

PRNU-based Detection of Morphed Face Images

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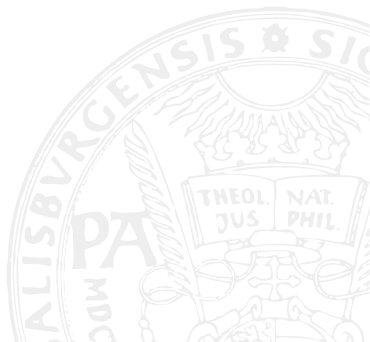
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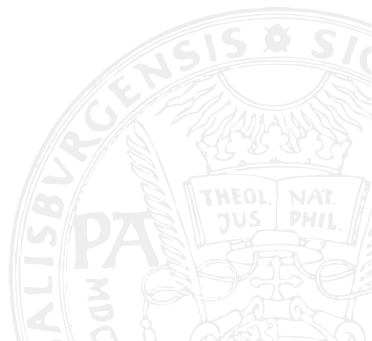
June 7th, 2018



- 1 Introduction and Motivation
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- 4 Conclusion and Future Work



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What is Face Morphing?

Morphing - Creating an in-between image by blending two images



(a) Subject 1

(b) Morph

(c) Subject 2

Figure: High Quality face morph of two subjects.

Steps for morphing face images:

- 1 Find location of facial feature points (landmarks) in both images
- 2 Compute Delaunay Triangulation for both images
- 3 Calculate affine transformations and warp triangles
- 4 Alpha blending of warped images

The Magic Passport

- Face selected as primary biometric trait for electronic Machine Readable Travel Documents (eMRTD) in 2002
- “The Magic Passport”[1]: Use morphed face images of multiple subjects for passport application



Figure: Passport application with morphed image.

The Magic Passport (cont.)

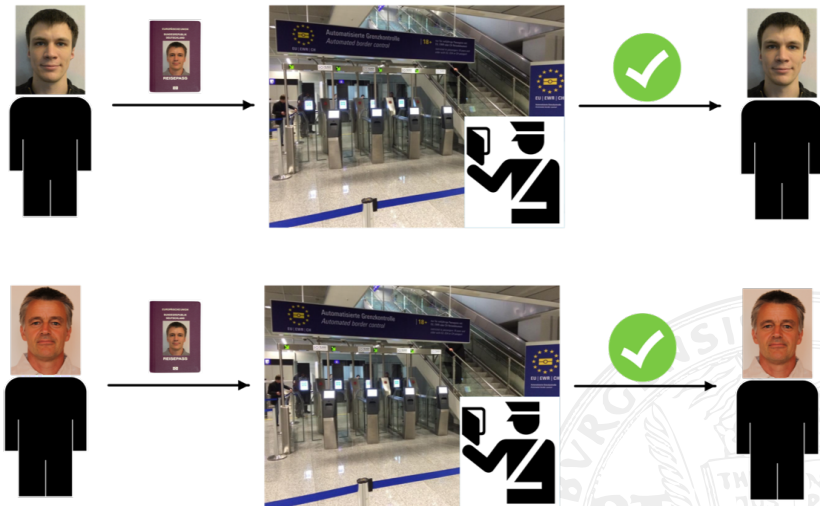
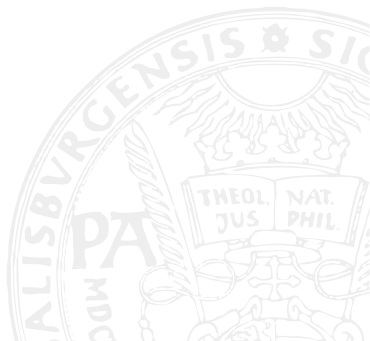
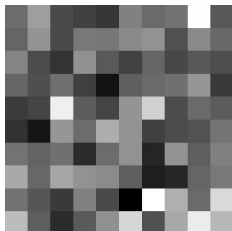


Figure: Both subjects are able to pass automated border control with the same passport.

