On the Influence of Texture Strength and Camera Signal on Micro-Texture Surface Classification

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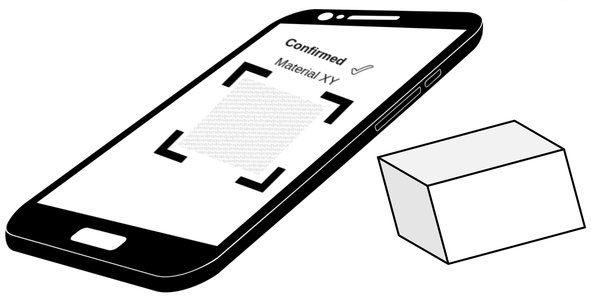
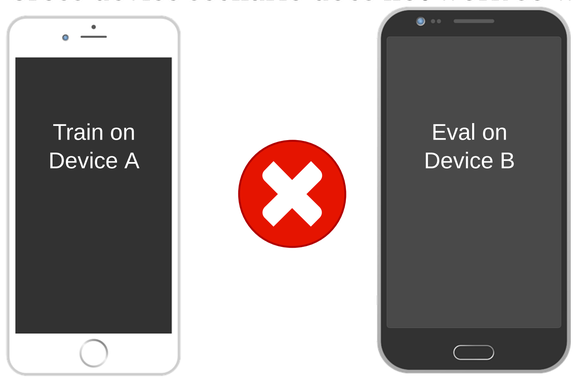
Task

Intrinsic product authentication: Classification of low texture surfaces based on smartphone imagery.



Problem

Cross device scenario does not work so well



This work

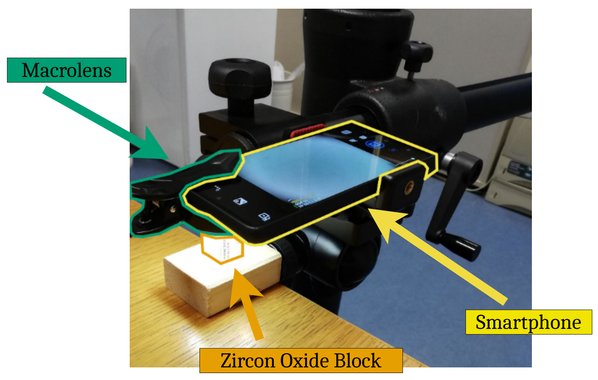
- Study **interdependence** of **image content** and **device-inherent signal** → employ images with increasing ”magnitudes of texture”
- Check, if **device-inherent signal** is **instance, model or brand specific** → use more smartphones of similar type

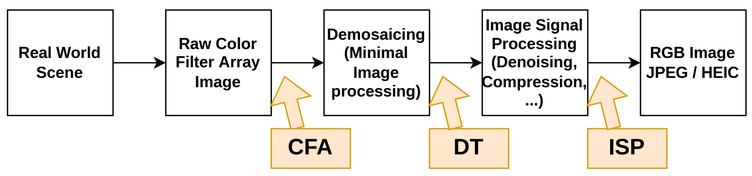
Main Result:

- Device-inherent signal which interferes with image content appears to be model specific

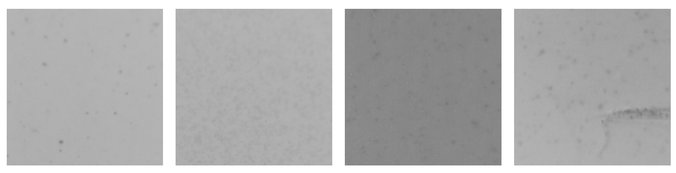
Setup

- Capture 3 types of texture in JPEG / HEIC and raw formats:



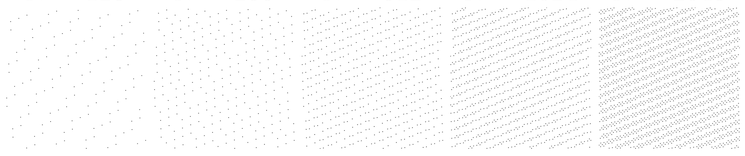


- **Texture 1:** Top side of **zircon oxide blocks** (3 different manufacturers = classes)

