Limiting Factors in Smartphone-Based Cross-Sensor Microstructure Material Classification

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Introduction & Motivation

- Counterfeit products are a problem
 - Causing economic damage to the original manufacturers
 - Especially in medical field they can directly influence patients' health
 - \rightarrow Product authentication:
 - Extrinsic: based on QR codes, external markers
 - Intrinsic: based on the product's properties, no external markers etc. needed
- Manufacturers do not favour extrinsic authenticity methods due to extra production costs
- Intrinsic product authentication is preferred

Goal: Classify manufacturer of dental ceramics using images captured with smartphone cameras (sensors)¹.

Findings:

Intra-sensor vert works well

Train/enroll on sensor A \rightarrow Test/evaluate on sensor A

Cross-sensor X results unsatisfying Train/enroll on sensor A \rightarrow Test/evaluate on sensor B

■ PRNU (sensor noise²) was eliminated as a reason

¹ Schuiki, J., Kauba, C., Hofbauer, H., & Uhl, A. (2023). Cross-sensor micro-texture material classification and smartphone acquisition do not go well together. *Proceedings of the 11th International Workshop on Biometrics and Forensics (IWBF'23)*

² Lukas, J., Fridrich, J. J., & Goljan, M. (2008).Digital camera identification from sensor pattern noise.. *IEEE Transactions on Information Forensics and Security*

Aim of this research

- Goal: Determine limiting factors why cross-sensor material classification yields inferior results
- Assumption: Signal of material property is much lower than device inherent signals & artefacts from image processing pipeline.



Dental Ceramic Data Acquisition

- 7 different smartphones
- Zircon oxide blocks from 3 manufacturers
- Acquisition of images in RAW mode via app:
 - Android: OpenCamera (https://opencamera.org.uk/)
 - iPhone: Halide Mark II (https://halide.cam/)
- Macro lens with built-in illumination



Smartphones and their imaging sensor resolution

Smartphono	Image	Scaling	
Smartphone	Resolution	Factor	
Google Pixel 4a (GP)	3024 x 4032	0.686	
Huawei P20 Lite (H20)	3456 x 4608	0.600	
Huawei P30 Pro (H30)	2736 x 3648	0.758	
iPhone 11 (i11)	3024 x 4032	0.686	
iPhone 13 Pro (i13)	3024 x 4032	0.686	
Samsung Galaxy A52 (SG)	3468 x 4624	0.598	
Xiaomi Mi A3 (XM)	3000 x 4000	0.691	

576 patches per smartphone for Ivoclar Vivadent (Manufacturer 1), 216 for Dentsply Sirona (Manufacturer 2) and 360 for 3M (Manufacturer 3).

Dental Ceramic Data Legend - Abbreviations



- ISP "Image Signal Processing" Pipeline: JPEG and HEIC files from smartphones.
- DT Color filter array image demosaiced using darktable-cli.
- DCA Color filter array demosaiced using *dcraw -a*: Average the whole image for white balance.
- CFA Color filter array extracted using *dcraw -d*: Document mode (no color, no interpolation)
 - DN Apply *bm3d* ³ denoising filter on the whole image.

³ Dabov, K., Foi, A., Katkovnik, V., & Egiazarian, K. (2007).Image denoising by sparse 3-d transform-domain collaborative filtering. *IEEE Transactions on Image Processing*

Samples of ceramic images per imaging modality



Texture Classification Toolchain

- Same as in ⁴, originally proposed in "Textures in the Wild" ⁵
- Different feature extraction schemes:
 - Dense SIFT
 - Dense Micro-block Difference
 - LBP
 - Local Phase Quantization
 - Weber Pattern

 \uparrow Followed by a PCA based dimensionality reduction, a Fisher Vector encoding and finally an SVM based classification §

Rotation invariant LBP

For brevity, only SIFT results shown in results

⁴ Kauba, C., Debiasi, L., Schraml, R., & Uhl, A. (2016). Towards drug counterfeit detection using package paperboard classification. Advances in Multimedia Information Processing – Proceedings of the 17th Pacific-Rim Conference on Multimedia

⁵ Cimpoi, M., Maji, S., Kokkinos, I., Mohamed, S., & Vedaldi, A. (2014).Describing textures in the wild. 2014 IEEE Conference on Computer Vision and Pattern Recognition

1) Test ISP as main factor: Use raw images

Train/enroll on 1 sensor \rightarrow Test/evaluate on 1 other sensor



Table: Average ceramic classification accuracy in inter-sensor setup using SIFT features and DCA images.

		Test						
		GP	H20	H30	i11	i13	SG	XM
	GP	_	0.837	0.852	0.707	0.832	0.607	0.997
	H20	0.605	—	0.515	0.333	0.352	0.455	0.465
	H30	0.846	0.716	_	0.676	0.854	0.751	0.906
<u>'a</u>	i11	0.480	0.663	0.381	_	0.864	0.380	0.613
Γ	i13	0.813	0.579	0.362	0.819	- //	0.344	0.552
	SG	0.831	0.668	0.603	0.675	0.963	57-8	0.943
	XM	0.982	0.804	0.451	0.787	0.903	0.358	THEO

1) Test ISP as main factor: Use raw images

- 2) Evaluate effect of color filter array
 - Baseline: Intra-Sensor

Train/enroll on sensor A \rightarrow Test/evaluate on sensor A

Cross-Sensor: Leave one out cross validation

Train/enroll on all but sensor A \rightarrow Test/evaluate on sensor A

Sensor Identification

Results (SIFT)



Classification accuracy results CFA unscaled

	Google Pixel4a	Huawei P20 Lite	Huawei P30 Pro	iPhone 11	iPhone 13 Pro	Samsung Gal. A52	Xiaomi MiA3
ЗМ							
Dentsply Sirong							
lvoclar Vivodont							

	Texture Classification		Sensor Identification		
	CFA	CFA DN	CFA	CFA DN	
SIFT	0.453	0.736	1.000	1.000	

Conclusion & Future Work

Conclusion:

- While raw (DT) tends to slightly increase cross-sensor accuracy, using only the mosaiced image (CFA) greatly reduces the accuracy
- Second, the CFA and the processing pipeline (ISP) signals can be used for sensor identification
- This suggests: CFA mainly interferes with the low-amplitude texture signal of the material

Future Work:

- Further investigations by employing smartphone pairs (multiple devices of same model)
- Try to remove CFA artefacts through deep learning (e.g. domain adaptation)

Thank You! Q & A