Enhanced Geometric Reflection Models for Paper Surface Based Authentication

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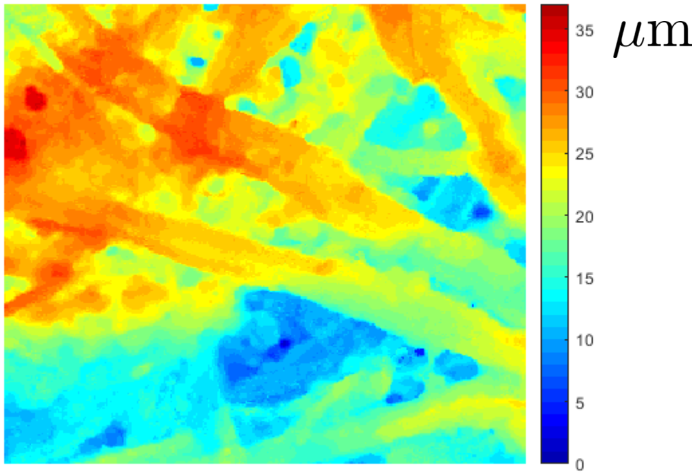
Introduction

- Paper surfaces:
  - Inter-twisted wood fibers, unique and physically unclonable
  - Unique randomness, may be regarded as "fingerprint"

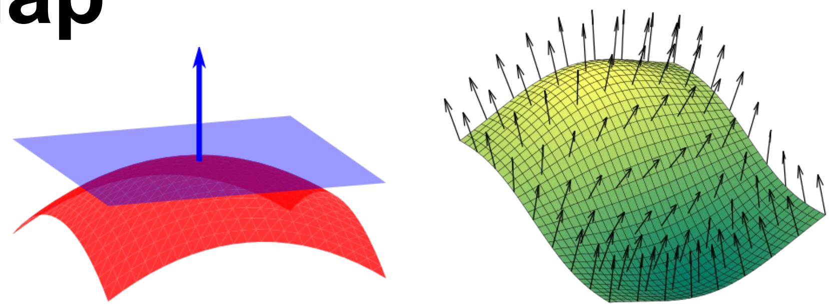
- Authentication applications:
  - Important documents, e.g., IDs, checks
  - label of wine bottles



0.2mm by 0.2mm paper under confocal microscope

Norm Map

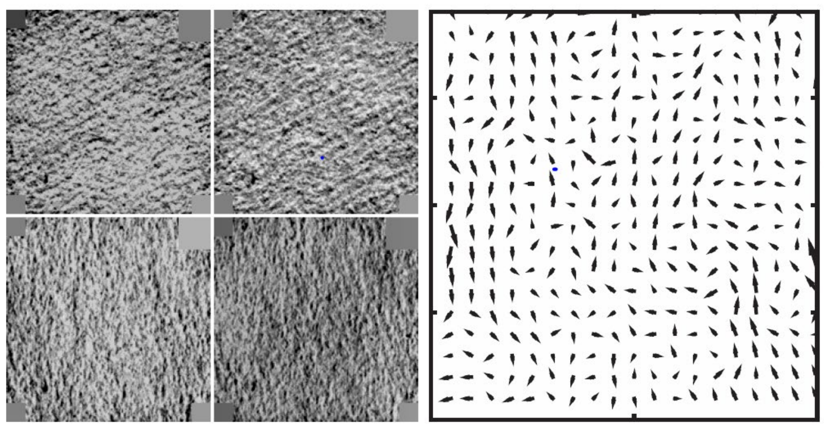
- Definition: surface normal



https://en.wikipedia.org/wiki/Normal_(geometry)

- Normal vector field: a collection of 3D normals over a 2D grid

- Norm map: 2D vector field on *x*-*y* plane

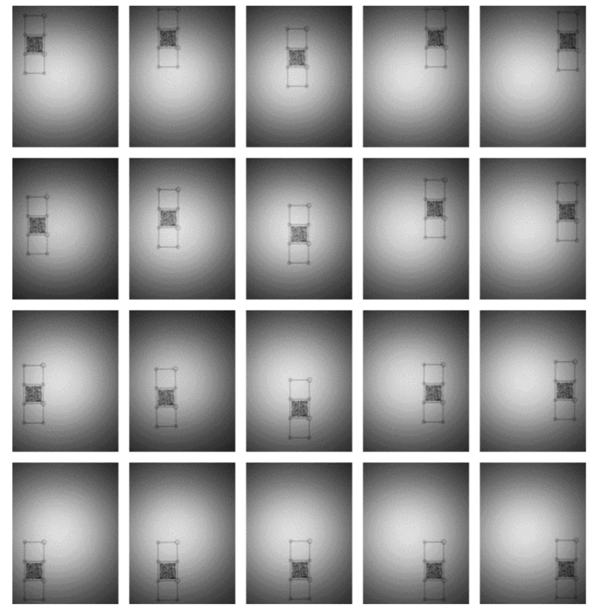


Scanned paper surfaces and a norm map [1]

[1] Chau-Wai Wong and Min Wu, "Counterfeit detection based on unclonable feature of paper using mobile camera," *IEEE Transactions on Information Forensics and Security (T-IFS)*, vol.12, no.8, pp.1885–1899, Aug. 2017

Dataset and Acquisition Conditions

- We used a publicly available dataset from our prior work [1]
- Experimental setup for the dataset:



Capture 20 images with different camera locations

- Dataset and minimally required source code for using the dataset is available upon request.