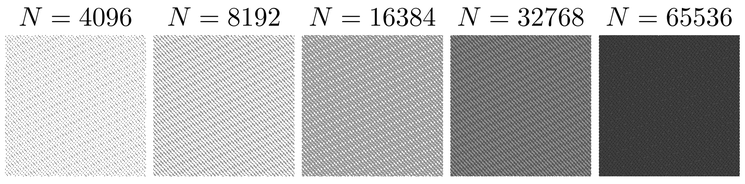


- **Texture 2: Zinterhof** sequences (simulate increasingly more texture)

$N = 128$ $N = 256$ $N = 512$ $N = 1024$ $N = 2048$

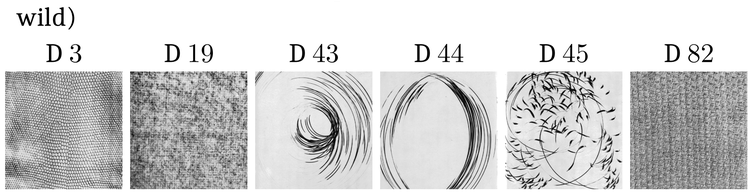


$N = 4096$ $N = 8192$ $N = 16384$ $N = 32768$ $N = 65536$



- **Texture 3:** 6 **Brodatz** samples (simulate random t exture in the wild)

D 3 D 19 D 43 D 44 D 45 D 82



Texture Classification Pipeline

- Two**feature extraction** schemes:
  - Dense SIFT (**SIFT**) followed by a **PCA** based dimensionality reduction, a **Fisher vector encoding**
  - Rotational invariant Local Binary Pattern (**LBP**)
- Classification using a Support Vector Machine (**SVM**)
- Why not use deep learning?
  - interpretability → straightforward evaluation of the classic texture features
  - lack of sufficient training data due to rather small sample datasets

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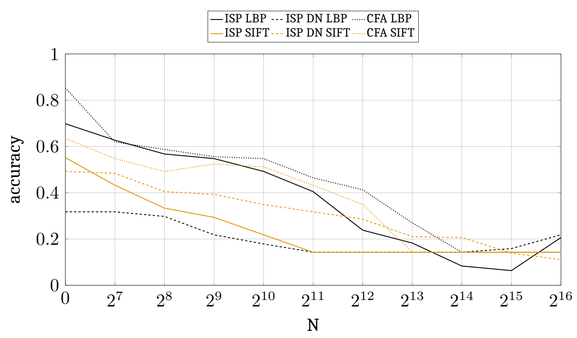
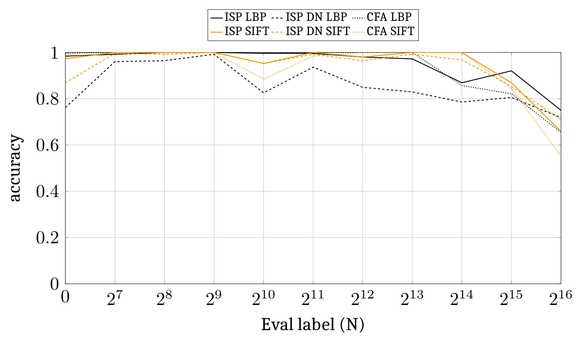
Experiments A: Impact of texture strength

- **General setting:** Device classification using 7 different smartphone devices.

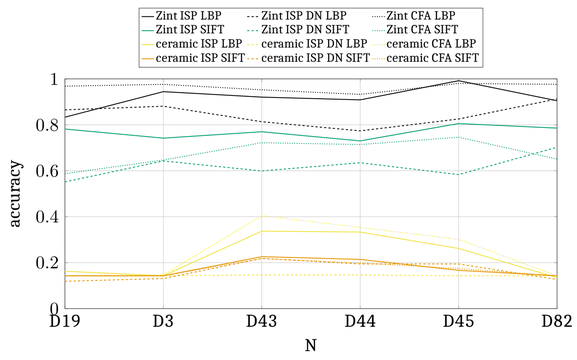
- **Assumption:** ceramic pattern is low in texture → device-inherent signal is dominant → hence device classification works well.
- **How to test:** Train on ceramic, test different ”magnitudes of texture” (Zinterhof)



