Residual-based forensic comparison of video sequences

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Increased prevalence of video content

Creator's side

- Visual content simpler to create and share than ever before
- Easy-to-use tools for editing videos are already widely present

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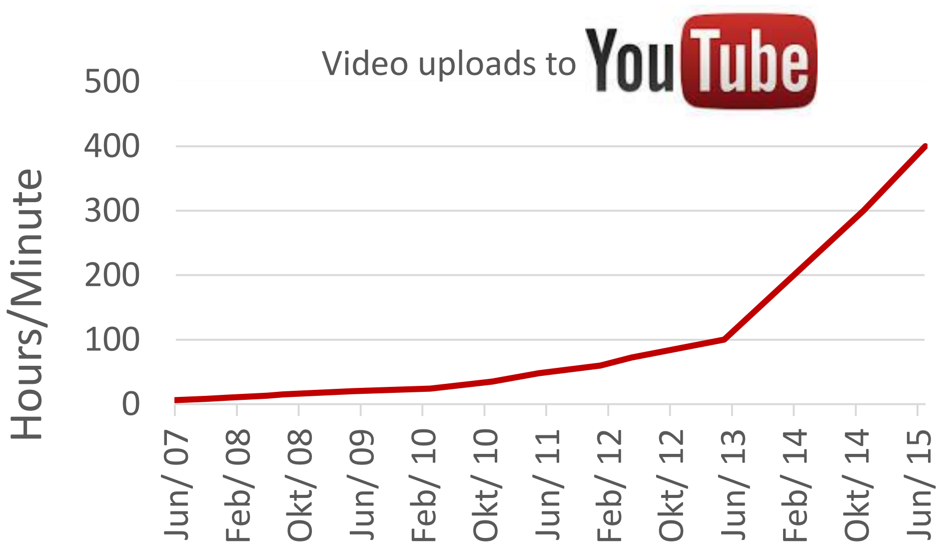

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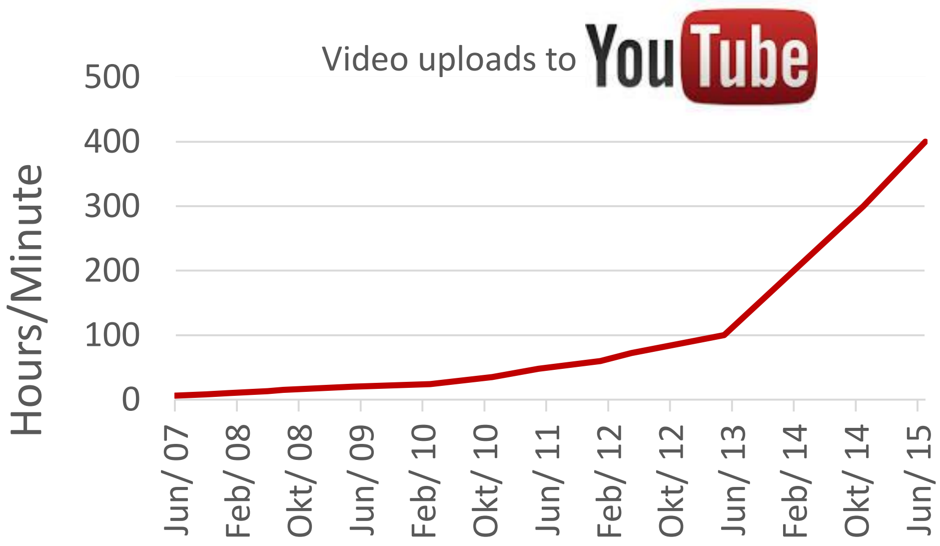
Analyst's side

- Some content is altered with malicious intents
- Few tools exist to automatically assess authenticity of video data



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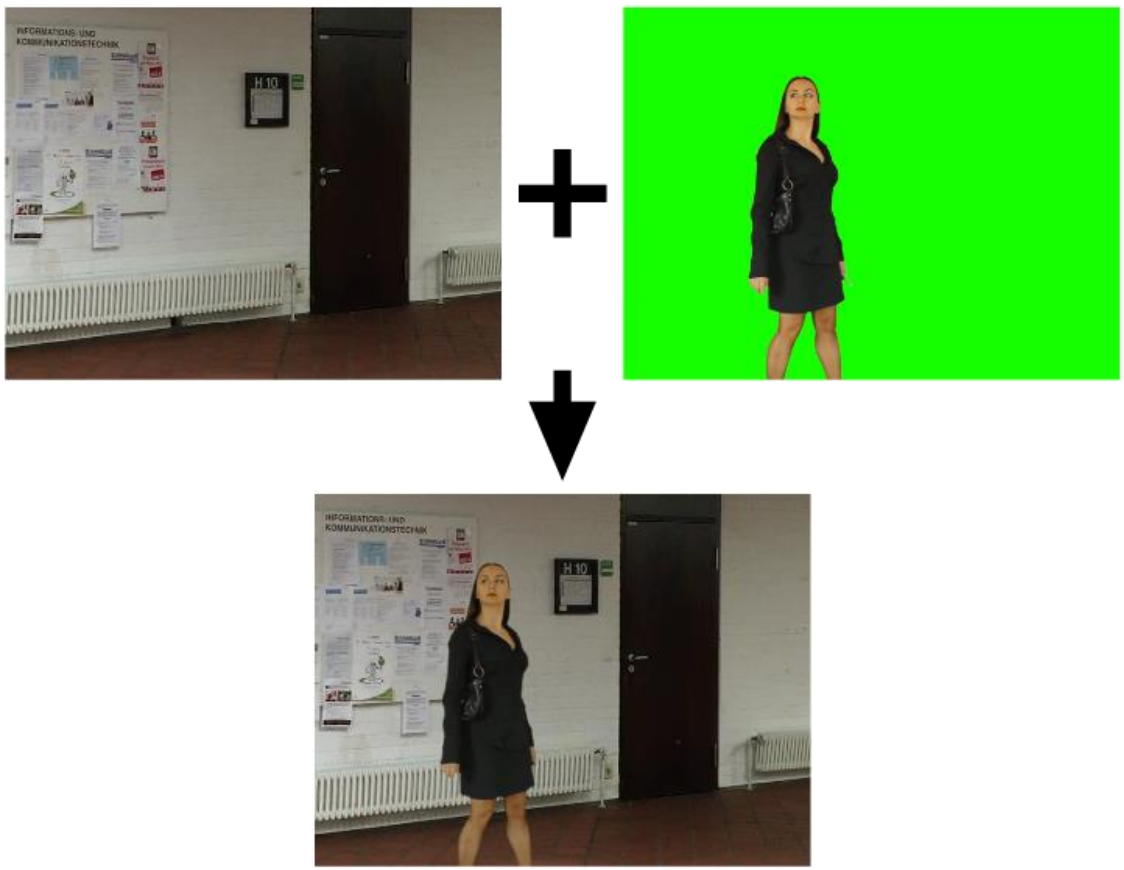
source: mediathek.zdf.de

