MULTI-TARGET TRACKING USING OCCLUSION GEODESICS

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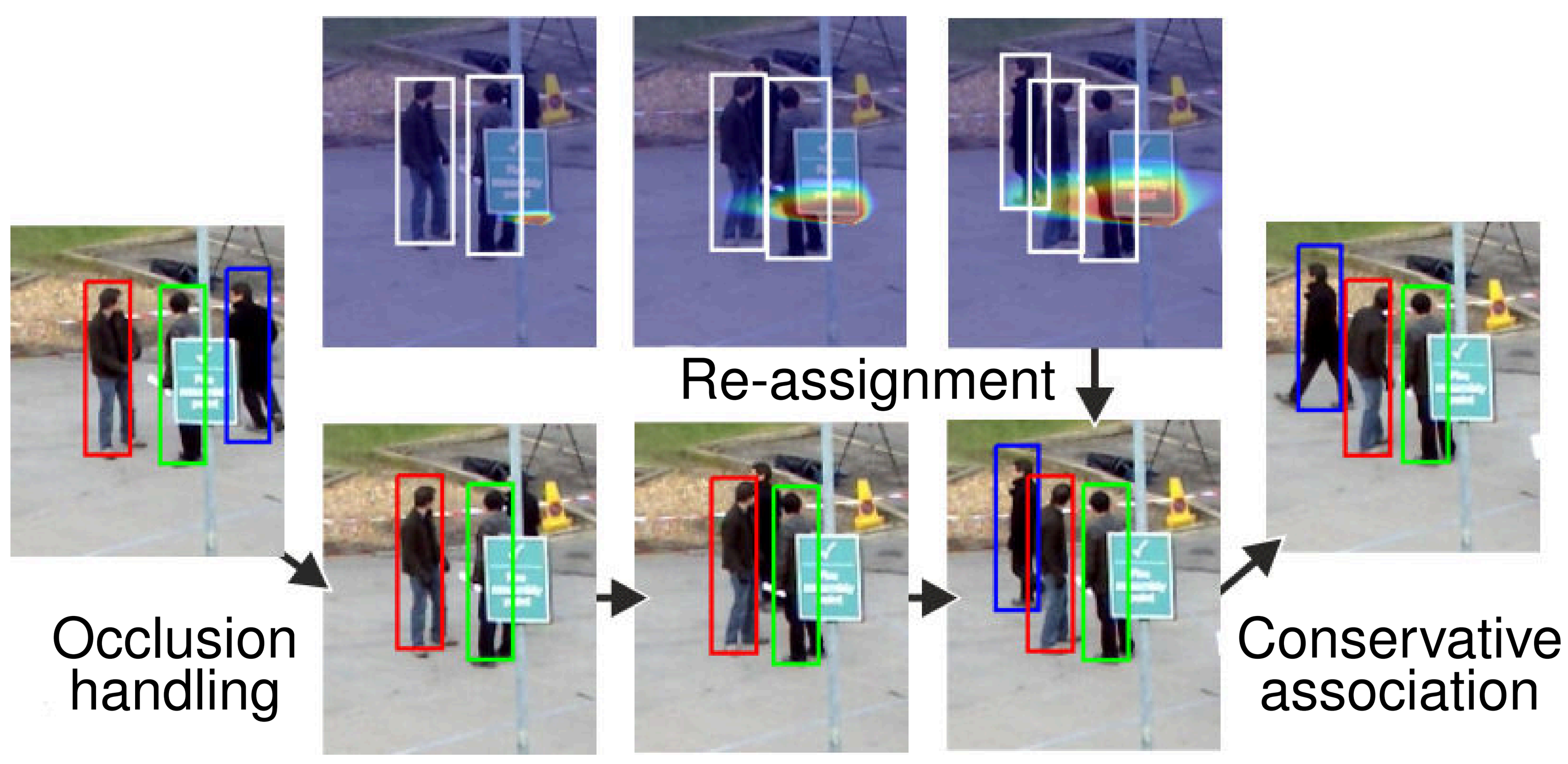
Abstract

