Evaluation of Random Field Models in Multi-modal Unsupervised Tampering Localization

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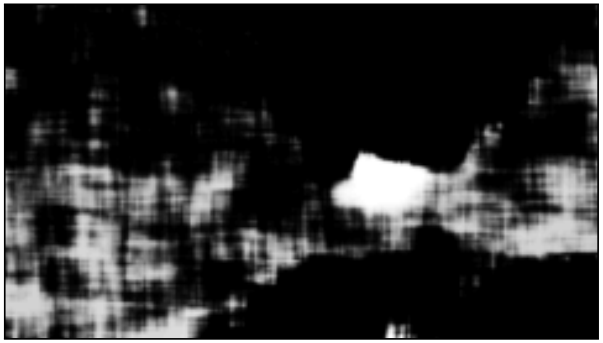
IEEE International Workshop on Information Forensics and Security,
4 - 7 Dec 2016, Abu Dhabi

Motivation and Goals (I)

- Reliable forensics should analyze various traces.
- Decision fusion studied in detail for tampering detection[1].
  - Fuzzy logic, Dempster-Shafer theory of evidence.
- In tampering localization - still an open problem[2].
  - Naive pixel-wise application of (even complicated) combination rules.
  - The simplest rules (summation / product) actually yield good performance.
- This naive approach is clearly sub-optimal - example problem:
  - Scale discrepancy: e.g., CFA (8×8) and PRNU (128×128).

tampering probability (CFA, 8 px window)

tampering probability (PRNU, 128 window)



[1] Fontani et al., TIFS 2013; Barni et al., ICASSP 2012
[2] Ferrara et al., ICMEW 2015; Cozzolino et al. IAP 2013

Motivation and Goals (II)

- Solution: cross-reference results with actual objects.
- Exploiting image content in forensics (before):
  - Manual image segmentation[3].
  - Guided image filtering[4] (feature correlation / structure transfer).
- Problems:
  - How to do reliable image segmentation? How to do it automatically?
  - How to handle object removal?
- Goals of our study:
  - Consider a scenario with mismatched detectors (scale discrepancy).
  - Evaluate random field models with content-dependent potentials.
  - Verify operation for subtle object removal forgeries.
  - Compare standard grid-based and dense CRF models.

[3] Barni et al., ISCS 2010; Chierchia et al., ICDSP 2011
[4] Chierchia et al., ICASSP 2014

Individual Detectors

- State-of-the-art CFA detector (small blocks, fine shape)[5]:
  - Exploits periodicity of resampling artifacts.
  - Compares prediction error of acquired vs. interpolated pixels.
  - GMM-based segmentation into tampered / pristine blocks.
  - Operates on small non-overlapping blocks (best performance for 8×8 px).
- Photo-response non-uniformity detector (large windows, coarse shape)[6]:
  - Validates (locally) presence of a known noise signature.
  - Uses a correlation predictor to locally estimate the strength of the signature.
  - Requires relatively large sample (we used overlapping 64×64 px windows).
  - Tampering probability from Bayesian analysis.
- Both detectors set up to yield same-size tampering probability maps:
  - localization resolution of 8×8 px image blocks.

[5] Ferrara et al., TIFS 2012; http://lesc.det.unifi.it/en/node/187
[6] Chen et al., TIFS 2008; https://github.com/pkorus/multiscale-prnu

Standard Combination Rules (I)

- Naive pixel-wise combination rules (τ - threshold):
  - Sum fusion:

$$t_i = \left(c_i^{(\mathrm{cfa})} + c_i^{(\mathrm{prnu})}\right)/2 > \tau$$

  - Product fusion:

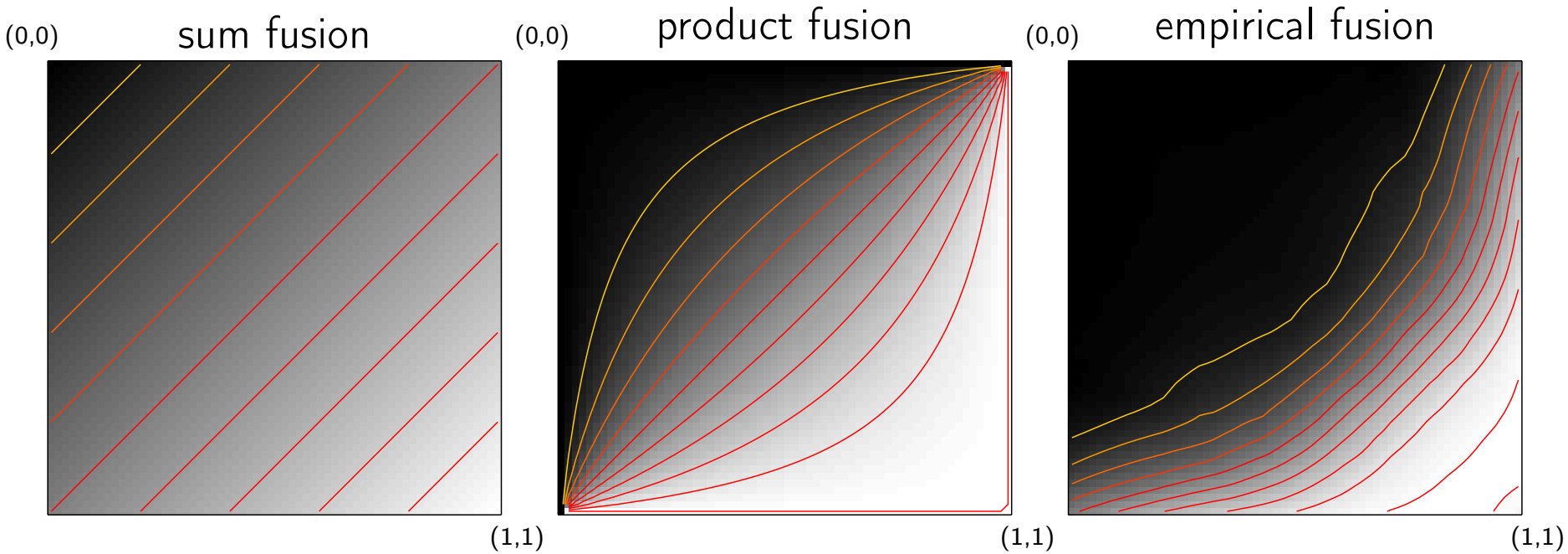
$$t_i = \left(c_i^{(\mathrm{cfa})} c_i^{(\mathrm{prnu})}\right)\left(c_i^{(\mathrm{cfa})} c_i^{(\mathrm{prnu})} + \tilde{c}_i^{(\mathrm{cfa})} \tilde{c}_i^{(\mathrm{prnu})}\right)^{-1} > \tau$$

  - Disjunction fusion (two variants of heuristic cleaning):

$$t_i = \left(c_i^{(\mathrm{cfa})} > \tau\right) \vee \left(c_i^{(\mathrm{prnu})} > \tau\right)$$

  - Empirical fusion: rule learned from data.
- Heuristic cleaning:
  - For fusion result: morphological opening (disk-shaped SE 15×15).
  - For individual detectors:
    - CFA - as above;
    - PRNU - disk-shaped SE 31×31 opening + 19×19 dilation

Standard Combination Rules (II)



Random Field Models

- Optimization of the following energy function:

$$E(\mathbf{t}) = \frac{1}{|D|} \sum_{d \in \mathcal{D}} \sum_{i=1}^{N} \psi_\tau(c_i^{(d)} | t_i) + \sum_{i=1}^{N} \sum_{j \in \Xi_i} \phi_p(t_i, t_j)$$

  where:

  - ψ_τ is the unary potential (favors solutions close to observations);
  - ϕ_p is a pairwise interaction potential (favors the same decisions among neighbors).