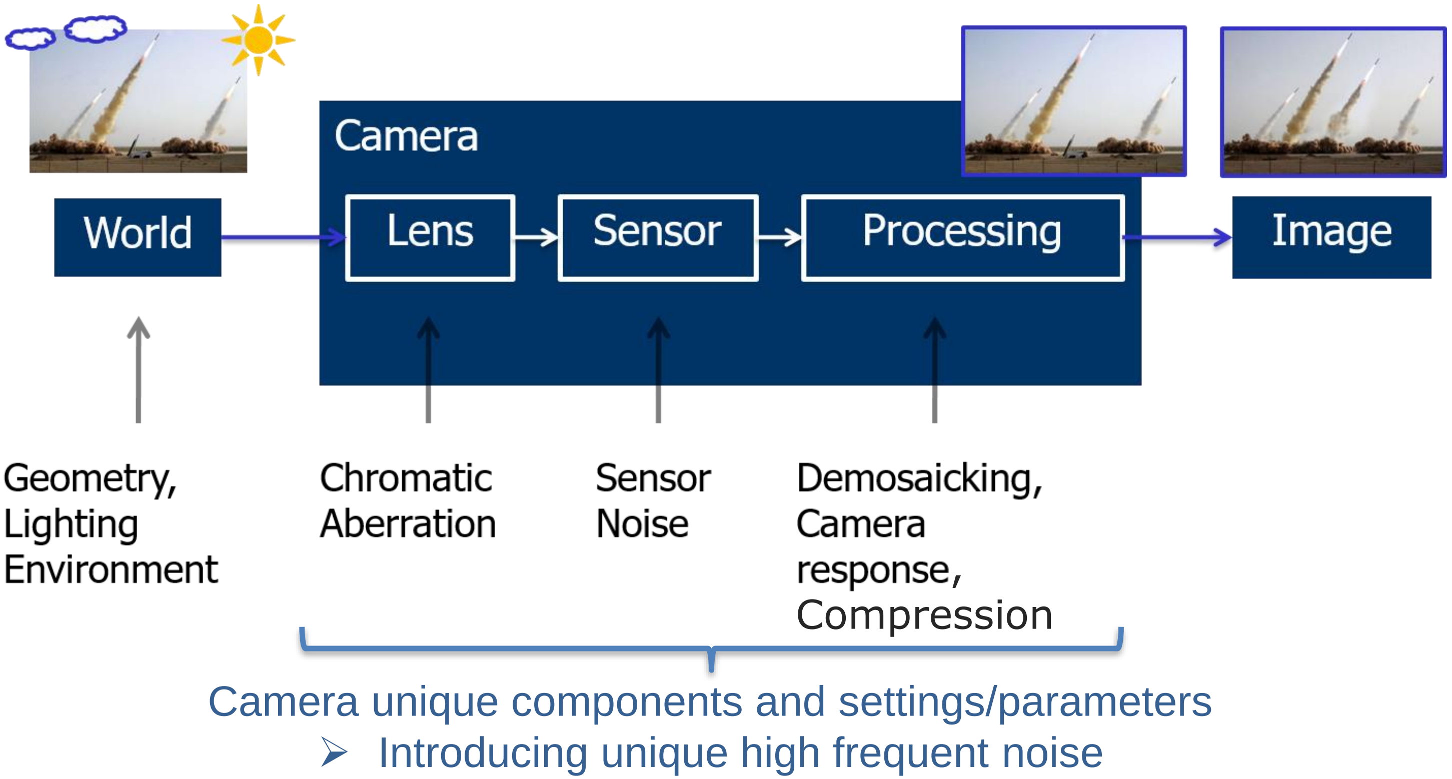
Chroma keying

- One manipulation attack is chroma keying (e.g. greenscreening)
- If done well, forged video offers no visual clues on manipulation



Assumption

- Each camera has its own, unique, processing pipeline
- They introduce characteristic, high frequent noise, in each frame and over frames
- Often not visually perceivable



