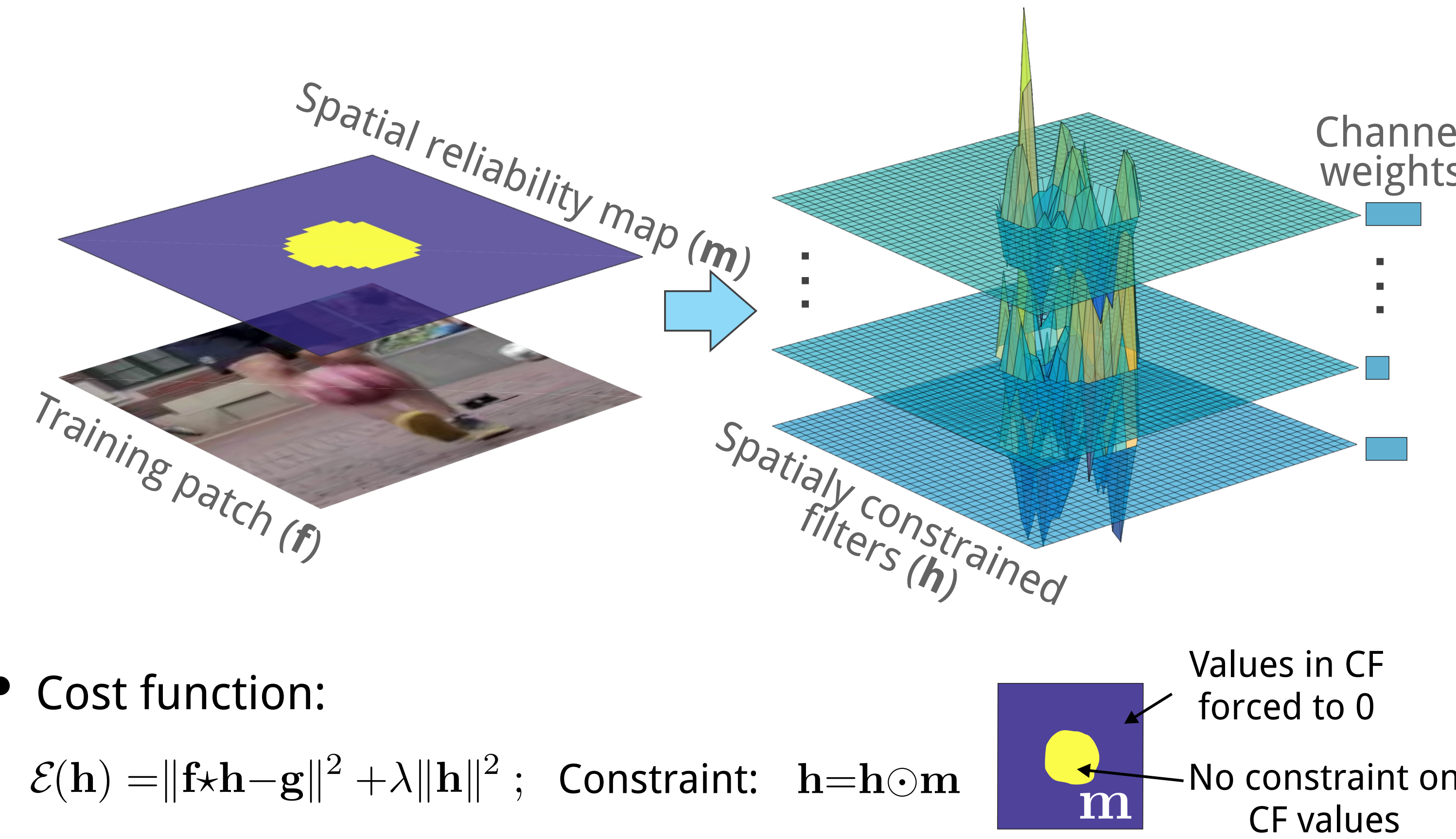
3. Contributions and Highlights

- Filter learning constrained by the spatial reliability map
- Feature combination according to discriminative power
- Highlights
- Principled way to **learn a DCF with distractors** and context
- Search range** of DCFs naturally **increased**
- Matlab implementation **runs realtime**
- Applicable to most existing DCF** trackers to reduce impact of the background in the filter

Correlation response drastically improves:



4. Filter Learning Step



- Cost function:

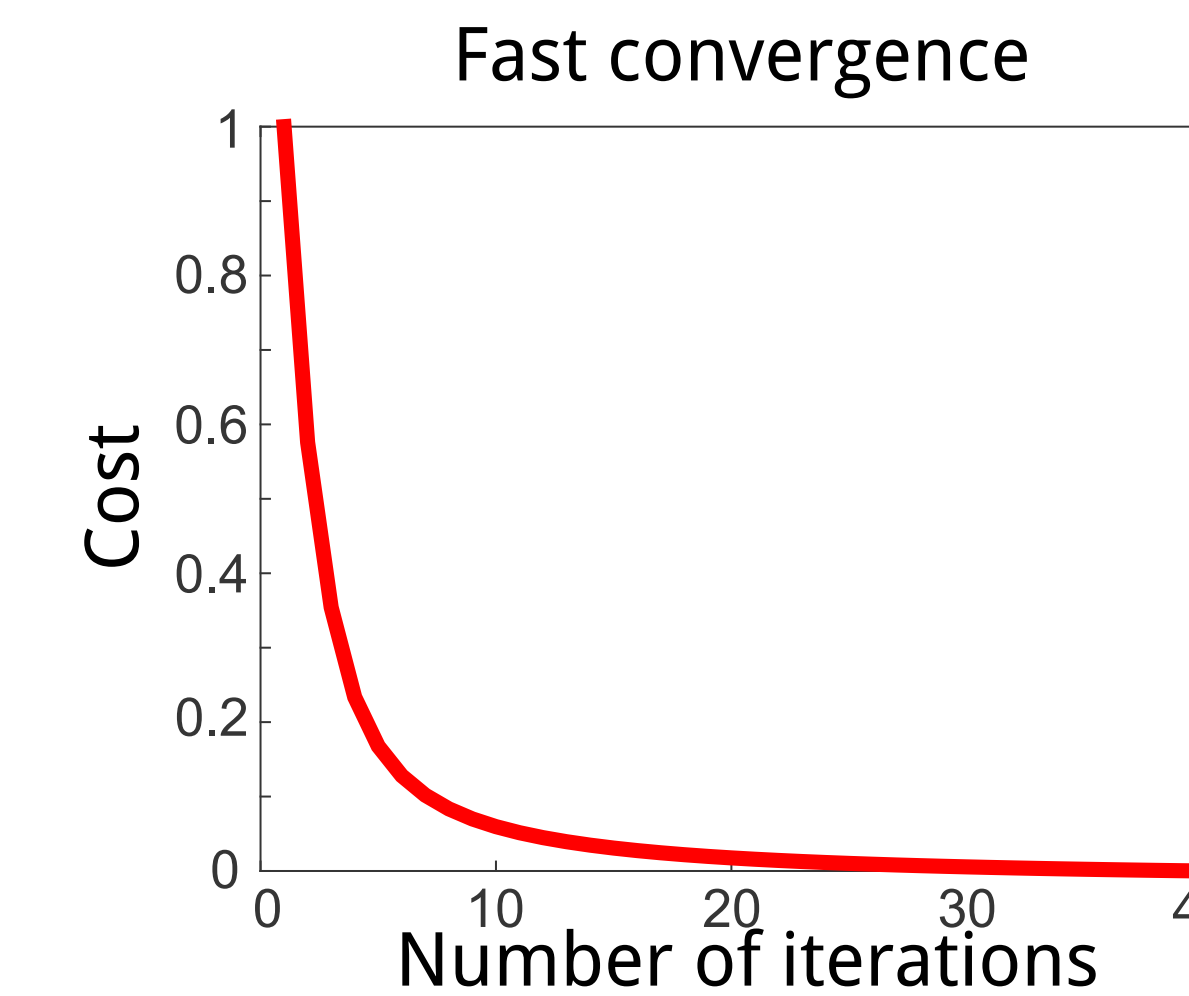
$$\mathcal{E}(\mathbf{h}) = \|\mathbf{f} \star \mathbf{h} - \mathbf{g}\|^2 + \lambda \|\mathbf{h}\|^2$$
; Constraint: $\mathbf{h} = \mathbf{h} \odot \mathbf{m}$
- Augmented Lagrangian:

$$\mathcal{L}(\mathbf{h}_c, \mathbf{h}, \mathbf{l}) = \|\mathbf{f} \star \mathbf{h}_c - \mathbf{g}\|^2 + \frac{1}{2} \lambda \|\mathbf{h} \odot \mathbf{m}\|^2 + \mathbf{l}^T (\mathbf{h}_c - \mathbf{h} \odot \mathbf{m}) + \frac{1}{2} \mu \|\mathbf{h}_c - \mathbf{h} \odot \mathbf{m}\|^2$$
- Solution (ADMM [3] equations):

