GM-PHD Filter Based Online Multiple Human Tracking using Deep Discriminative Correlation Matching

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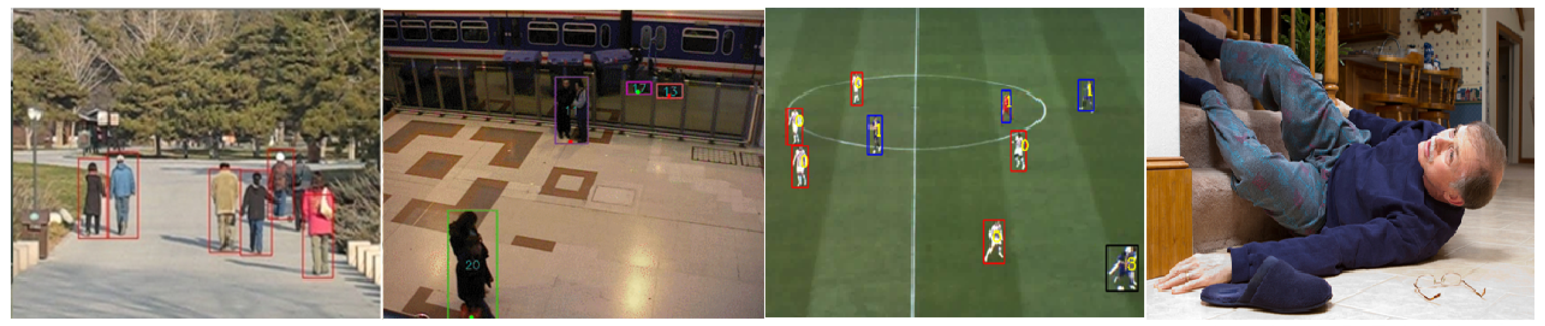
1. Introduction



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- **Challenges:**
  Variable number of targets, Targets moving in close proximity, False alarms, and Long-term occlusions.
- **Our contributions:**
  - Develop individual target-specific classifiers built on the CNN-based discriminative correlation filter (DCF) to discriminate the desired targets from noisy background and other appearing targets.
  - Present a hybrid likelihood function to address the target ambiguity.

2. Baseline Method

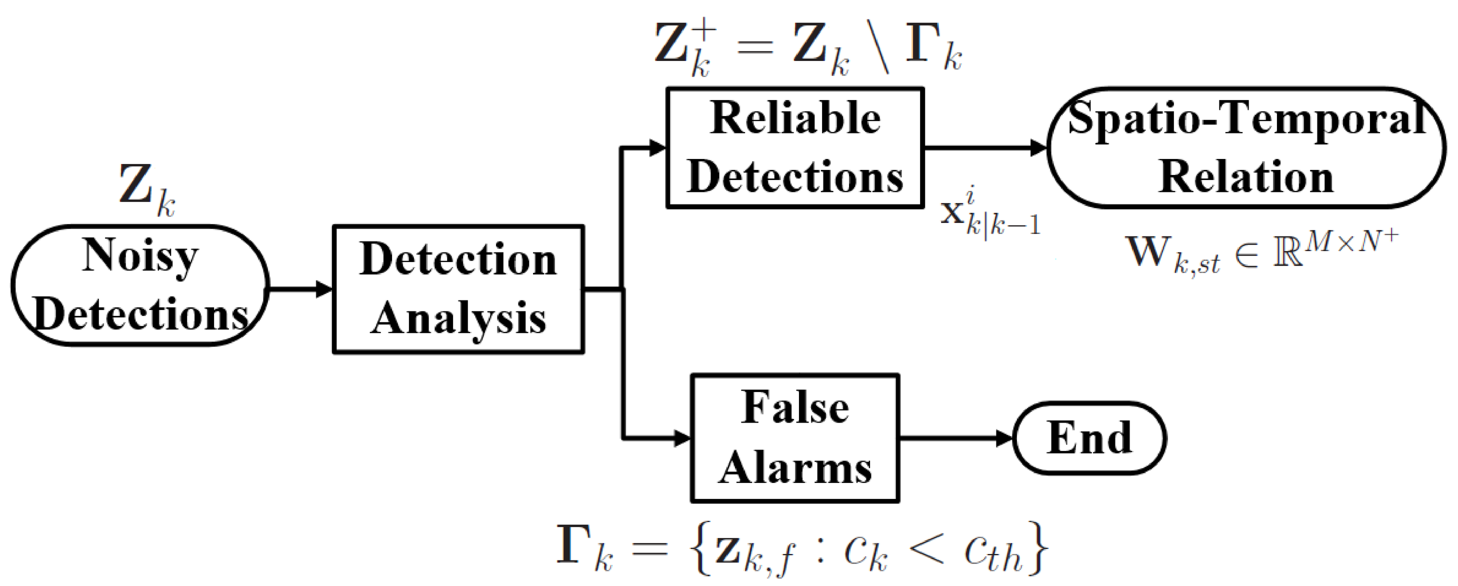
- **The Gaussian Mixture PHD Filter**
  The PHD filter with the GM implementation [1] is much more efficient than its SMC counterpart. The posterior PHD intensity function can be represented by a sum of weighted Gaussian components that are propagated analytically in time.
  - Prediction:

$$\nu_{k|k-1}(\mathbf{x}) = \sum_{j=1}^{J_{k|k-1}} w^j_{k|k-1}\mathcal{N}(\mathbf{x}; \mathbf{m}^j_{k|k-1}, \mathbf{P}^j_{k|k-1}) \quad (1)$$

  - Update:

$$\nu_k(\mathbf{x}) = p_M \nu_{k|k-1}(\mathbf{x}) + \sum_{\mathbf{z}\in\mathbf{Z}^+_k}\sum_{j=1}^{J_{k|k-1}} w^j_k(\mathbf{z})\mathcal{N}(\mathbf{x}; \mathbf{m}^j_{k|k}(\mathbf{z}), \mathbf{P}^j_{k|k}) \quad (2)$$

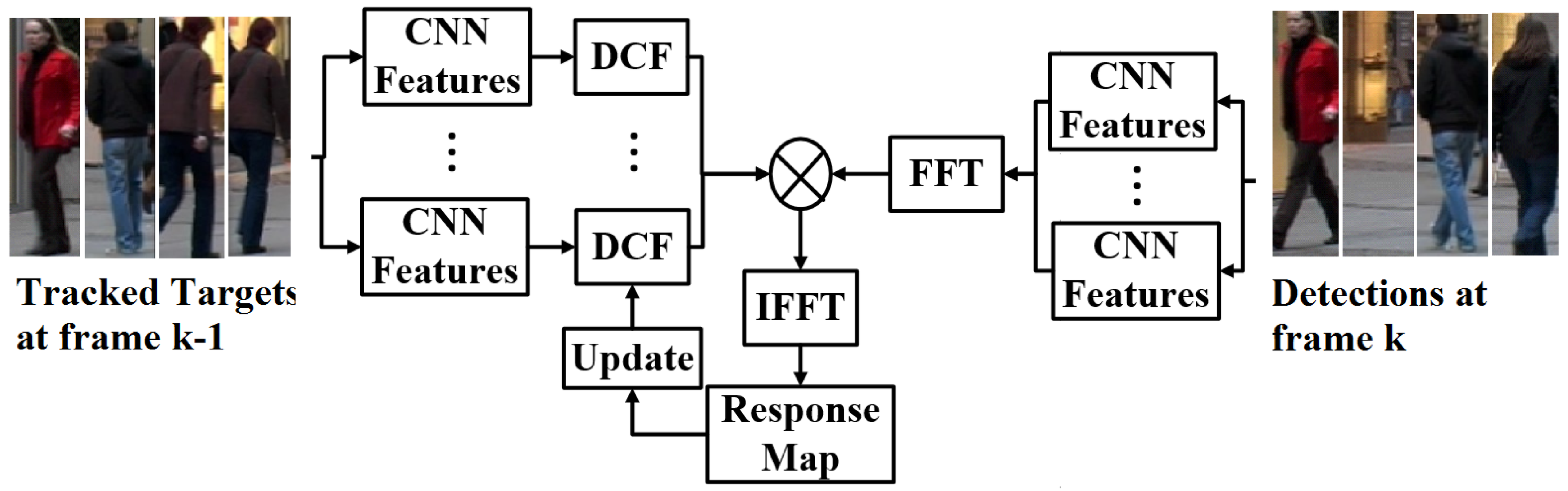
3. Detection Analysis and Spatio-Temporal Relation