- Ferrara *et al.* [1]: Morphed face images are successfully verified against both subjects using 2 commercial face recognition tools in verification mode at False Accept Rate (FAR) of 0.1%
- Ferrara *et al.* [2]: High quality morphed face images are realistic enough to fool human examiners
- Scherhag *et al.* [3]: Presentation attack detection using general purpose texture descriptors and machine learning techniques fail at reliably detecting morphed face images
- Detection of morphed face images becomes even more challenging if images are printed and scanned
→ **SERIOUS RISK** for automated border control

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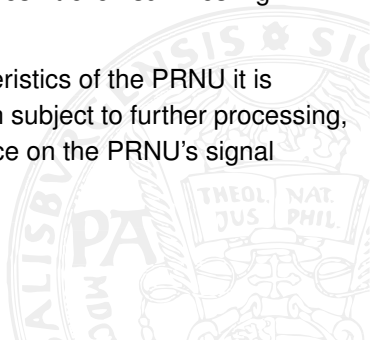


- PRNU: Photo-response non-uniformity
- Intrinsic property of CCD/CMOS sensors
- Noise-like pattern
- Variations in quantum efficiency among pixels
- PRNU noise residual W_I :

$$W_I = I - F(I)$$

- 1 Universality:** All imaging sensors exhibit PRNU.
- 2 Generality:** The PRNU is present in every picture independently of the camera optics, camera settings, or scene content.
- 3 Robustness:** It survives lossy compression, filtering, gamma correction, and many other typical processing procedures. It even survives high quality printing and scanning [4].

By investigating the spectral and spatial characteristics of the PRNU it is possible to detect whether the images have been subject to further processing, e.g. non-geometrical operations have an influence on the PRNU's signal strength [5].



PRNU-based Morphing Detection Approach

- Goal: Blind detection of morphed images without the need of reference image
- Exploit the effects caused by morphing in spectral domain through non-linear warping

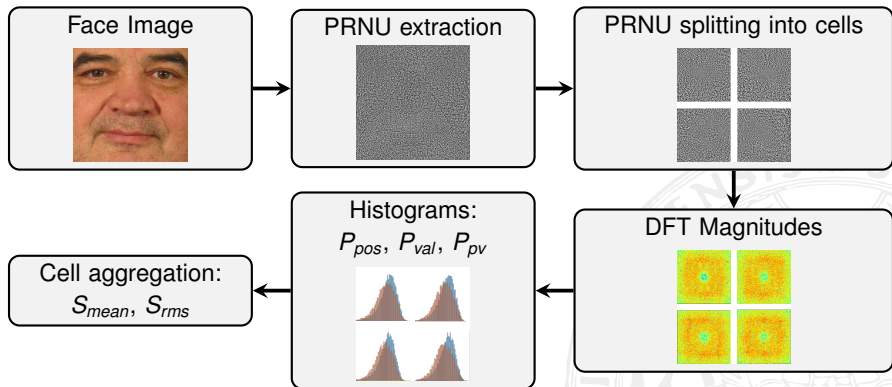
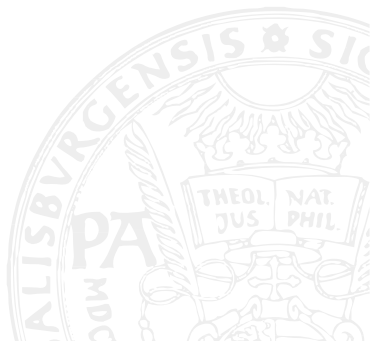


Figure: Processing steps.

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- Dataset: Subset of FRGCv2
 - Face images with resolution of 320x320 pixels (ICAO compliant)
 - 961 bona fide images (male and female), 2414 morphed images
- PRNU extraction: Mihcak denoising filter [6] + FDR enhancement [7]
- Different block configurations: 1x1 ... 10x10
- Experiments:
 - Experiment A: Detection of morphed face images
 - Experiment B: Face recognition vulnerability assessment
 - Experiment C: Detection of post-processed morphs
- Post-processings of morphs used in Experiment B and C:
 - SHRP: Sharpening (unsharp masking)
 - SCL: Downscaling (75% and 50%) with subsequent upscaling
 - EQU: Histogram equalization (CLAHE)