- The pairwise potential has two components:
  - β_0 - default interaction strength,
  - β_1 - content-dependent interaction strength (based on color similarity).

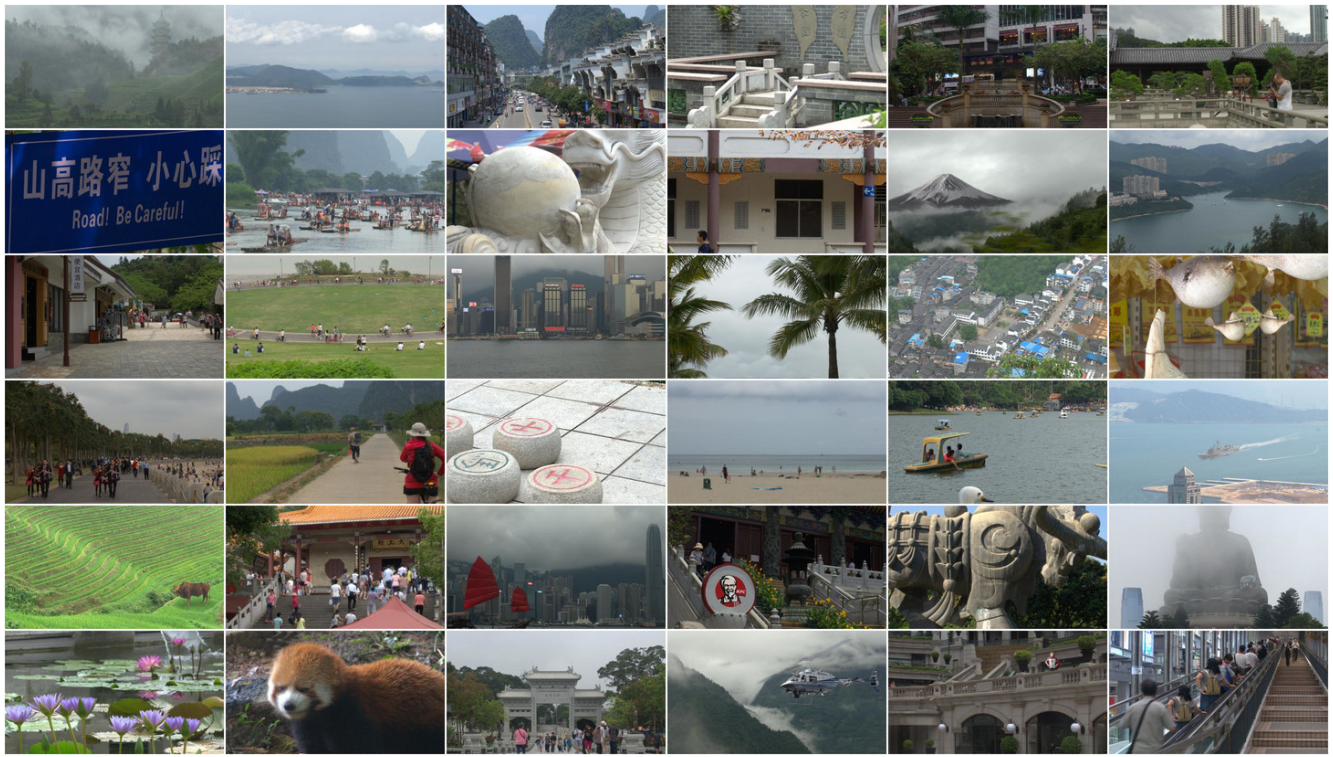
- We consider two versions:
  - *grid* CRF - only nearest 8-connected neighborhood,
  - *dense* CRF - fully connected pairwise field (Gaussian).

- Solvers: graph cuts[7] / iterative mean-field approximations[8].

[7] UGM Toolbox, http://www.cs.ubc.ca/~schmidtm/Software/UGM.html
[8] Krähenbühl et al., NIPS 2011

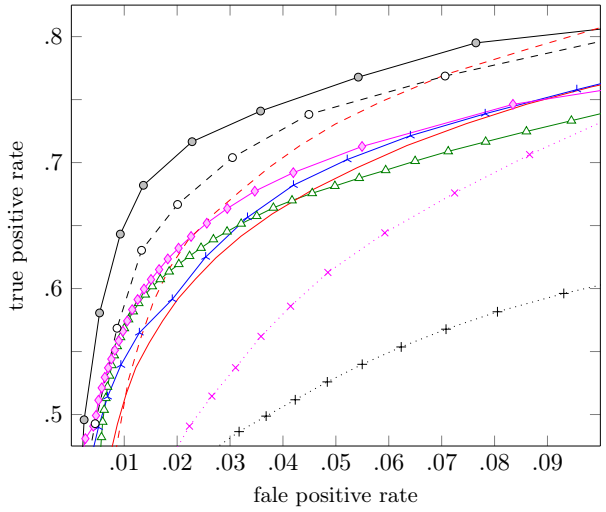
Evaluation Scenario

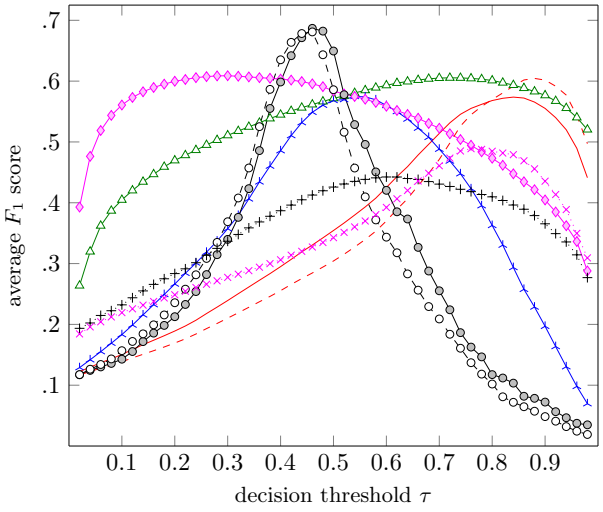
- Evaluation of localization performance on realistic forgeries:
  - Challenging realistic data set crafted by hand in modern photo editors.
  - 120 images (3 cameras, 1920 × 1080 px uncompressed TIFFs).
  - An extended version is publicly available for research purposes[9].
- Performance metrics: F_1 score, ROC