- A spatio-temporal cost matrix $\mathbf{W}_{k,st} \in \mathbb{R}^{M\times N^+}$ for target association :

$$S(\mathbf{x}^i_{k|k-1}, \mathbf{z}^j_k) = \frac{1}{(2\pi\sigma_s)^{1/2}}\exp\left(-\frac{|\mathbf{H}\mathbf{x}^i_{k|k-1} - \mathbf{z}^j_k|}{2\sigma_s^2}\right) \quad (3)$$

4. Proposed Approach



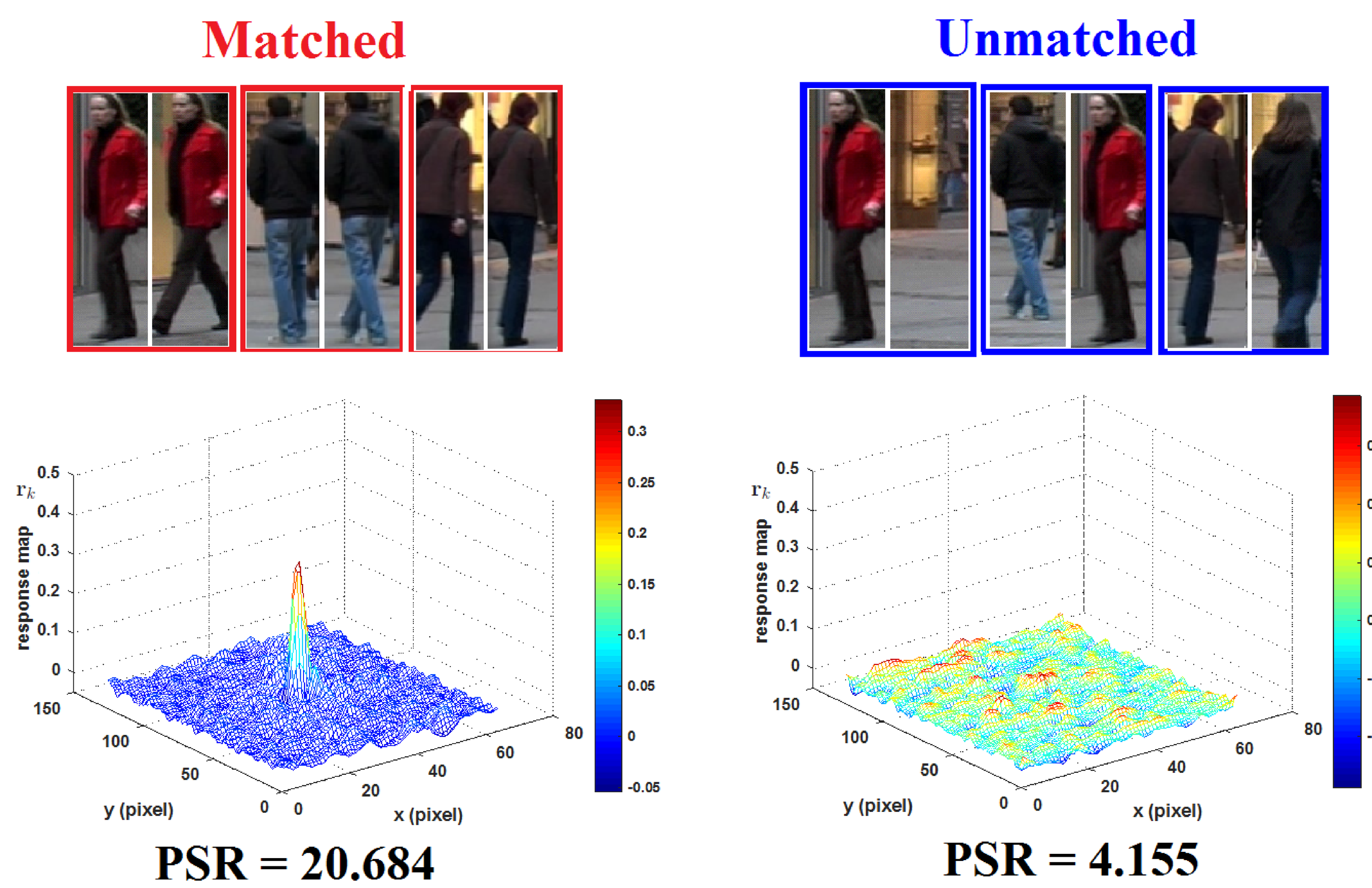
- **Training Phase:** Perform the fast Fourier transform (FFT) in the frequency domain with CNN features $\mathbf{f}$ and Gaussian label matrix $\mathbf{g}$ [2],

$$\hat{\mathbf{c}}^d_{k-1} = \frac{\hat{\mathbf{g}}\odot(\hat{\mathbf{f}}^d)^\dagger}{\sum_{d=1}^{D}\hat{\mathbf{f}}^d\odot(\hat{\mathbf{f}}^d)^\dagger + \lambda} \quad (4)$$