- Face recognition vulnerability assesment (according to [8])
 - How well do both subjects match against the mated morphed image?
 - Evaluation using a commercial face recognition system
 - **MMPMR**: Mated Morph Presentation Match Rate
 - **RMMR**: Relative Morph Match Rate (considering match rate of subjects)

- Detection of morphed face images (according to ISO/IEC 30107-3 [9])
 - How well are morphed images correctly classified?
 - **APCER**: Attack Presentation Classification Error Rate - attacks incorrectly classified as bona fides
 - **BPCER**: Bona Fide Presentation Classification Error Rate - bona fides incorrectly classified as attacks
 - **D-EER**: Detection Equal Error Rate, $APCER = BPCER$

Experiment A: Morphing Detection

Feature	Cells				
	1×1	2×2	4×4	8×8	10×10
$P_{val} S_{mean}$	2.1	2.0	1.9	3.2	3.8
$P_{val} S_{rms}$	2.1	2.0	1.9	3.3	3.9
$P_{pos} S_{mean}$	5.1	3.3	2.9	2.2	2.4
$P_{pos} S_{rms}$	5.1	3.2	2.8	2.3	2.6
$P_{pv} S_{mean}$	2.2	1.7	1.5	1.4	1.8
$P_{pv} S_{rms}$	2.2	1.6	1.5	1.5	1.8

Table: D-EERs in % for detection of morphed images.

Experiment B: Face Recognition Vulnerability Assessment

- **MMPMR** > **99.99%** for morphed and post-processed images
- **RMMR** > **99.99%** for morphed and post-processed images

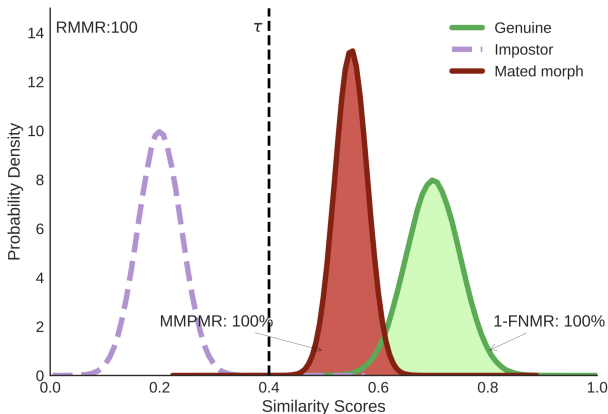
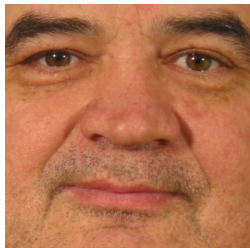


Figure: Illustration of score distributions for RMMR = MMPMR = 100%.

→ **Nearly all face images are matched against their morphs**

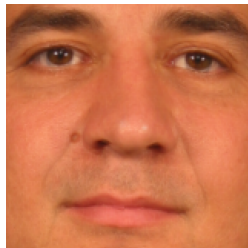
Experiment C: Post-processing Examples



(a) Original



(b) Morphed



(c) SCL 50%



(d) SCL 75%

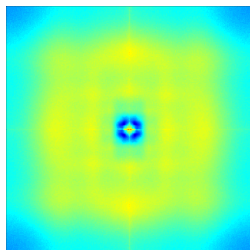


(e) SHRP

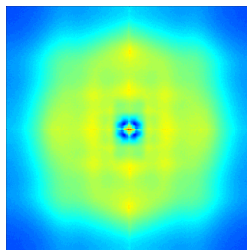


(f) EQU

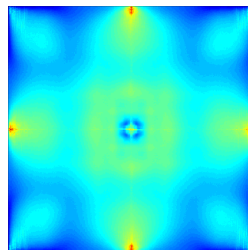
Experiment C: Averaged DFT Magnitude Spectra