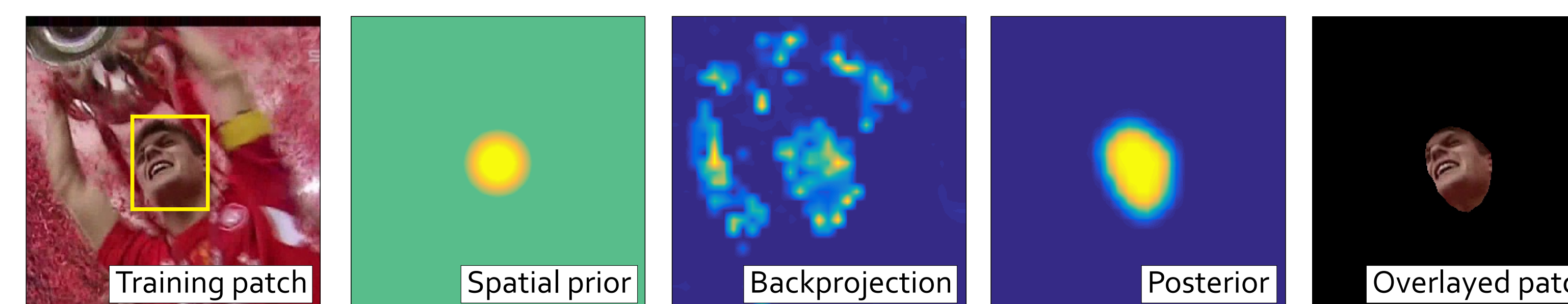
$$\hat{\mathbf{h}}_c^{i+1} = \frac{\hat{\mathbf{f}} \odot \hat{\mathbf{g}} + \mu (\hat{\mathbf{h}}^i \odot \mathbf{m}) - \hat{\mathbf{l}}^i}{\hat{\mathbf{f}} \odot \hat{\mathbf{f}} + \mu}$$

$$\mathbf{h}^{i+1} = \mathbf{m} \odot \frac{\mathcal{F}^{-1}(\hat{\mathbf{l}}^i + \mu \hat{\mathbf{h}}_c^{i+1})}{\frac{\lambda}{2D} + \mu}$$

$$\hat{\mathbf{l}}^{i+1} = \hat{\mathbf{l}}^i + \mu (\hat{\mathbf{h}}_c^{i+1} - \mathbf{h}^{i+1})$$