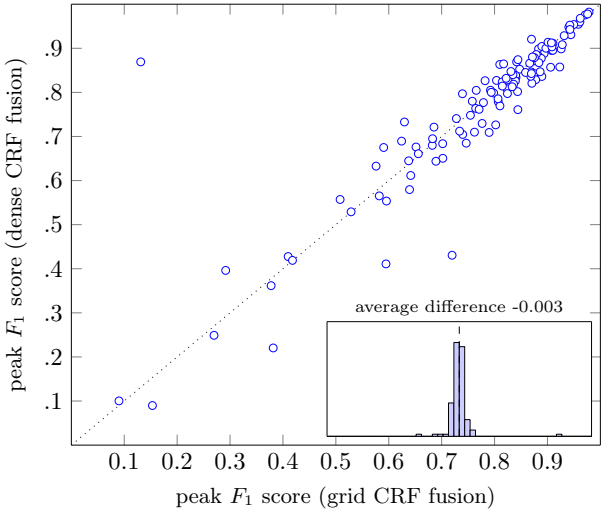
[9] http://kt.agh.edu.pl/~korus/downloads/dataset-realistic-tampering/

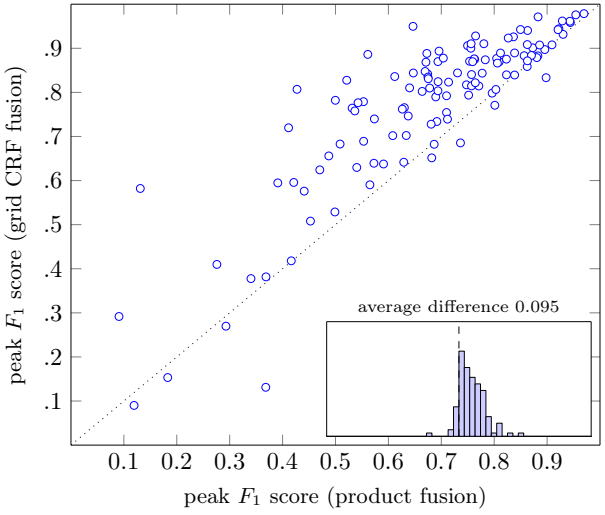
Evaluation Results

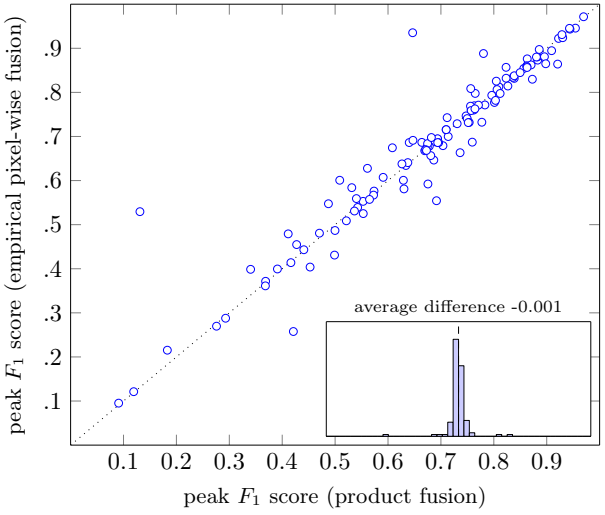




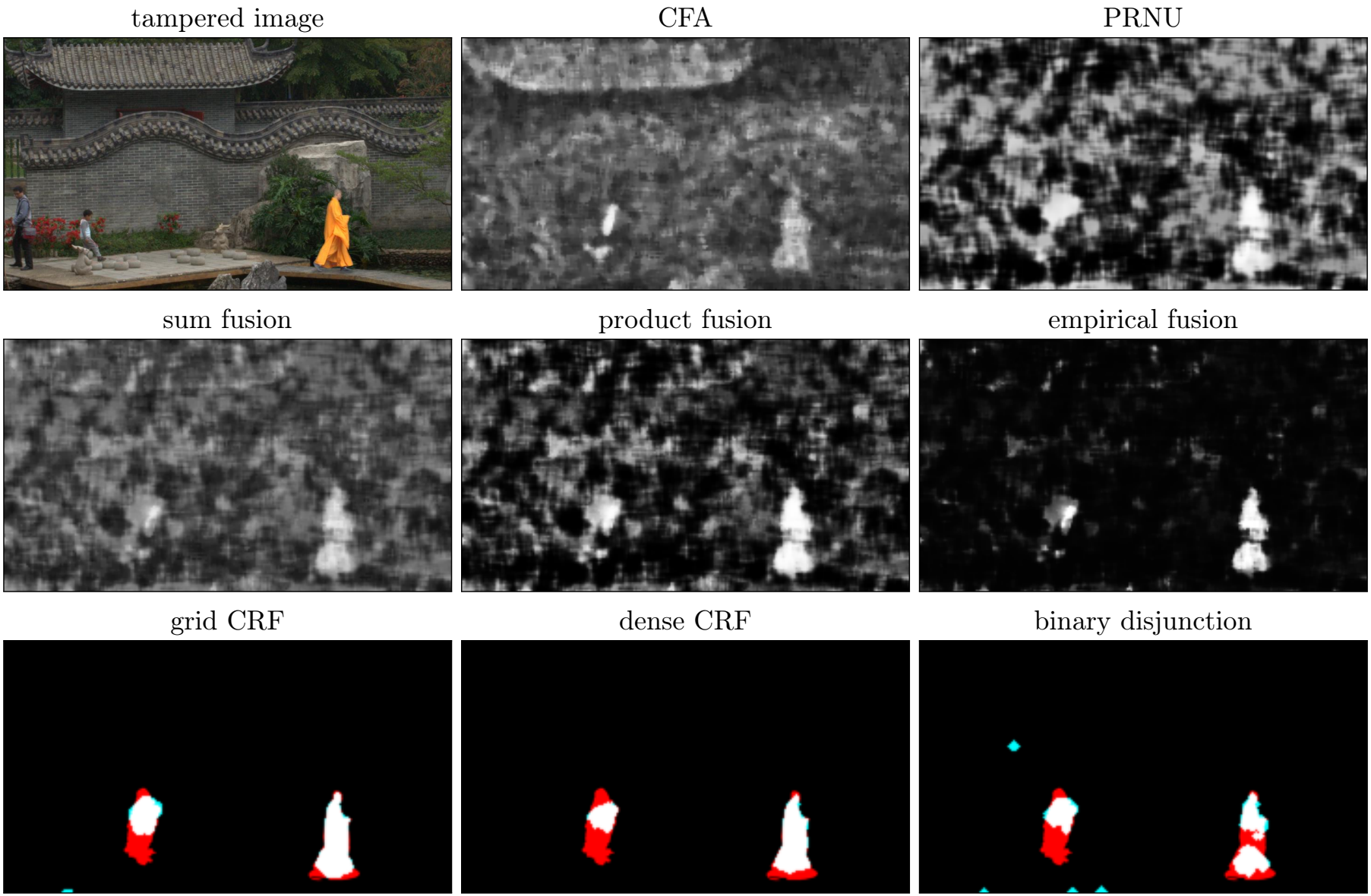
style	detector	max F_1
	sum	0.57
	product	0.61
	disjunction (CC)	0.57
	disjunction (IC)	0.60
	empirical	0.61
	grid CRF	0.69
	dense CRF	0.68
	CFA	0.44
	PRNU	0.49