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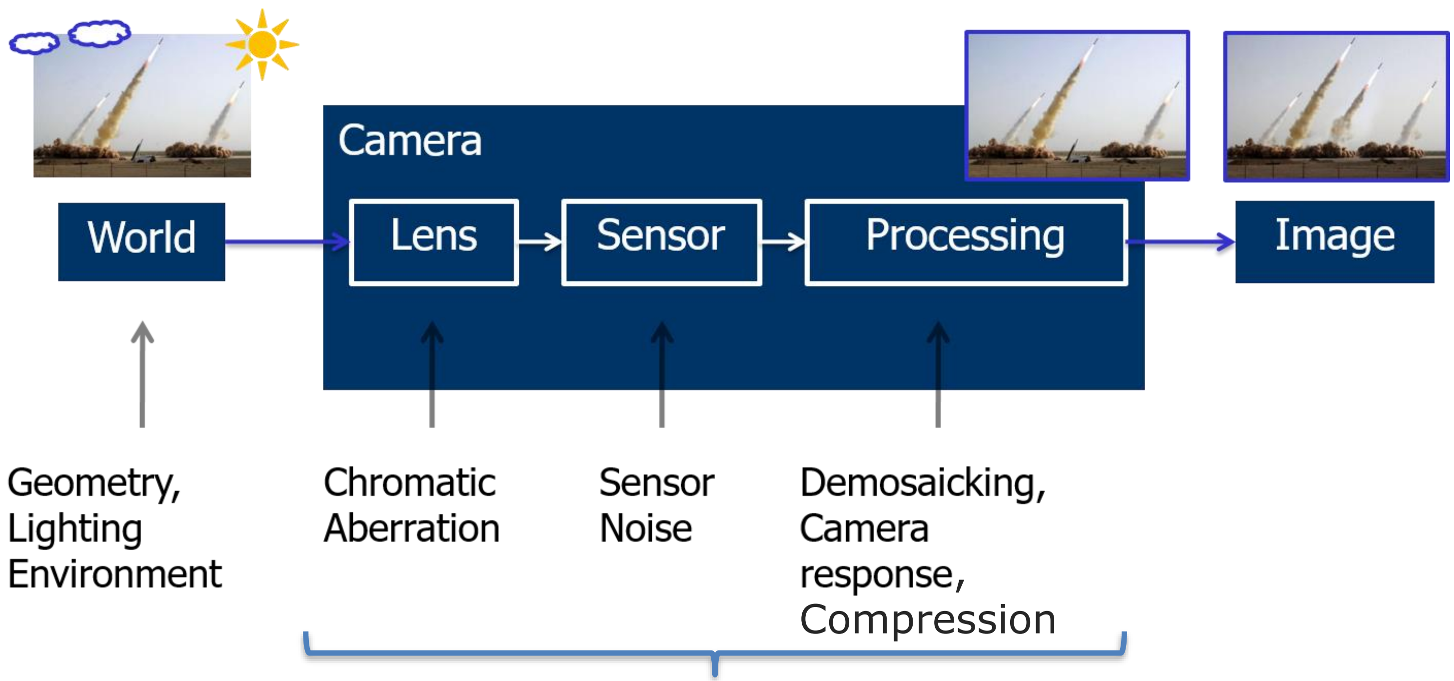
➢ Manipulations break those statistics or make them inconsistent



Camera unique components and settings/parameters

➢ Introducing unique high frequent noise

Feature extraction from noise

Inconsistencies in noise patterns well exploited in different fields:
For example, in “steganography” [1] or “forgery detection in images” [2]

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1. High-pass filtering input image I, returning residual image R, where image I has pixels at $I_{xy} \in [0|255]$
   → retrieves noise domain

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2. Quantize and truncate: $R^*_{xy} = \min\{t, \max\{-t, round(\frac{R_{xy}}{q})\}\}$
   → large residuals (like edges) are all mapped to t or $-t$
   → the “interesting” coefficents lie between $[-t+1 \mid t-1]$

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3. Build co-occurences of length d: $C_{nm} = \{R^*_{xy}, R^*_{xy+1}, \ldots, R^*_{xy+d}\}$
   → incorporates neighborhood relationships

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Descriptors applied to image forensics

Grayscale input frame

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High-pass
[1,-3,3,-1]

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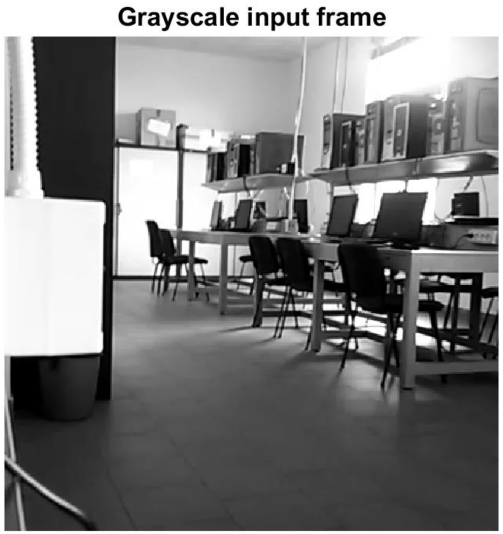

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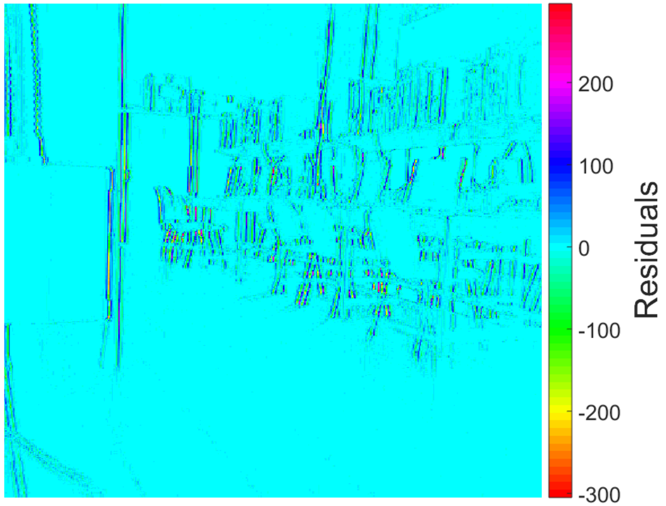

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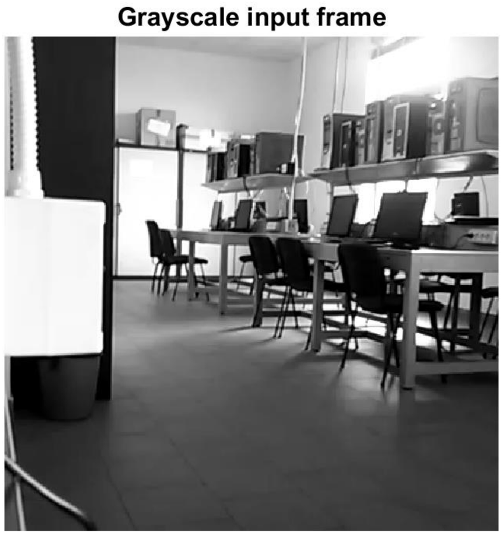