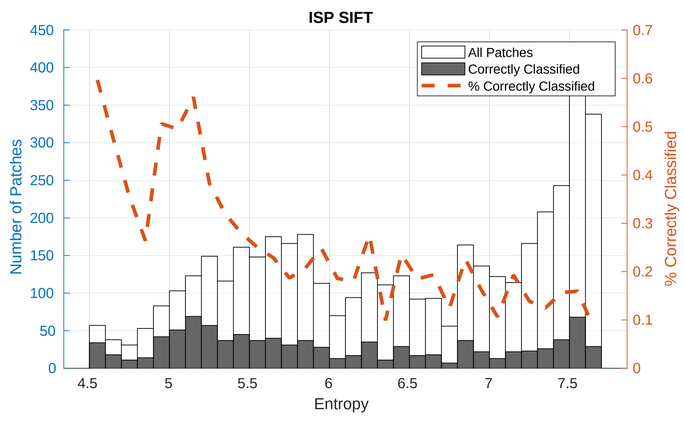
- **Assumption:** Different ”magnitudes of texture” would alleviate previous trend (ceramic texture strength is rather consistent)
- **How to test:** Leave one out cross validation on Zinterhof



- **Assumption:** Training on Zinterhof pattern images generalizes well, while ceramic does not
- **How to test:** Train on Zinterhof and ceramic textures respectively, test on some random textures in the wild (we chose 6 Brodatz samples)



- **Assumption:** ”Texture strength” in this setting can be measured using image entropy
- **How to test:** Train on ceramic, test on all remaining samples but sort samples based on their entropy



Experiments B: Smartphone pairs and triples

- **General setting:** Device and texture classification using a total of 19 smartphones, including **4 pairs** and **1 triplet** of the same model.
- The devices are split into subsets:
  - **all** – uses all 19 Smartphones
  - **NDF (non-duplicates filtered)** – uses only devices where we have a pair or triplet
  - **uid** – remember user id, e.g. two different iPhones 13 count as separate classes

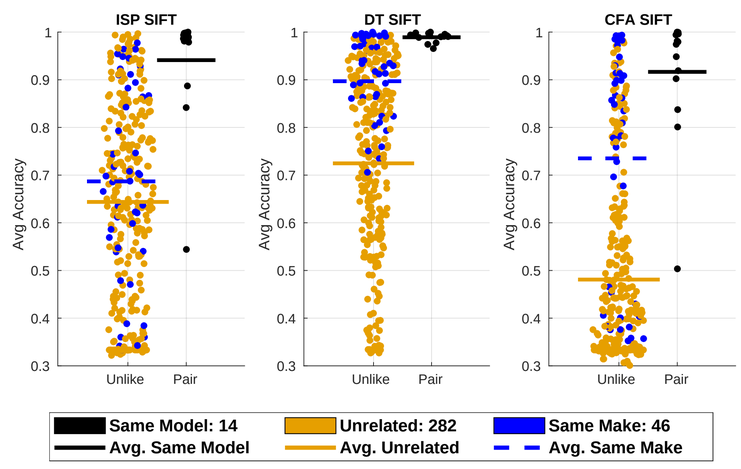
- **Assumption:** Device classification (ceramic only):
  - If device-inherent signal is instance specific → uniform results are expected
  - If signal is model specific → NDF results should be higher

Source	**all**	**all uid**	**NDF**	**NDF uid**
CFA LBP	0.952	0.832	0.999	0.787
DT LBP	0.877	0.700	0.990	0.661
ISP LBP	0.959	0.793	0.992	0.641
CFA SIFT	0.873	0.939	0.999	0.955
DT SIFT	0.805	0.775	0.974	0.765
ISP SIFT	0.878	0.881	0.994	0.826

- **Assumption:** Texture classification (ceramic only):
  - If device-inherent signal is instance specific → uid and non-uid should be similar
  - If signal is model specific → uid results should be higher

Source	**all**	**all uid**	**NDF**	**NDF uid**
CFA LBP	0.969	0.887	0.500	0.945
DT LBP	0.963	0.974	0.856	0.983
ISP LBP	0.898	0.933	0.833	0.977
CFA SIFT	0.980	0.988	0.957	0.999
DT SIFT	0.995	0.998	0.994	0.999
ISP SIFT	0.982	0.990	0.996	0.999

- **Assumption:** Train texture classification on one device, and test on another device
  - If device-inherent signal is instance specific → results should be distributed randomly
  - If signal is model specific → results between pairs of the same model should be superior to random matches



Summary

Device-inherent signal is ...

- ... interdependent with image content and weak in nature
- ... suppressed as ”texture magnitude” / entropy increases
- ... rather model than instance / device specific