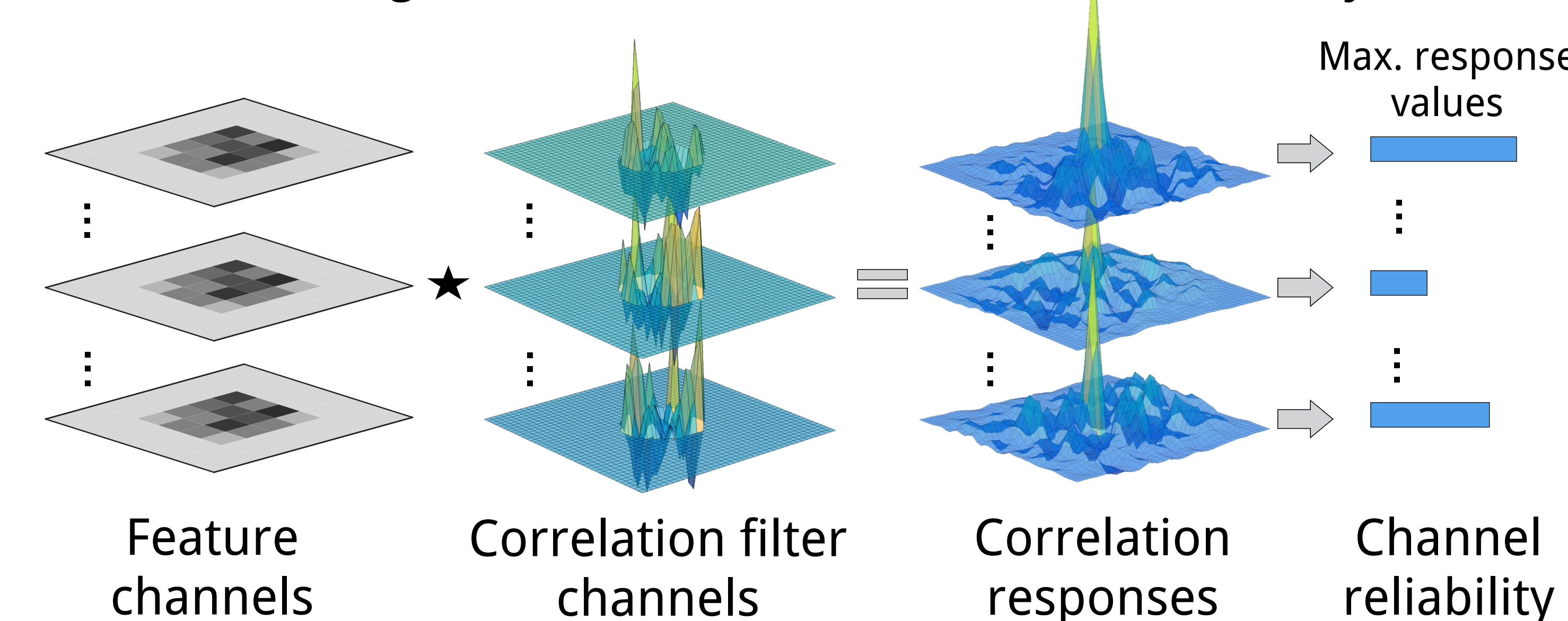
5. Spatial Reliability Map Estimation



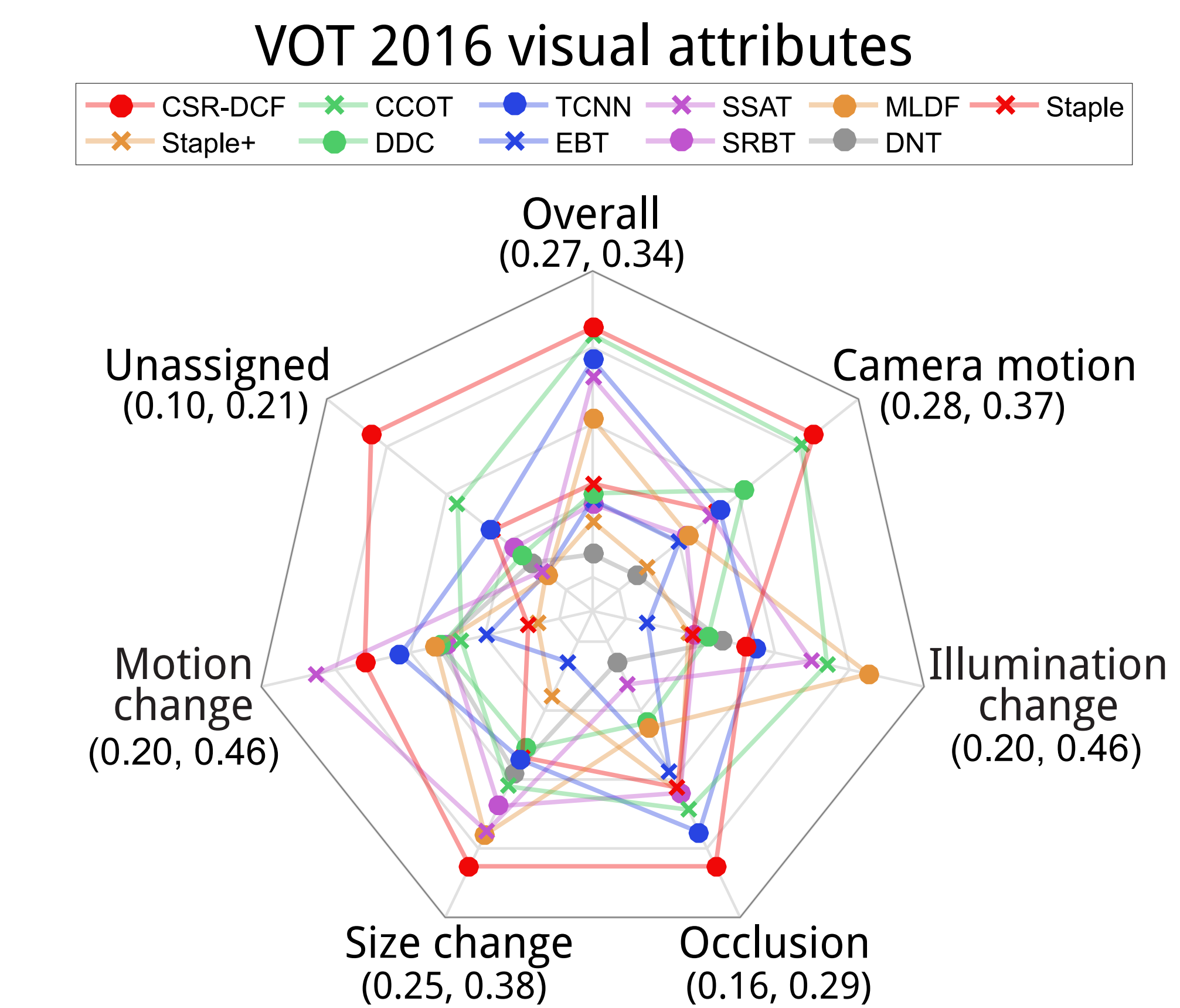
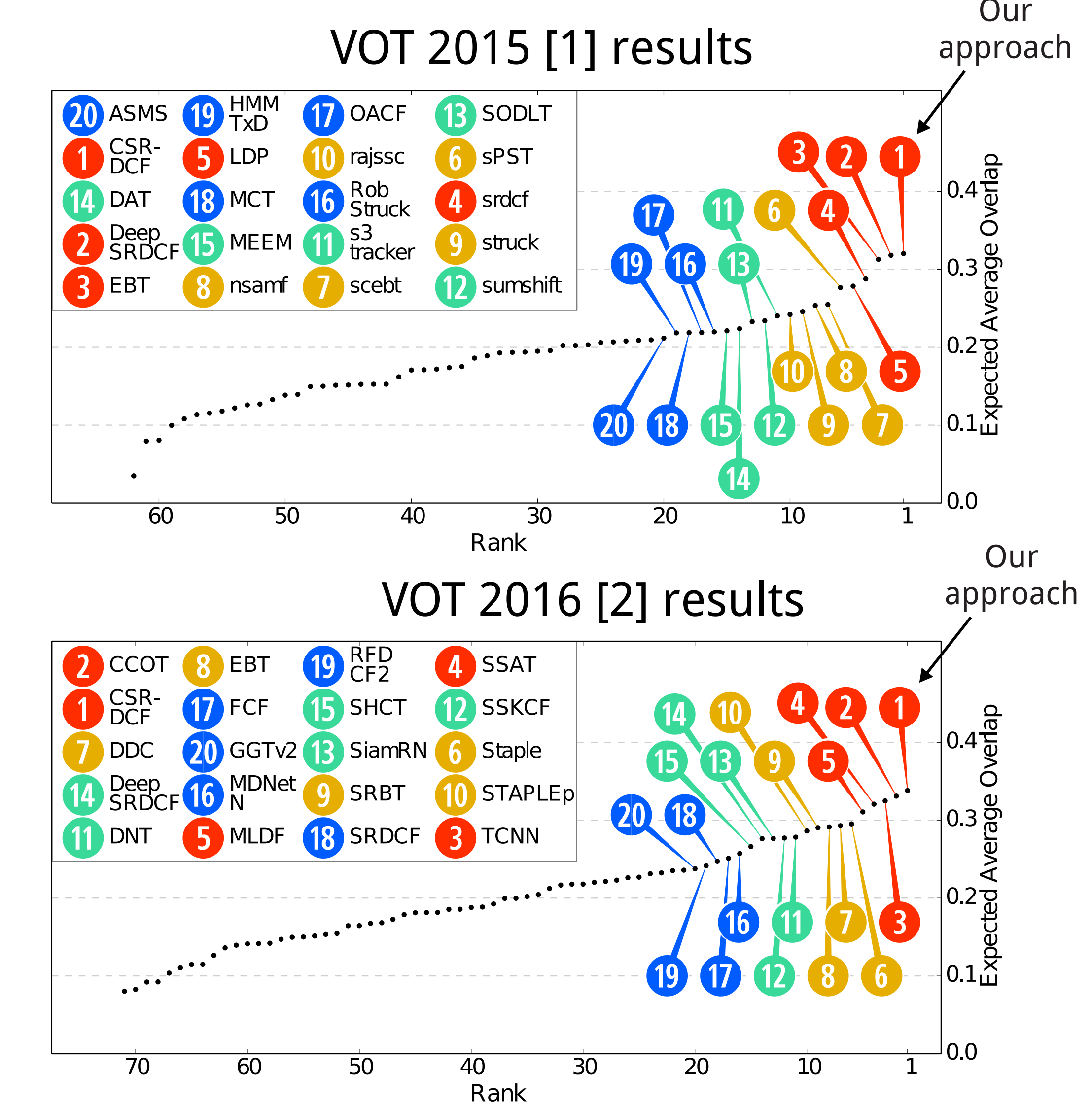
Fast MRF color segmentation [4] + weak spatial prior = object posterior mask

6. Channel Reliability Weights Estimation

Per-channel weights calculated to reflect channel reliability



7. Experiments



8. Conclusions

- Top performance on VOT15 [1] and VOT16 [2]
- Balanced performance over all visual attributes
- Outperforms other [5,6] distractor learners
- Features: HoG + Colornames, no CNN
- Speed: 13 fps, optimized: 20fps

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