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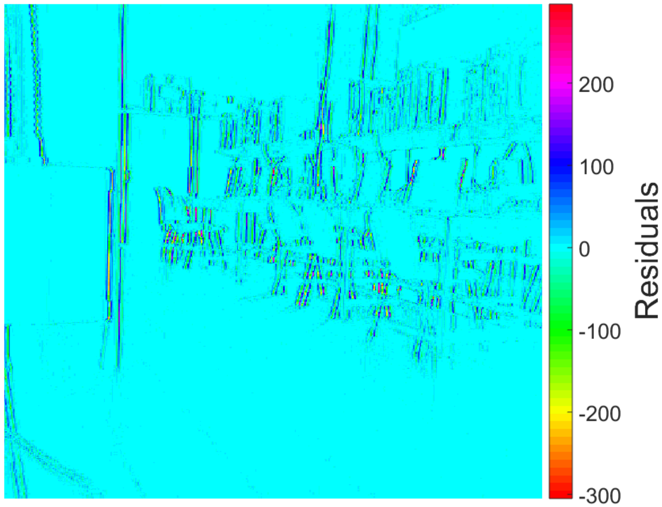

Quantize
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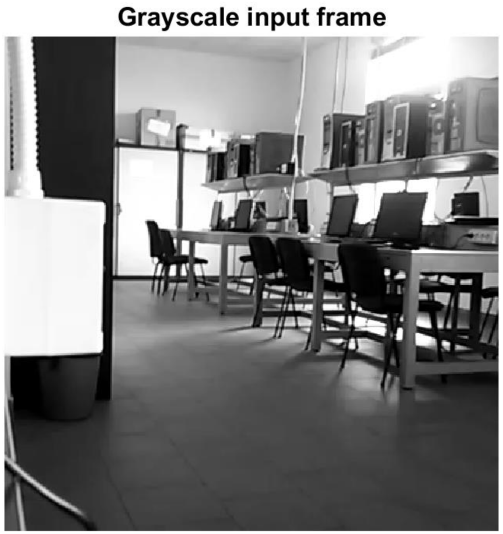

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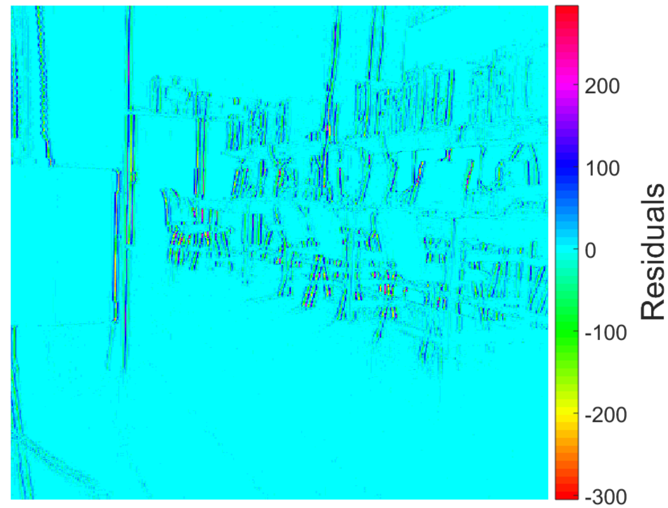

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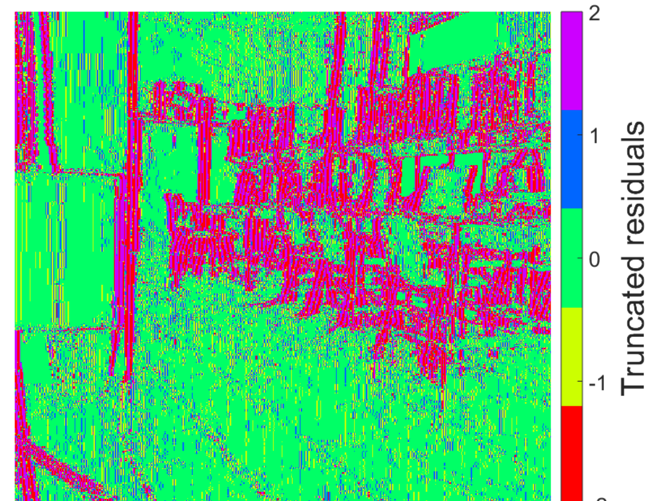

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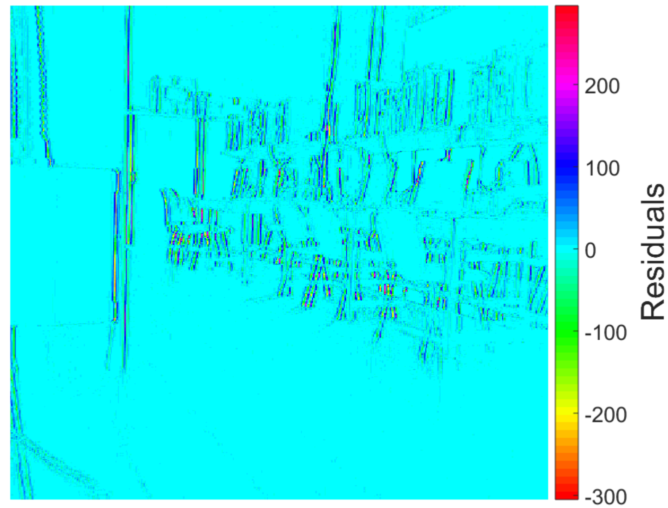

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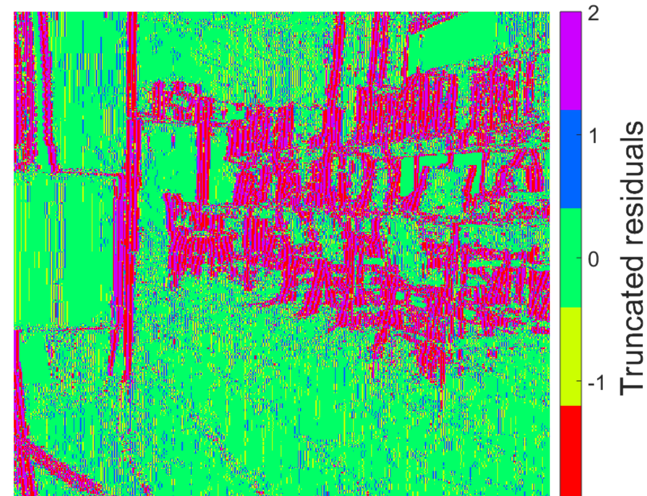