Example Localization Results (best F-score wise)



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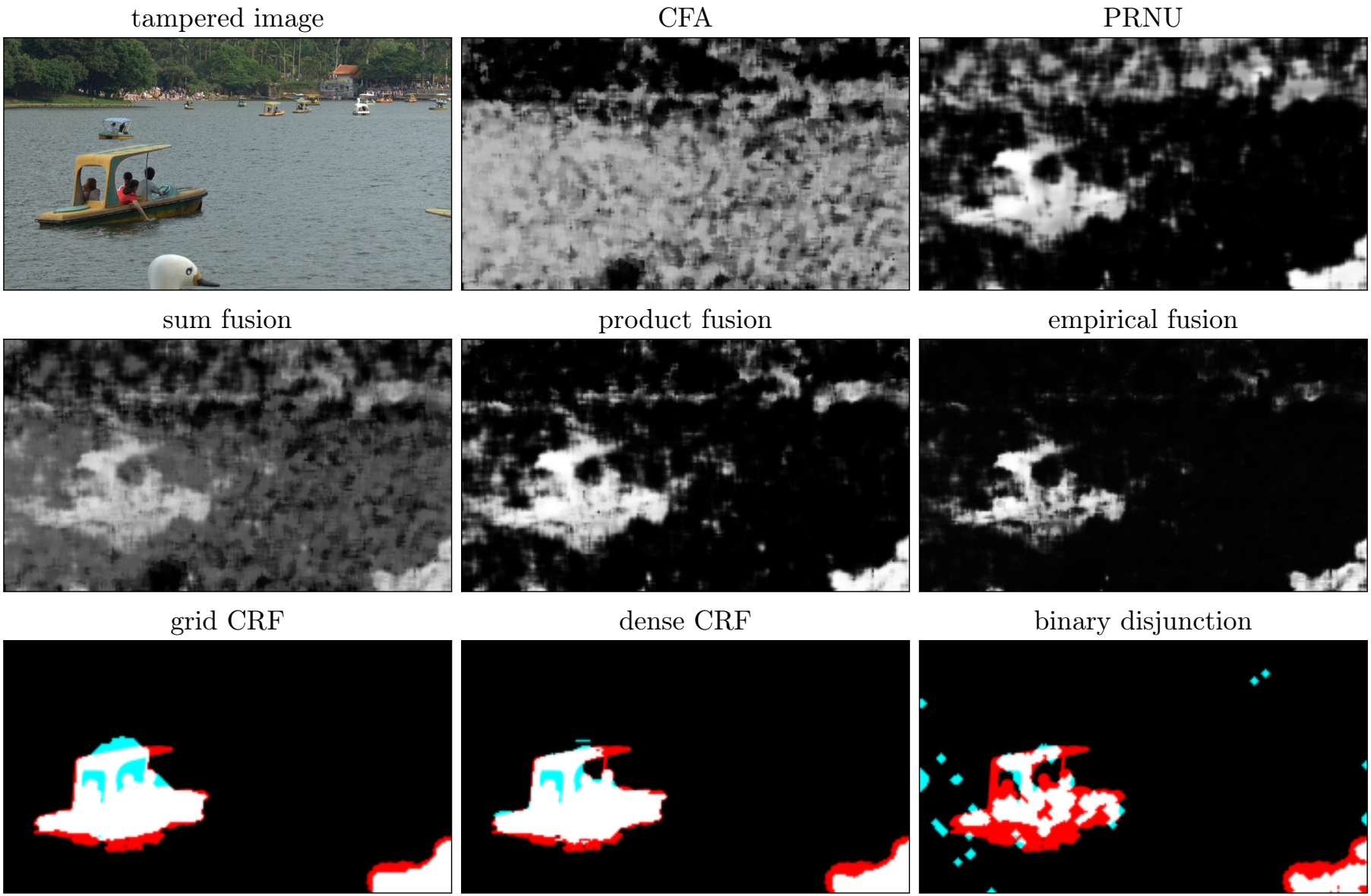