- **Correlation Matching:**
  - Response Map:

$$\mathbf{r}_k = \mathscr{F}^{-1}\left\{\sum_{d=1}^{D}\hat{\mathbf{c}}^d_{k-1}\odot(\hat{\mathbf{y}}^d_k)^\dagger\right\} \quad (5)$$

  - Pairwise matching score: $sigmoid(x) = \frac{1}{1+e^{-(\alpha x+\beta)}}$ squashes the PSRs to a range of $[0, 1]$. These scores form a cost matrix $\mathbf{W}_{k,dcm} \in \mathbb{R}^{M\times N^+}$.



- **Model Update**: Update the DCFs of matched targets during tracking for handling the appearance variations.
- **Hybrid likelihood function:**

$$\mathbf{W}_{k,h} = \mathbf{W}_{k,st}\odot\mathbf{W}_{k,dcm} \quad (6)$$

  Advantage: Compensate for unreliability present in the individual likelihood functions, especially when targets ambiguities occur in either motion dynamics or visual content.
- **Target initialization:** We only add a new-born target and simultaneously initialise a discriminative correlation filter for its appearance modelling, if it can be tracked in the next frame.

5. Experiments

- We evaluate on the MOTChallenge Benchmark [3] using the standard detections for all sequences.
- CLEAR MOT metrics are employed to evaluate the tracking performance.

Method	Mode	MOTA(↑)	MOTP(↑)	FP(↓)	FN(↓)	IDS(↓)
Proposed	**Online**	**46.5**	**77.2**	23,859	**272,430**	**5,649**
GMPHD-KCF	**Online**	40.3	75.4	47,056	283,923	5,734
GM PHD	**Online**	36.2	76.1	**23,682**	328,526	8,025
FWT	Offline	**51.3**	77.0	24,101	247,921	2,648
EDMT17	Offline	50.0	**77.3**	32,279	**247,297**	**2,264**
IOU17	Offline	45.5	76.9	19,993	281,643	5,988
DP_NMS	Offline	43.7	76.9	**10,048**	302,728	4,942

- **Quantitative results:**
  - Competitive performance compared to other state-of-the-art methods on the leaderboard.
  - Best performance amongst GM-PHD filtering methods.
- **Visual results:** MOT Benchmark 2017.

MOT17-03 #209 | MOT17-06 #183 | MOT17-07 #499 | MOT17-08 #171 | MOT17-14 #473 | MOT17-12 #03 | MOT17-01 #181

6. Conclusions and Future Work

- Developed a unified tracking algorithm that incorporates deep discriminative correlation matching with the GM-PHD filter for online multiple human tracking.
- Experimental Results on MOT17 Challenge demonstrate the effectiveness of the proposed method.
- We plan to integrate an interaction model to further address the occlusions.

7. References

[1] B.-N. Vo and W. K. Ma, “The Gaussian Mixture Probability Hypothesis Density Filter”, IEEE Transactions on Signal Processing, vol. 54, no. 11, pp. 4091–4104, 2006.
[2] C. Ma, J. B. Huang, X. Yang, and M. H. Yang, “Hierarchical Convolutional Features for Visual Tracking”, in ICCV, 2015, pp. 3074–3082.
[3] A. Milan, L. Leal-Taixe, I. Reid, S. Roth, and K. Schindler, “MOT16: A Benchmark for Multi-Object Trackings”, arXiv:1603.00831 [cs.CV], pp. 1–13, 2016.
[4] Z. Fu, P. Feng, F. Angelini, J. Chambers, and S. M. Naqvi, “Particle PHD Filter Based Multiple Human Tracking using Online Group-Structured Dictionary Learning”, IEEE Access, vol. 6, pp. 14764 - 14778, 2018.

VIDEO Tracking Results

VIDEO Multimodal Signal and Information Processing Team