Co-occurrence
matrix

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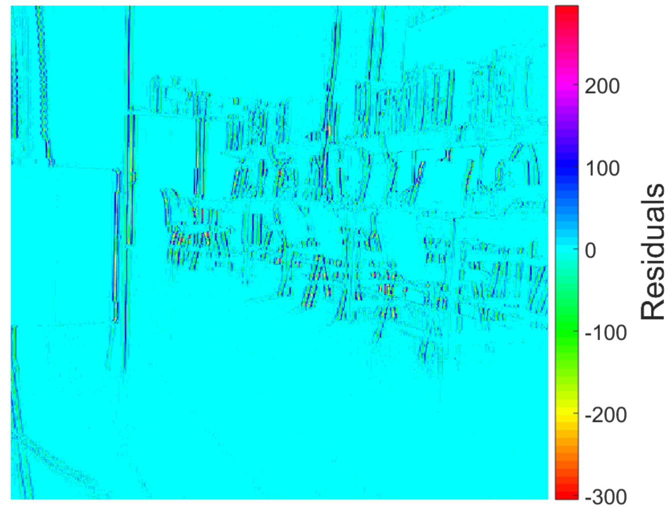

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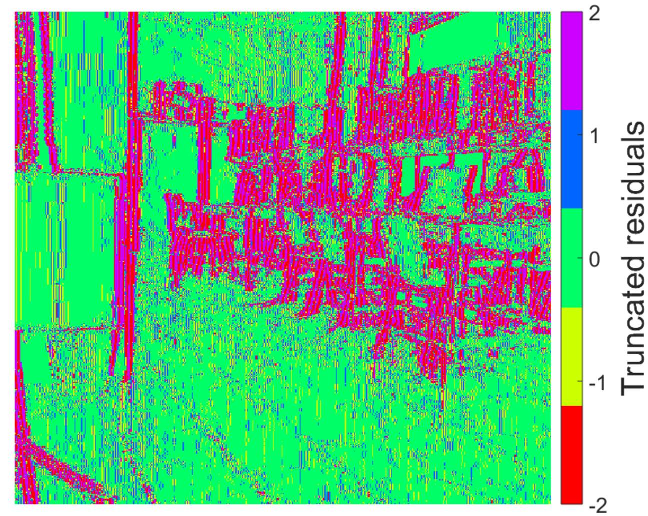
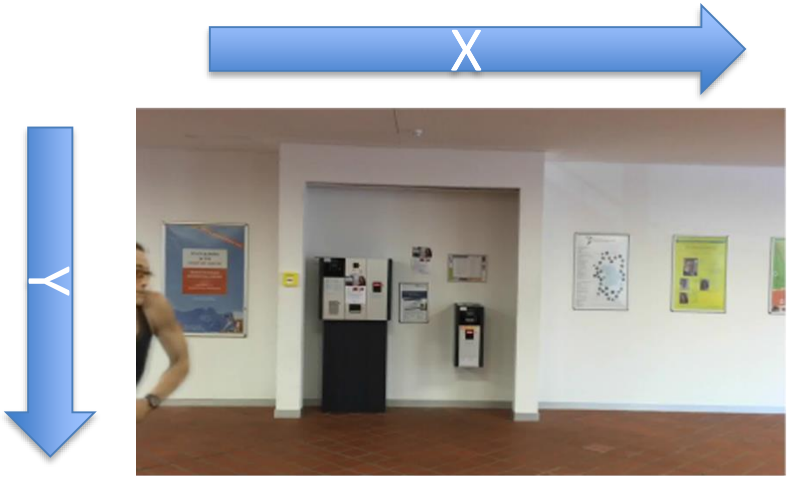


Co-occurrence matrix

	-2	-1	0	1	2
-2	8087	1256	2317	2713	15095
-1	1163	947	12097	11592	2600
0	2147	11892	84896	10277	2475
1	2732	11587	10317	854	1255
2	15340	2755	2182	1316	8208

Directions



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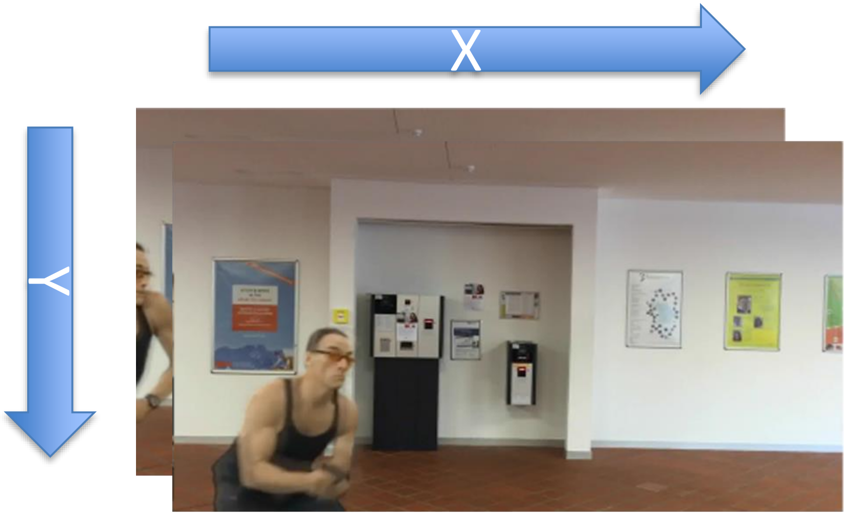

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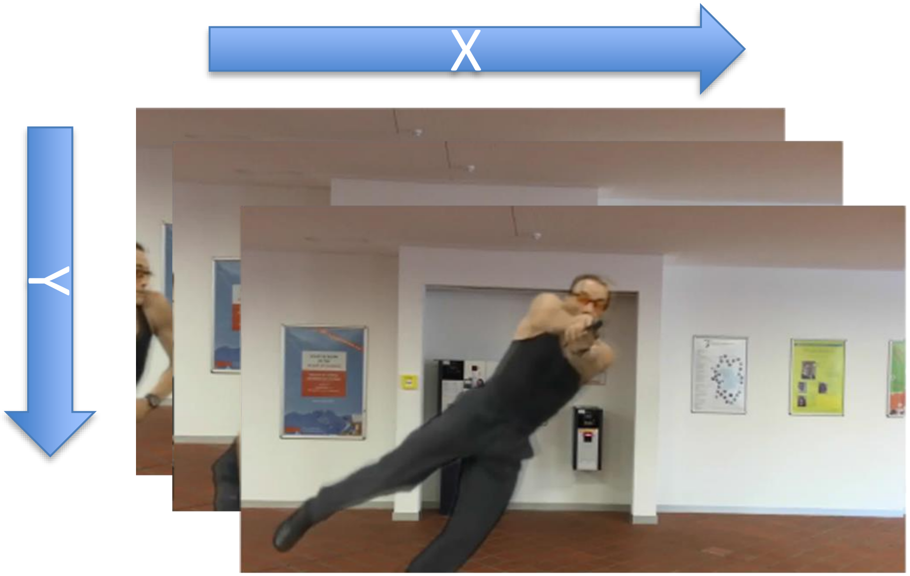