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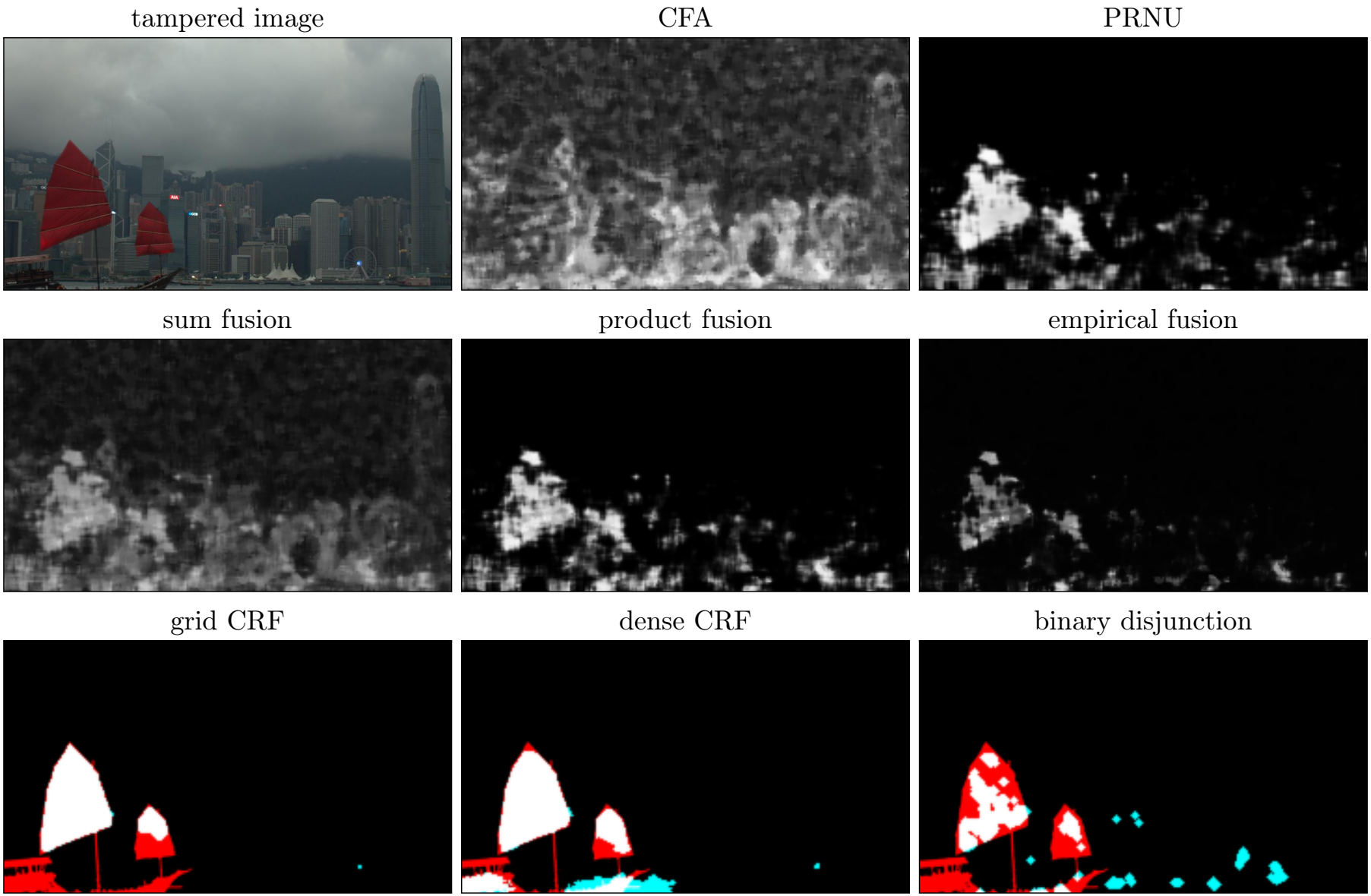
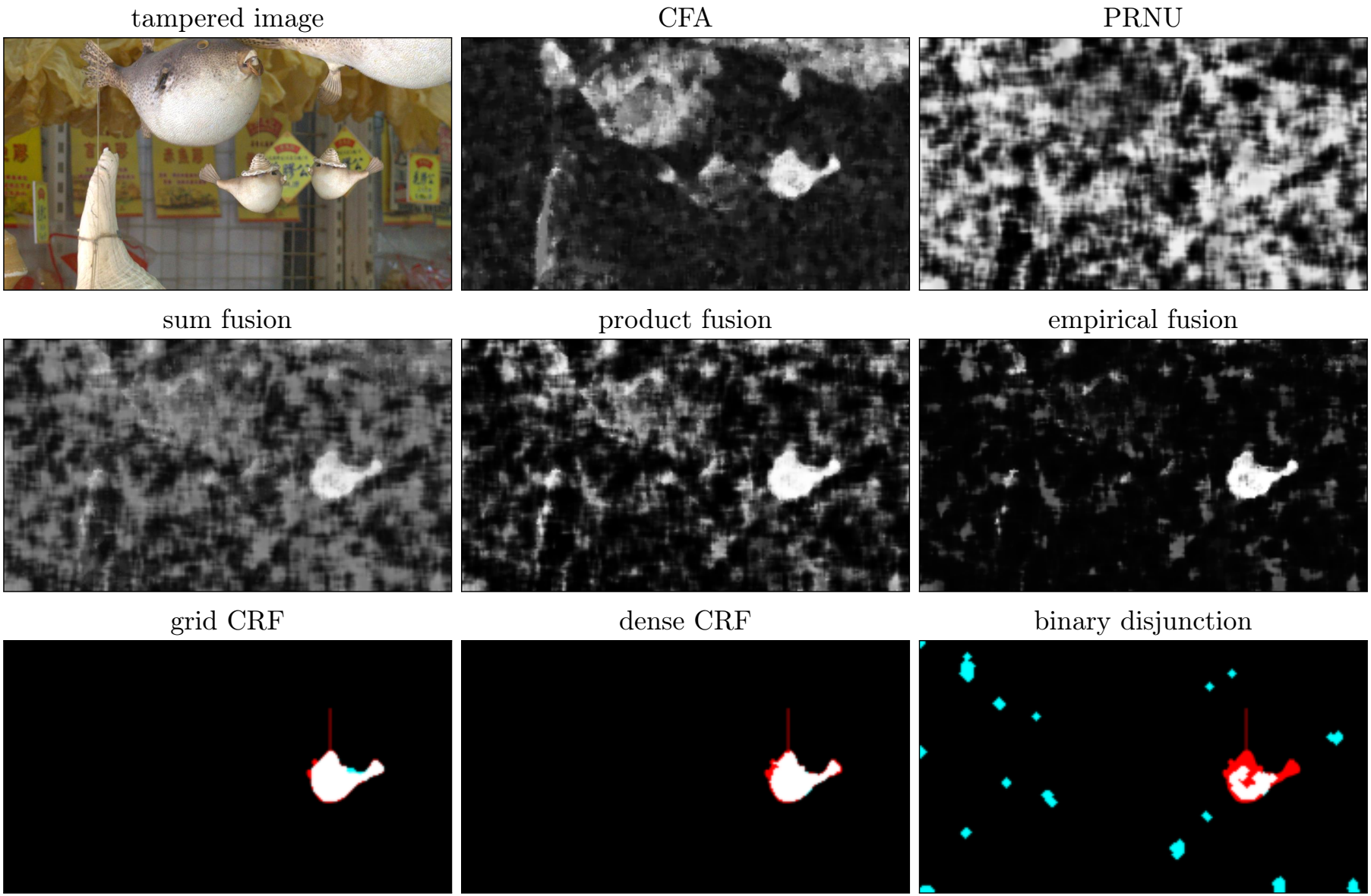


Example Localization Results (best F-score wise)