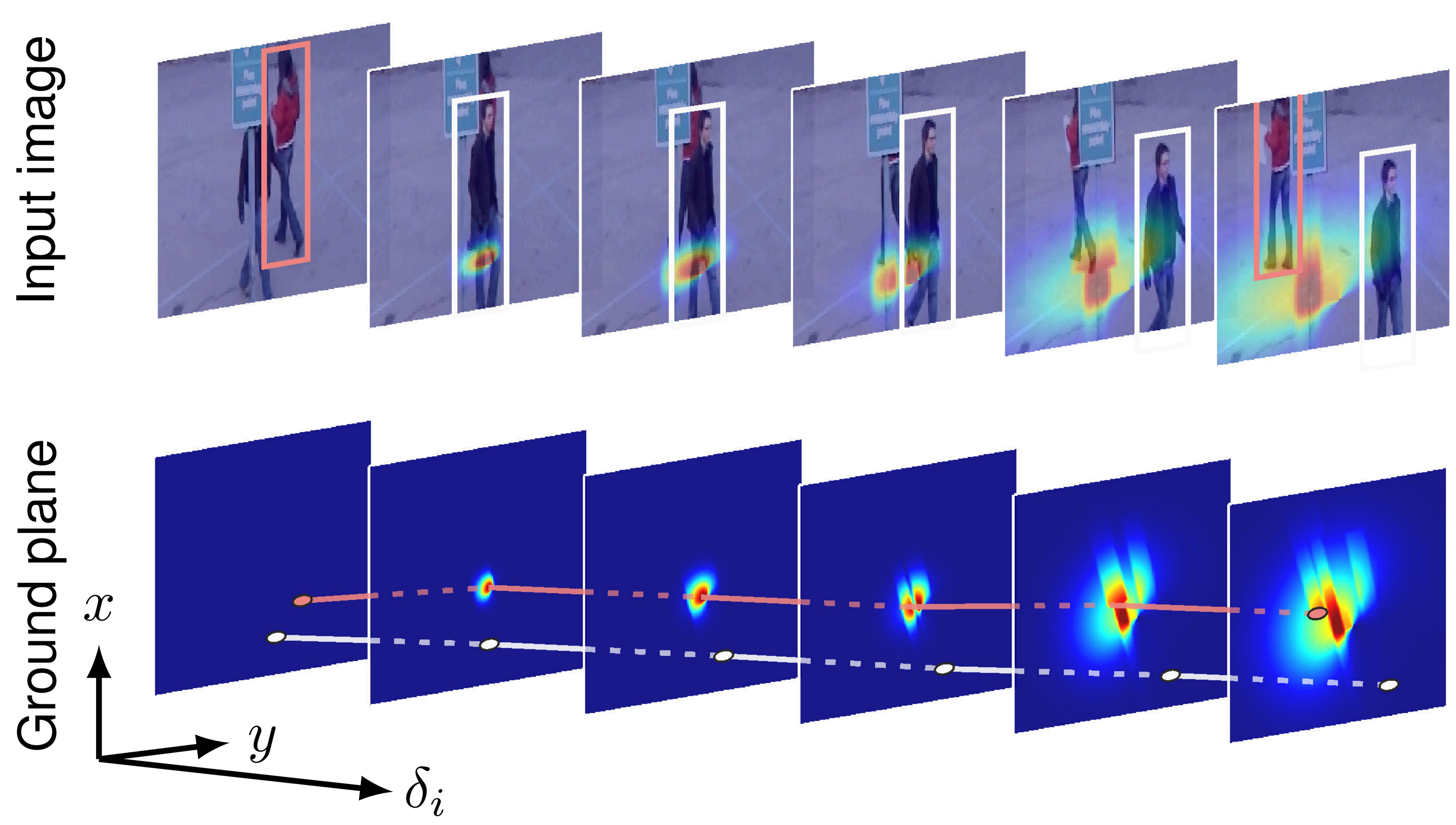
Robust multi-target tracking-by-detection requires the correct assignment of noisy detections to object trajectories. We address this problem by exploiting the spatio-temporal evolution of occlusion regions, detector reliability, and target motion prediction to handle missed detections. In combination with a conservative association scheme for visible objects, this allows for real-time online tracking of multiple targets from a single static camera.