Directions

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Video:

- Enlarges feature space
  → time offers new, third dimension
- Can be used to track motion by optical flow
  → to align slided windows of features

Classification pipeline

<u>Feature Extraction</u>

- Histogram of co-occurrence residuals
- In different directions
- On sliding windows
- Optional: align features by "optical flow"

<u>Classification</u>

- Calculate mahalanobis distance
- Can be thresholded

<u>Decision</u>

- Frame authentic?
- Frames from same camera?

<u>Training</u>

Train on known pristine frames

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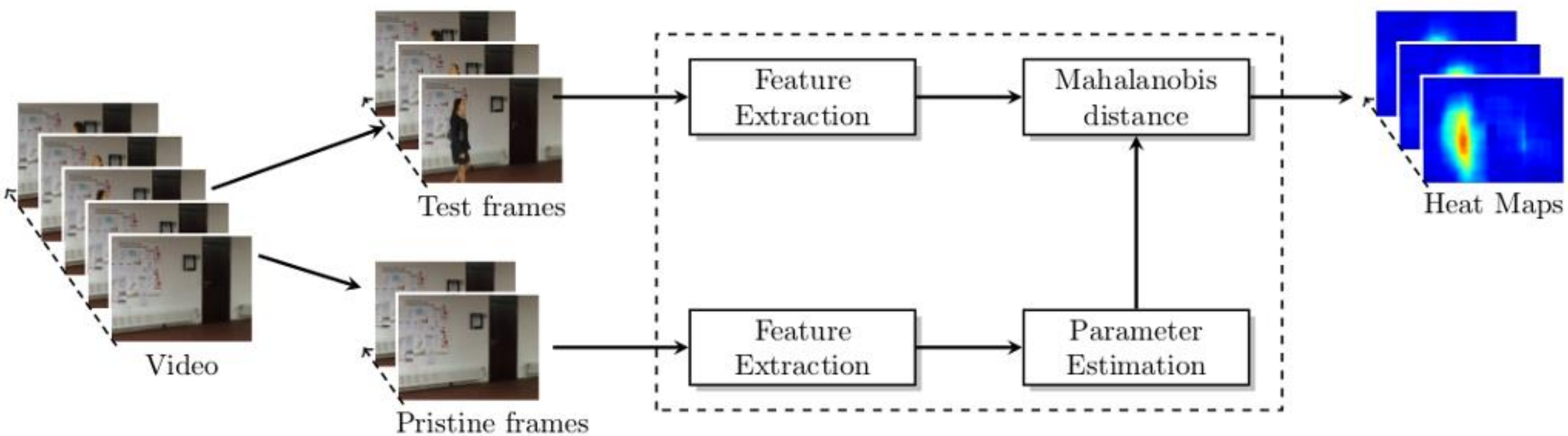
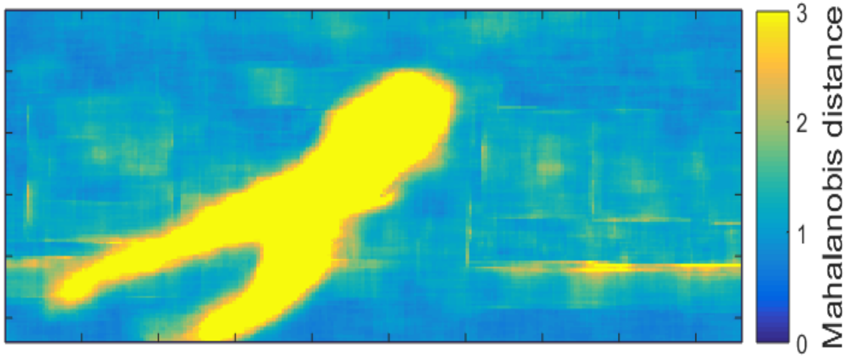
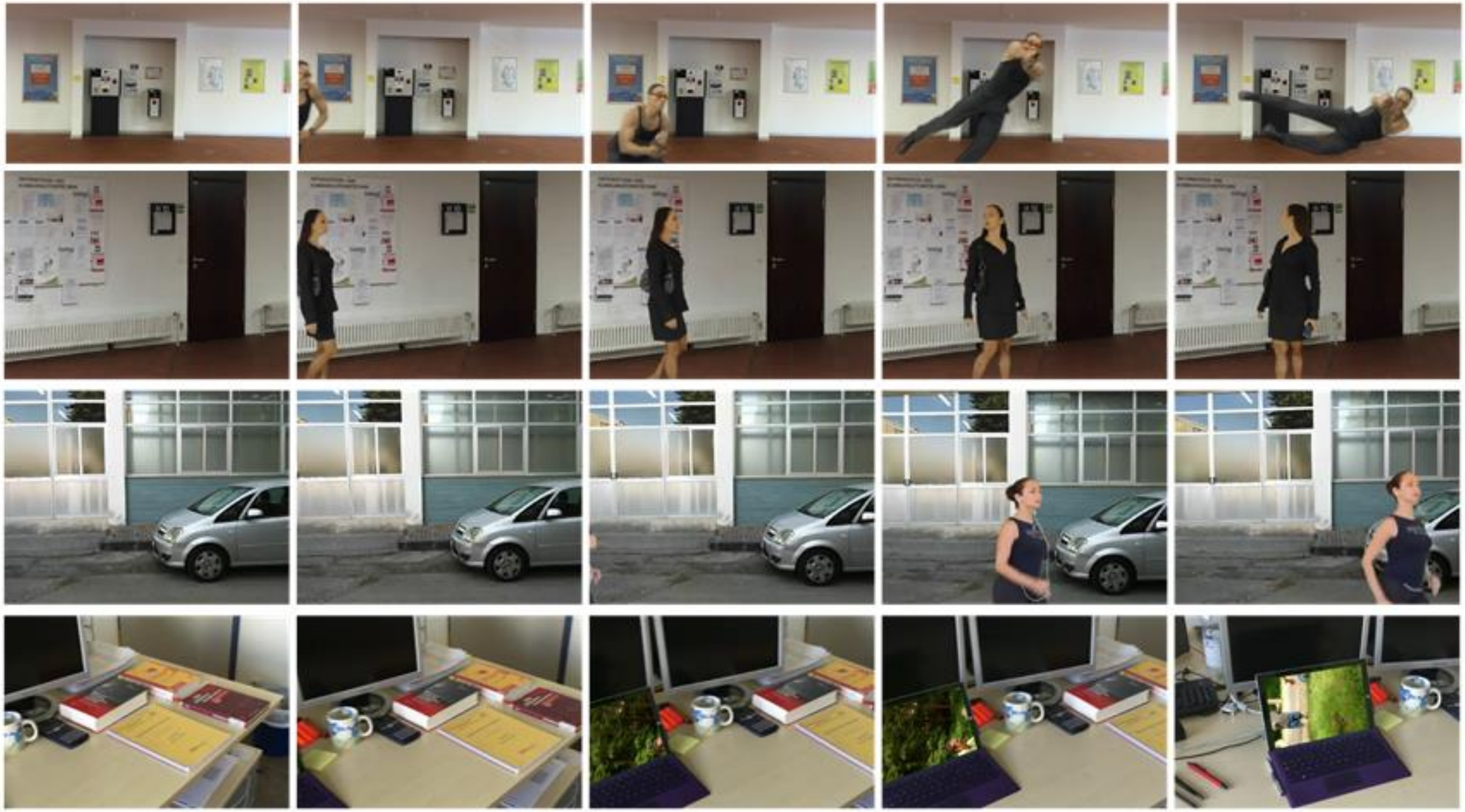