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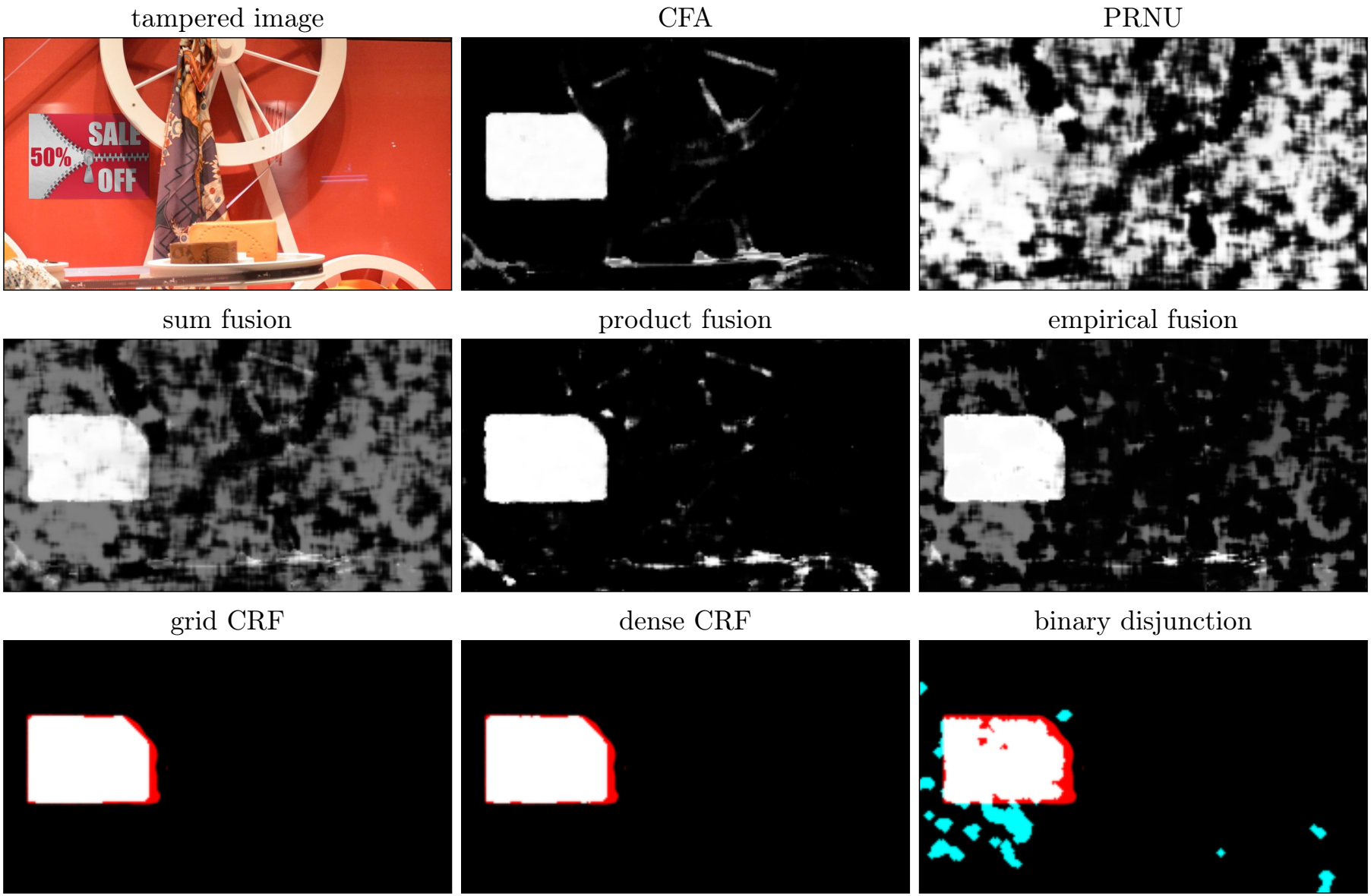