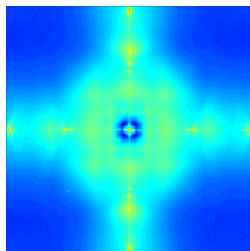
(g) Original



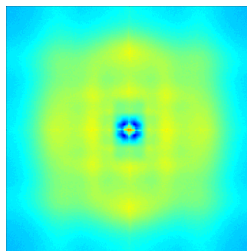
(h) Morphed



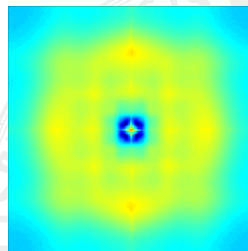
(i) SCL 50%



(j) SCL 75%



(k) SHRP



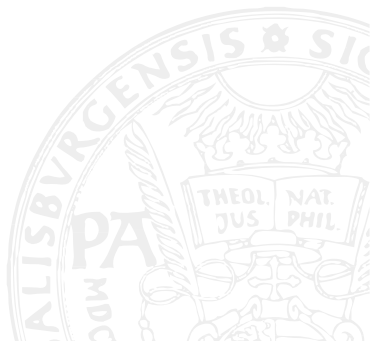
(l) EQU

Experiment C: Detection of Post-processed Morphs

Feature	Cells	Morph	EQU	SCL ₅₀	SCL ₇₅	SHRP
$P_{val} S_{mean}$	1×1	2.1	34.8	0.7	2.2	46.4
$P_{val} S_{rms}$		2.1	34.8	0.7	2.2	46.4
$P_{pos} S_{mean}$		5.1	36.4	4.5	0.3	20.1
$P_{pos} S_{rms}$		5.1	36.4	4.5	0.3	20.1
$P_{pv} S_{mean}$		2.2	32.9	0.9	0.2	36.9
$P_{pv} S_{rms}$		2.2	32.9	0.9	0.2	36.9
$P_{val} S_{mean}$	2×2	2.0	36.3	0.7	2.0	45.8
$P_{val} S_{rms}$		2.0	36.3	0.6	2.0	45.9
$P_{pos} S_{mean}$		3.3	33.4	2.5	0.2	17.1
$P_{pos} S_{rms}$		3.2	33.1	2.4	0.2	17.0
$P_{pv} S_{mean}$		1.7	32.8	1.0	0.1	32.6
$P_{pv} S_{rms}$		1.6	32.6	1.0	0.1	33.1
$P_{val} S_{mean}$	8×8	3.2	35.5	0.4	7.4	34.5
$P_{val} S_{rms}$		3.3	35.6	0.4	7.6	35.8
$P_{pos} S_{mean}$		2.2	33.8	0.7	0.0	10.8
$P_{pos} S_{rms}$		2.3	33.6	0.8	0.0	11.0
$P_{pv} S_{mean}$		1.4	31.8	0.3	0.1	15.9
$P_{pv} S_{rms}$		1.5	31.3	0.3	0.0	17.3

Table: D-EERs in % for detection of morphed images.

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Conclusion

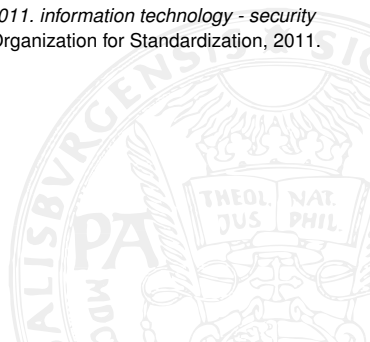
- Creating morphed face images affects the PRNU.
- Reliable detection of morphed face images possible with the proposed cell-based PRNU approach.
- Robust against some post-processings (SHRP, SCL).
- Detection can be attacked with EQU post-processing.

Future work

- Improve robustness against post-processing of morphed images.
- Is the approach robust against PRNU insertion/substitution?
- How well does it work for images from different cameras?
- Does it also work as well for printed and scanned images?

- [1] M. Ferrara, A. Franco, and D. Maltoni, “The magic passport”, in *Proc. Int. Joint Conf. on Biometrics (IJCB)*, 2014, pp. 1–7.
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Thank you for your attention!
Any questions?