Mahalanobis distance as heatmap

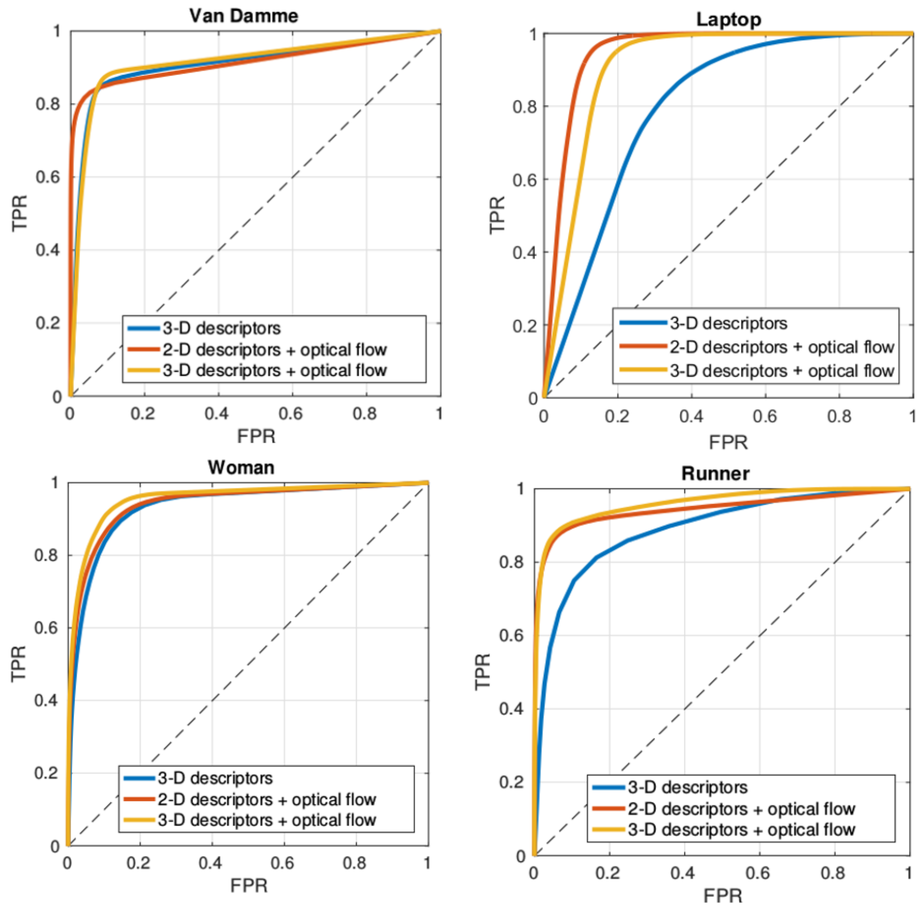
- Mahalanobis distances can be illustrated in heatmaps
- Objects spliced onto the background are revealed visually