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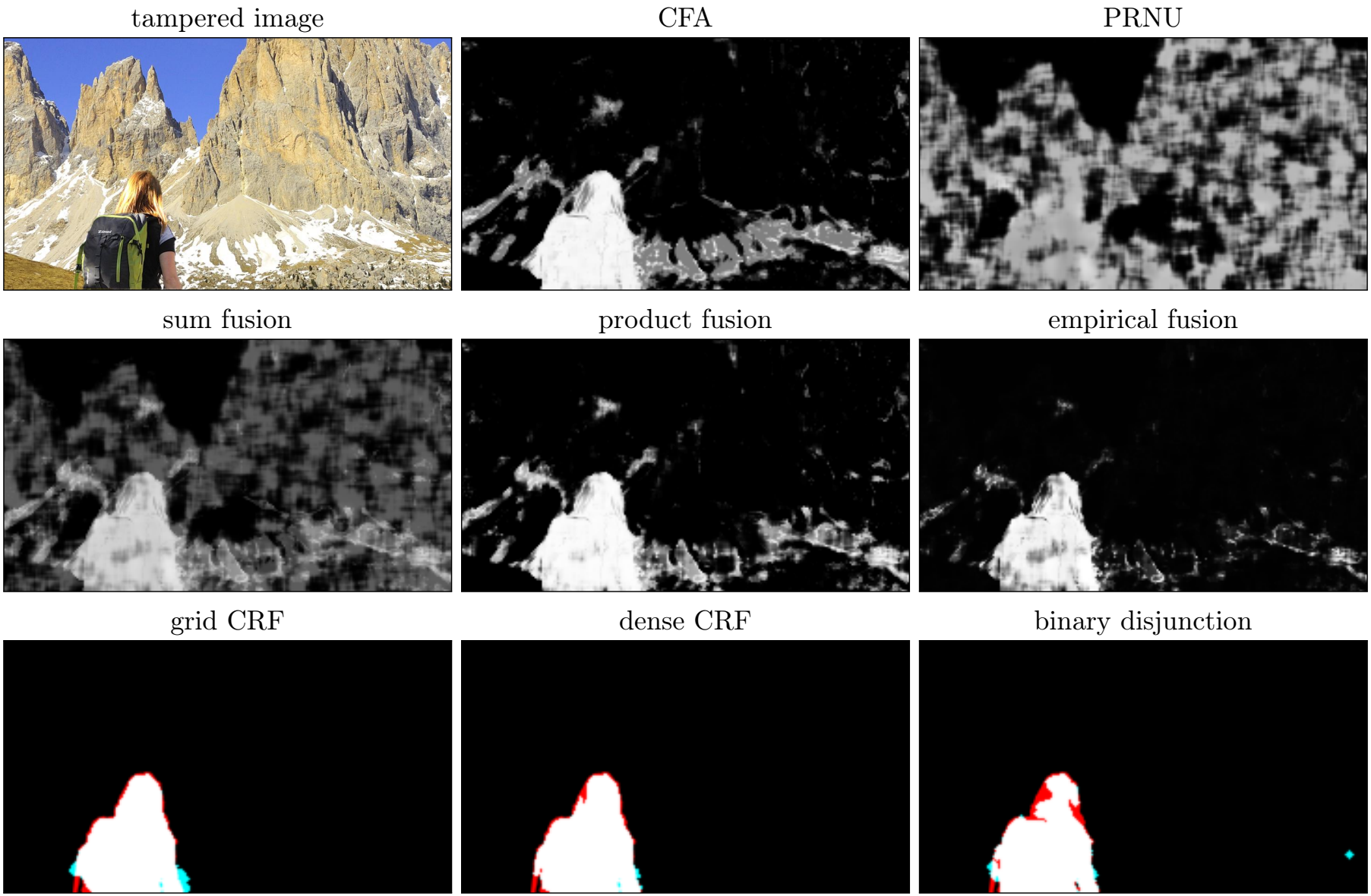
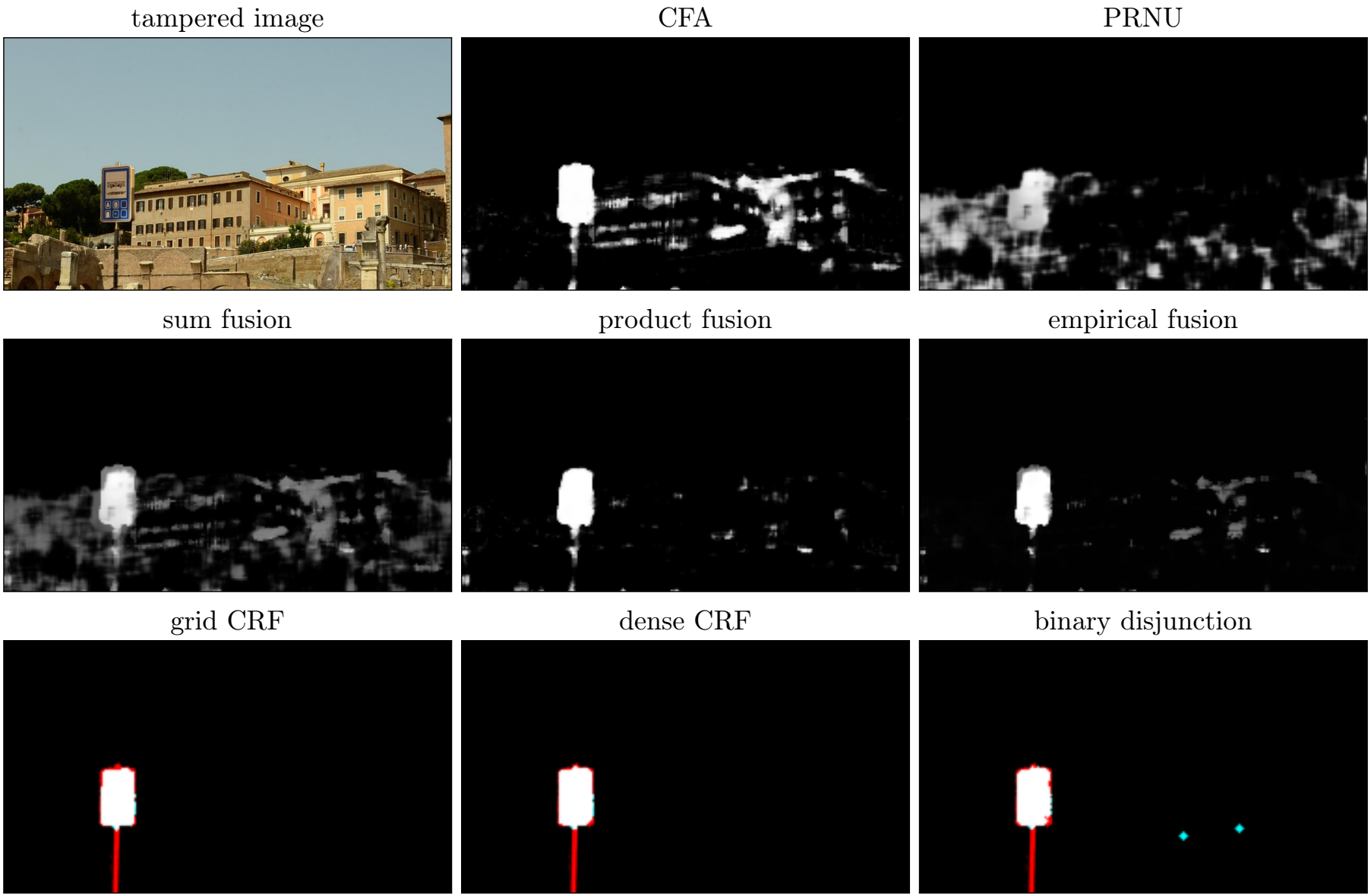
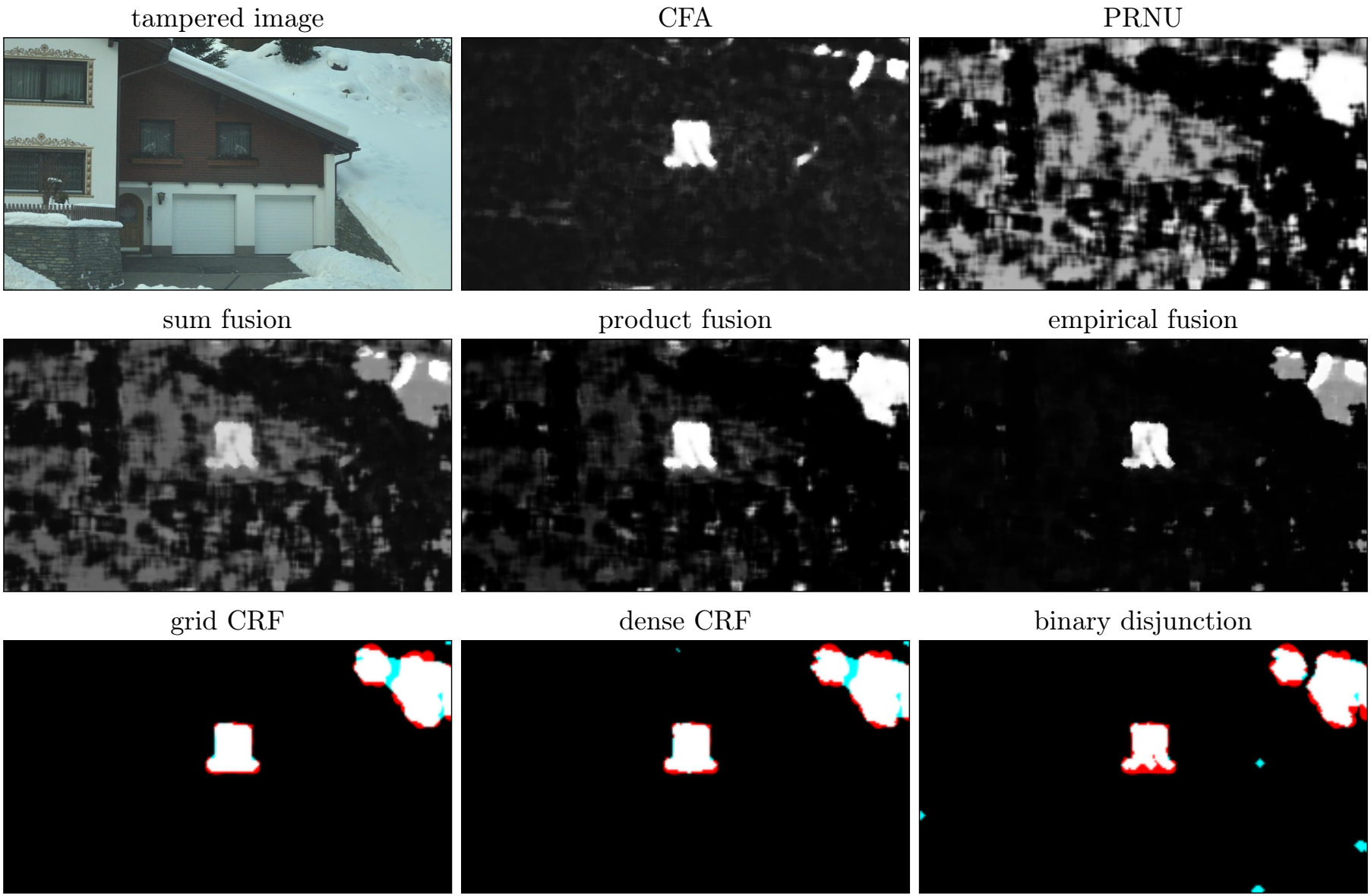


Example Localization Results (best F-score wise)