Overview



- Focus on re-assignment of missed/occluded targets once they are re-detected.
- Exploit only geometric cues to weight physically plausible paths for re-assignment using Hungarian algorithm.

Occlusion Geodesics



- Compute instance-specific confidence maps φ_i for missed targets at each time step.
- Check each re-assignment candidate position for a valid and plausible path to the last known object position $\hat{\mathbf{x}}_i$.
- Efficiently compute cost $\Psi_i^{(\delta_i)}$ of a valid path to a candidate location $\mathbf{x} = (x, y)^\top$ via recursive accumulation:

$$\Psi_i^{(\delta_i)}(\mathbf{x}) = 1 - \varphi_i^{(\delta_i)}(\mathbf{x}) + \inf_{\mathbf{z}} \Psi_i^{(\delta_i - 1)}(\mathbf{x} + \mathbf{z}), \quad \|\mathbf{z}\| \leq v_{\text{avg}}$$

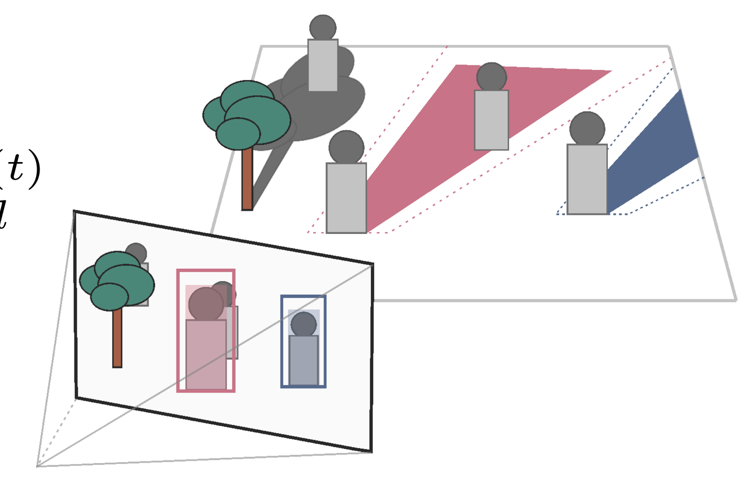
Confidence Scores

- Confidence score $\varphi_i^{(\delta_i)}$ indicating the presence of object i at location $\mathbf{x} \in \mathbb{R}^2$ after being missed for δ_i time steps:

$$\varphi_i^{(\delta_i)}(\mathbf{x}) = c_{o,i}^{(\delta_i)}(\mathbf{x})\, c_{p,i}^{(\delta_i)}(\mathbf{x})\, c_{d,i}^{(\delta_i)}(\mathbf{x})$$

- Occlusion information and detector reliability $\beta \in [0, 1]$:

$$c_{o,i}^{(\delta_i)}(\mathbf{x}) = \begin{cases} 1 & \text{if } \mathbf{x} \in \mathcal{P}_s \cup \mathcal{P}_d^{(t)} \\ 1 - \beta^{\delta_i} & \text{otherwise} \end{cases}$$



- Physically plausible distance:

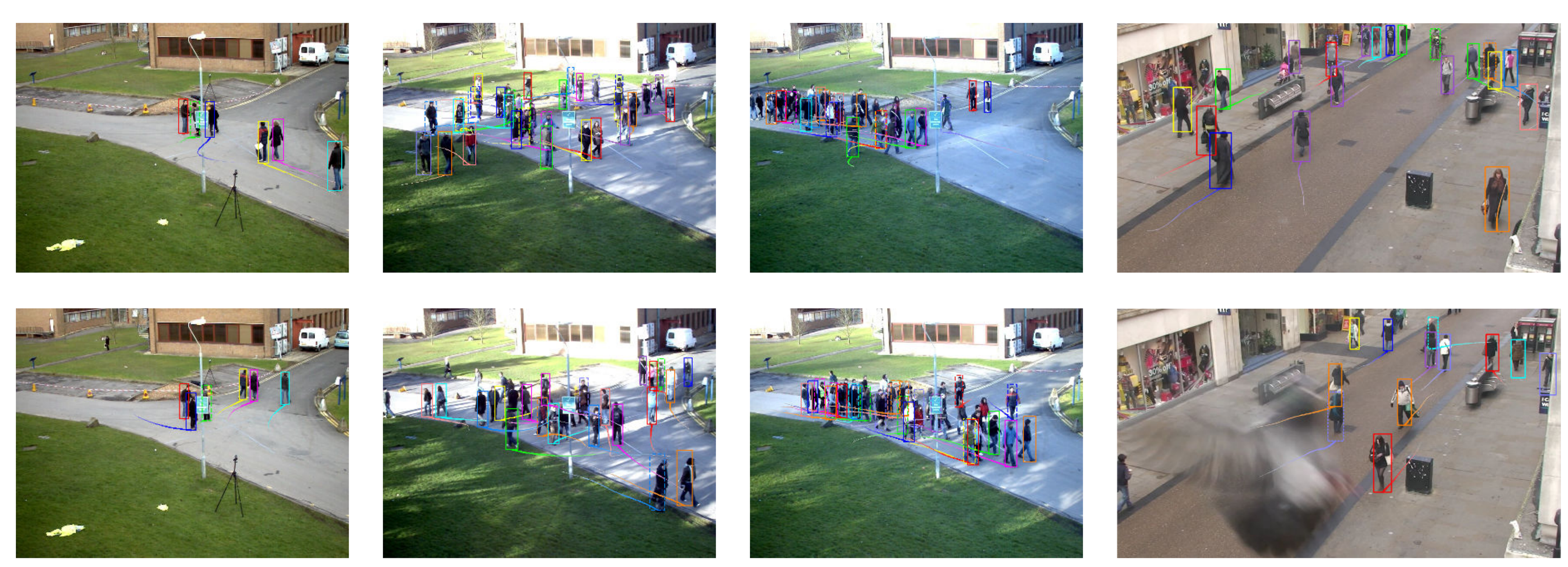
$$c_{p,i}^{(\delta_i)}(\mathbf{x}) = \exp\left(- \frac{\|\mathbf{x} - \hat{\mathbf{x}}_i\|^2}{2\sigma_p^2 \delta_i^2 \max\left(\|\hat{\mathbf{d}}_i\|, v_{\text{avg}}\right)^2} \right)$$

- Inertia term based on predicted motion direction $\hat{\mathbf{d}}_i$ (IQM):

$$c_{d,i}^{(\delta_i)}(\mathbf{x}) = \exp\left(- \frac{\left(\left\langle \hat{\mathbf{d}}_i, \mathbf{d}_j \right\rangle - \|\hat{\mathbf{d}}_i\|\|\mathbf{d}_j\|\right)^2}{2\sigma_d^2 \|\hat{\mathbf{d}}_i\|^2 \|\mathbf{d}_j\|^2} \right)$$

Evaluation

- Experiments on standard benchmark datasets [1, 2] (See our CVPR'14 paper [3] for detailed results).
- State-of-the-art performance compared to online and offline approaches.
- Fully online and real-time capable (~ 11 fps, MATLAB).



PETS'09 S2.L1 | PETS'09 S2.L2 | PETS'09 S2.L3 | Town Centre

References & Acknowledgments

[1] B. Benfold and I. Reid, Stable Multi-Target Tracking in Real-Time Surveillance Video. In *Proc. CVPR*, 2011.

[2] J. Ferryman and A. Shahrokni, PETS2009: Dataset and Challenge. In *Proc. Winter-PETS*, 2009.

[3] H. Possegger, T. Mauthner, P. M. Roth, and H. Bischof, Occlusion Geodesics for Online Multi-Object Tracking. In *Proc. CVPR*, 2014.

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Implementation, paper, and supplemental material publicly available (scan QR code).