Dataset

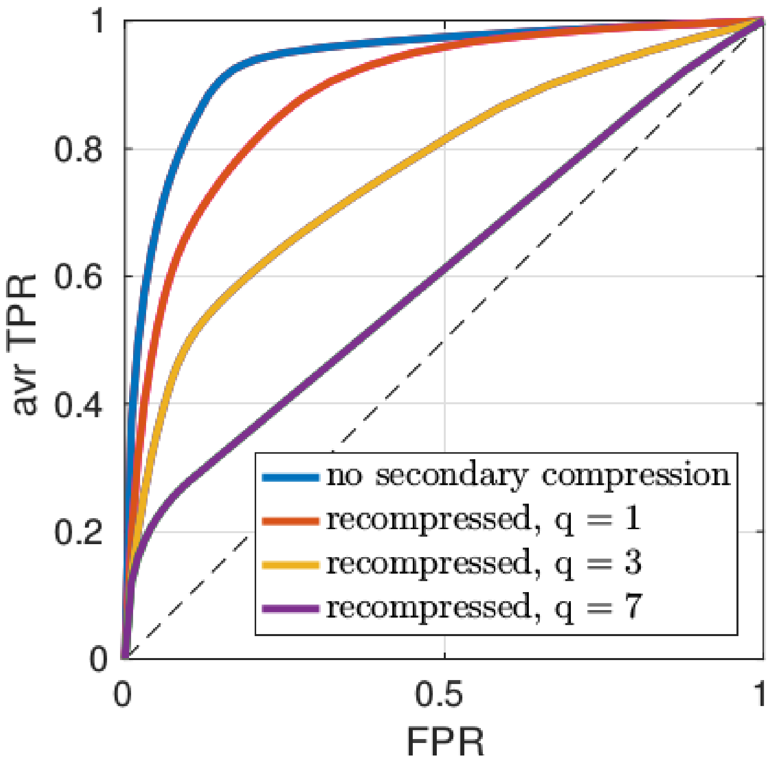


Evaluation



- Suggested method detects splicing reliable
- Incorporating optical flow to can improve results

Evaluation under compression

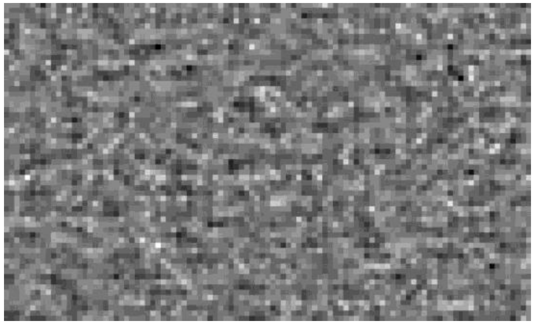


Secondary recompression of spliced material:

- Weakens its localization
- Detection results correlates (negatively) with compression factor

Related work

- Photo-response nonuniformity (PRNU) based:
  - PRUN is a profoundly unique pattern inherently present in any imaging device [1]
  - Also applied to localize video manipulations [2]



Example PRNU, amplified

[1] J. Lukás, J. Fridrich, M. Goljan, “Detecting digital image forgeries using sensor pattern noise,” in *Proceedings of the SPIE*, vol. 6072, 2006
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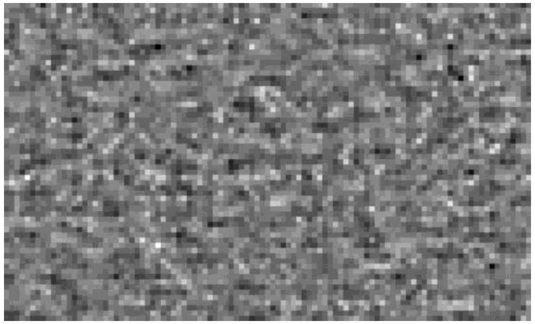


Example PRNU, amplified

- Autoencoder (AE) based [3]:
  - AEs are a special neural network architecture
  - Training subject to reconstruct input from compressed state z with little error as possible: $\min\{\mathcal{L}(f, \hat{f})\} \rightarrow$ If new input differs, $\mathcal{L}$ becomes large

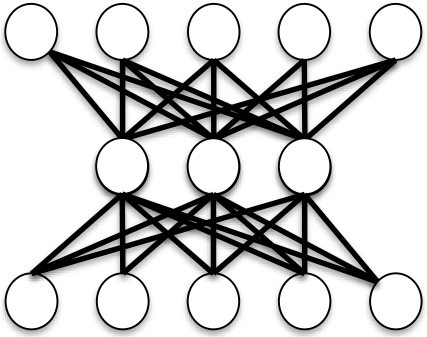
Output vector $\hat{f}$

↑

Compressed state z

↑

Input vector f



Decode

Encode

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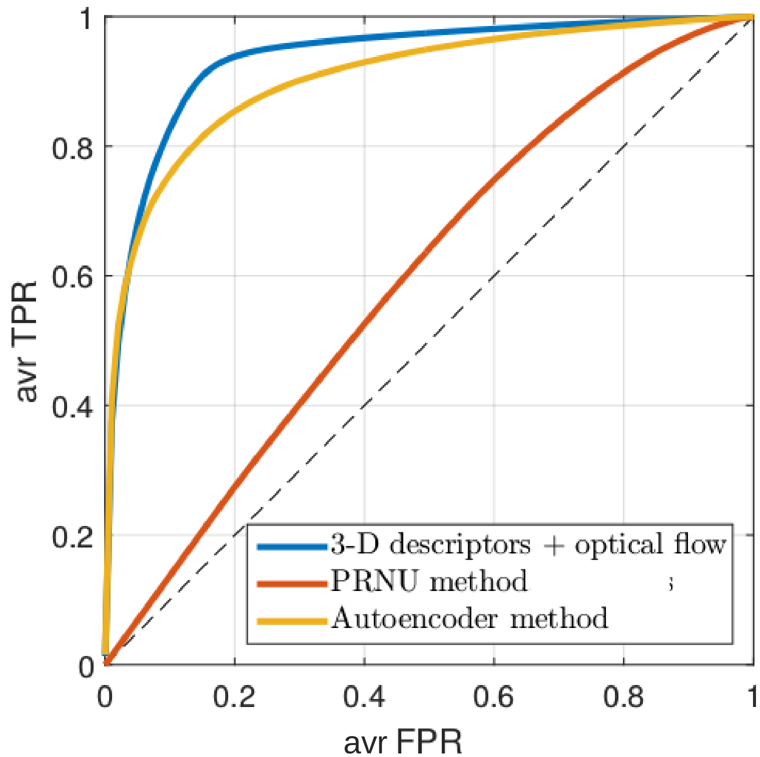
Comparison with other methods



- Suggested framework can produce better results then other works
- AE does not utilize information about movement in videos, like incorporating optical flow in the suggested framework
- PRNU might have difficulties to build a meaningful model from correlated frames

Summary and Outlook

Presented Algorithm:

- Distinguishes different noise distributions, present in a spliced video
- Tested successfully on green screen splicing
- Additional secondary compression influences performance

Future Work:

- Build up bigger database
- Apply algorithms to different kinds of forgeries
- Also apply to video source identification (e.g. on non-forged videos)

Thanks for your attention!
Questions?

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