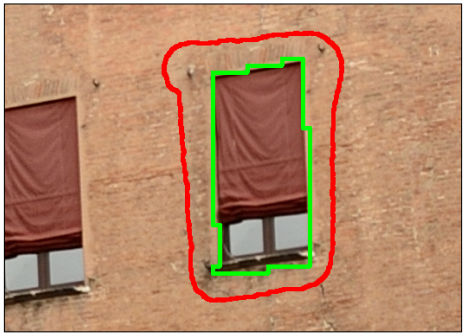
Example Localization Results (best F-score wise)



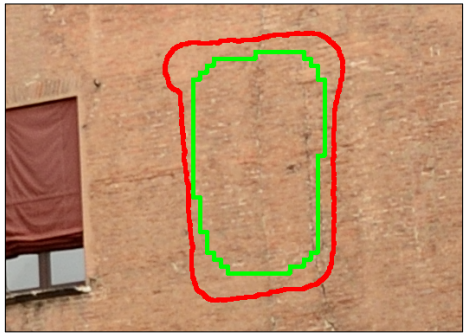
Object Insertion vs Object Removal

- Problems with existing evaluation metrics.
  - Oblivion to spatial relationships + collateral damage.
  - Better detection often leads to marginal improvement (bottom) or even deterioration (top) of measurable performance.
- Impact of content guidance on the MRF fusion (see below).

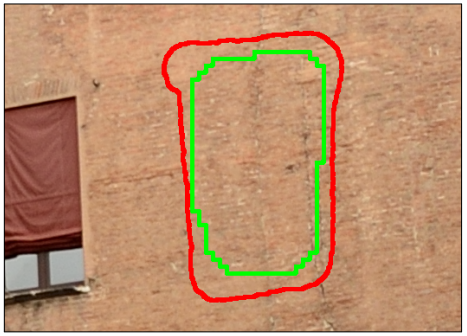
CRF guided by tampered image ($F_1 = 0.664$ / $A = 0.749$)



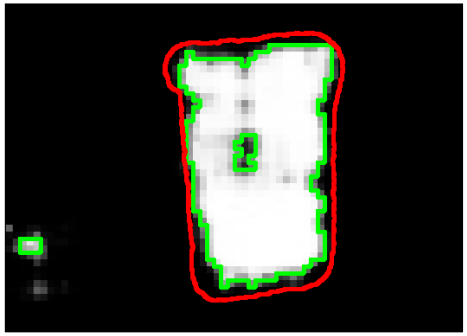
CRF guided by orignal image ($F_1 = 0.806$ / $A = 0.838$)



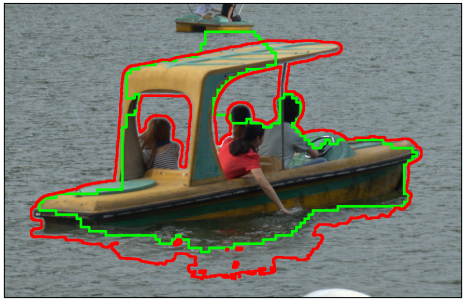
CRF with no content guidance ($F_1 = 0.812$ / $A = 0.842$)



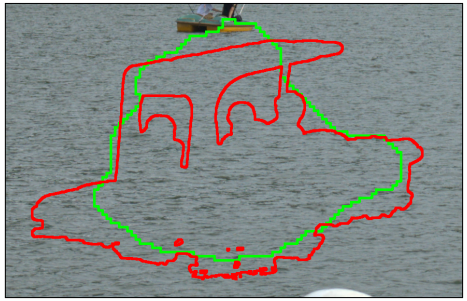
pixel-wise product fusion ($F_1 = 0.844$ / $A = 0.866$)



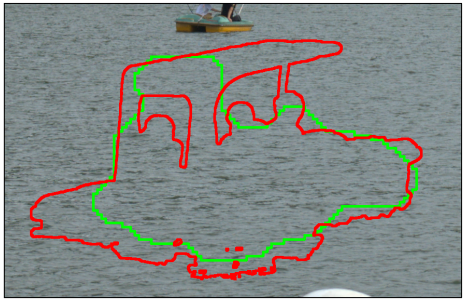
CRF guided by tampered image ($F_1 = 0.820$ / $A = 0.851$)



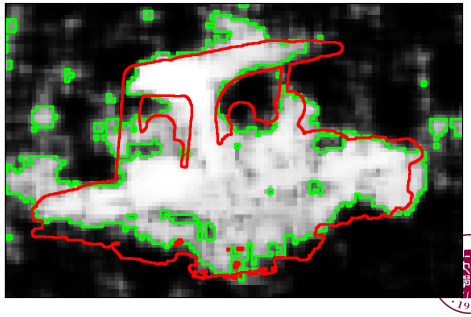
CRF guided by orignal image ($F_1 = 0.804$ / $A = 0.844$)



CRF with no content guidance ($F_1 = 0.805$ / $A = 0.840$)



pixel-wise product fusion ($F_1 = 0.799$ / $A = 0.841$)



Conclusions & Future Work (I)

- Even naive fusion leads to significant improvement over individual detectors.
- Disjunction fusion has an advantage of customized post-processing.
- Product fusion is not an accurate combination model but it seems to be of limited importance in practice.
- **Scale discrepancy in multi-modal analysis** makes pixel-wise fusion sub-optimal.
- Fusion in localization:
  - **not only combination rules matter**.
  - need to cross-reference results with image content.

Conclusions & Future Work (II)

- Adoption of neighborhood dependencies further improves performance.
- **Content-dependent interactions** are an effective tool to exploit image content - **no problems with object removal**.
- No significant quantitative differences between CRF models, but...
  - ...existing evaluation protocols and metrics are imperfect,
  - ...important qualitative differences are obvious.
- Future work:
  - Understanding of actual **map utility for forensic analysis** (humans in general?).
  - Better evaluation metrics aware of **spatial dependencies** and **collateral damage**.

Limitations and Possible Extensions of the Framework

- Need to test more diverse detectors.
  - Some may work on even larger blocks (e.g., 256×256 px).
  - Some may not yield tampering probabilities.
  - Some may not work on square blocks at all (segments / super-pixels).
- The current framework does not support compatibility of traces.
  - Should be feasible with proper definition of unary potentials.
- Limited improvement for overconfident detectors.
  - Common for popular Bayesian formulations.
  - Valid traces present in tampered area.
  - To some extent, alleviated by truncated unary potentials.
- Training limitations:
  - Imperfect performance measures.
  - Parameter generalization in diverse conditions, e.g., for varying image size?
  - Is it possible to choose the parameters for each case individually?

Thank You

- **Thank you for your attention.**
- Discussion?

- Contact: pkorus@agh.edu.pl
- Web: http://kt.agh.edu.pl/∼korus/
- Supplement:
  - more details + additional experiments,
  - http://kt.agh.edu.pl/∼korus/publications/2016-wifs
- Dataset:
  - 220 images + 3-level GT
  - http://kt.agh.edu.pl/∼korus/downloads/dataset-realistic-tampering/
- Matlab code:
  - https://github.com/pkorus/multiscale-prnu