Fully Diffuse Model

- Fully diffuse light reflection model:

$$l_r(\mathbf{p}) = \lambda \cdot l(\mathbf{p}) \cdot \mathbf{n}(\mathbf{p})^T \mathbf{v}(\mathbf{p})$$

- Effect of ambient lights and cameras' brightness/contrast adjustment processes

$$l_r(\mathbf{p}) = \alpha \cdot \lambda l(\mathbf{p}) \mathbf{n}(\mathbf{p})^T \mathbf{v}(\mathbf{p}) + \text{ bias caused by ambient lights}$$

- Prior work [1]: estimating normal vectors at each location separately, which we refer to as Model 0:

$$\tilde{y}(\mathbf{p}) \approx \mathbf{n}(\mathbf{p})^T \mathbf{v}(\mathbf{p})$$

Proposed Enhanced Model 1

- Model 1: distinct intercept (ambient light) for each image k

$$y^{(k)}(\mathbf{p}) = \lambda l^{(k)}(\mathbf{p})\mathbf{n}(\mathbf{p})^T\mathbf{v}^{(k)}(\mathbf{p}) + \beta_0^{(k)}(\mathbf{p}), \quad k = 1, \ldots, M$$

- Decompose the estimation problem: first estimate λl and β use the spatial smoothness assumption

$$\begin{bmatrix} \tilde{y}^{(k)}(\mathbf{p}_0) \\ \vdots \\ \tilde{y}^{(k)}(\mathbf{p}_4) \end{bmatrix} \approx \begin{bmatrix} v_z^{(k)}(\mathbf{p}_0) & 1 \\ \vdots & \vdots \\ v_z^{(k)}(\mathbf{p}_4) & 1 \end{bmatrix} \begin{bmatrix} \lambda l^{(k)}(\mathbf{p}_0)m_z \\ \beta_0^{(k)}(\mathbf{p}_0) \end{bmatrix}.$$

	1	
2	0	3
	4	

- Then estimate normal vector $\mathbf{n}(\mathbf{p})$

$$\begin{bmatrix} \tilde{y}^{(1)}(\mathbf{p}) \\ \vdots \\ \tilde{y}^{(M)}(\mathbf{p}) \end{bmatrix} - \begin{bmatrix} \widehat{\beta_0^{(1)}}(\mathbf{p}) \\ \vdots \\ \widehat{\beta_0^{(M)}}(\mathbf{p}) \end{bmatrix} \approx \begin{bmatrix} \widehat{\lambda l^{(1)}}(\mathbf{p})\mathbf{v}^{(1)T}(\mathbf{p}) \\ \vdots \\ \widehat{\lambda l^{(M)}}(\mathbf{p})\mathbf{v}^{(M)T}(\mathbf{p}) \end{bmatrix} \begin{bmatrix} n_x(\mathbf{p}) \\ n_y(\mathbf{p}) \\ n_z(\mathbf{p}) \end{bmatrix}$$

Proposed Enhanced Model 2

- Model 2: same intercept (ambient light) for all images

$$y^{(k)}(\mathbf{p}) = \lambda l^{(k)}(\mathbf{p})\mathbf{n}(\mathbf{p})^T\mathbf{v}^{(k)}(\mathbf{p}) + \beta_0(\mathbf{p}) \qquad k = 1, \ldots, M$$

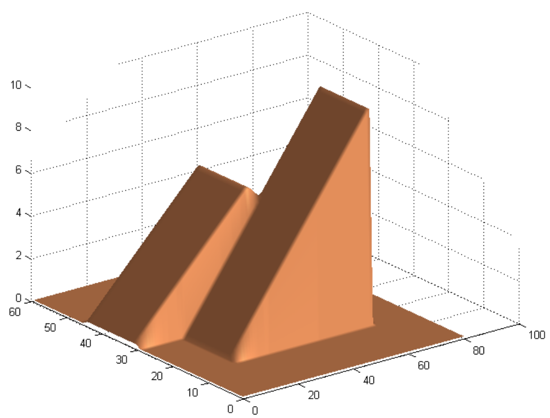
- Formulate a LS problem with data matrix in block diagonal form:

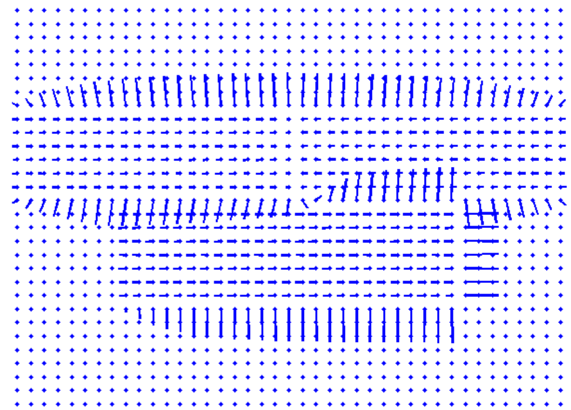
$$\begin{bmatrix} \tilde{y}^{(1)}(\mathbf{p}_0) \\ \vdots \\ \tilde{y}^{(1)}(\mathbf{p}_4) \\ \vdots \\ \tilde{y}^{(M)}(\mathbf{p}_0) \\ \vdots \\ \tilde{y}^{(M)}(\mathbf{p}_4) \end{bmatrix} \approx \begin{bmatrix} v_z^{(1)}(\mathbf{p}_0) & 0 & \ldots & 0 & 1 \\ \vdots & \vdots & & \vdots & \vdots \\ v_z^{(1)}(\mathbf{p}_4) & 0 & \ldots & 0 & 1 \\ \vdots & & & & \vdots \\ 0 & \ldots & 0 & v_z^{(M)}(\mathbf{p}_0) & 1 \\ \vdots & & \vdots & \vdots & \vdots \\ 0 & \ldots & 0 & v_z^{(M)}(\mathbf{p}_4) & 1 \end{bmatrix} \begin{bmatrix} \lambda l^{(1)}(\mathbf{p}_0)m_z \\ \vdots \\ \lambda l^{(M)}(\mathbf{p}_0)m_z \\ \beta_0(\mathbf{p}_0) \end{bmatrix}.$$

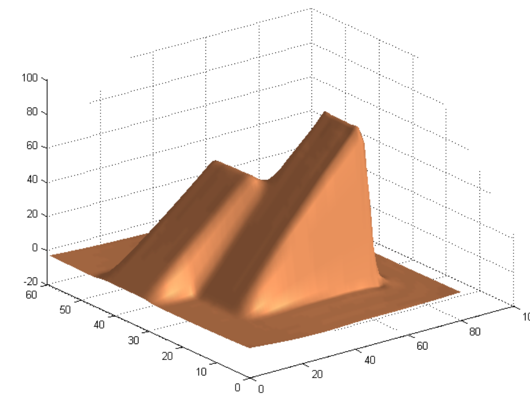
Surface Reconstruction from Normal Vector Field

- Norm map [1]: difficult to visualize; limited discriminative power
- 3D surface:
  - more appealing to human eyes
  - use off-the-shelf image/surface analysis tools

- Ex: Reconstruction of surface from normal vector field



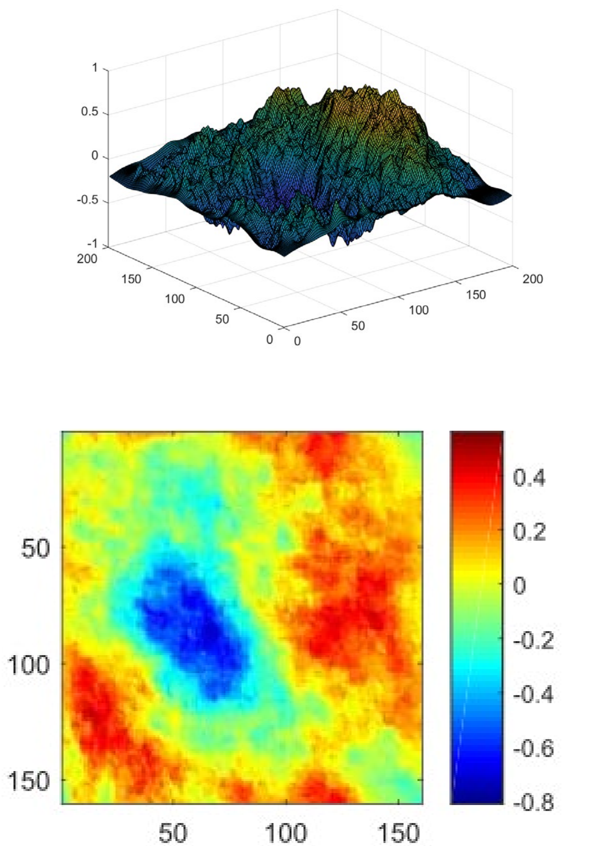




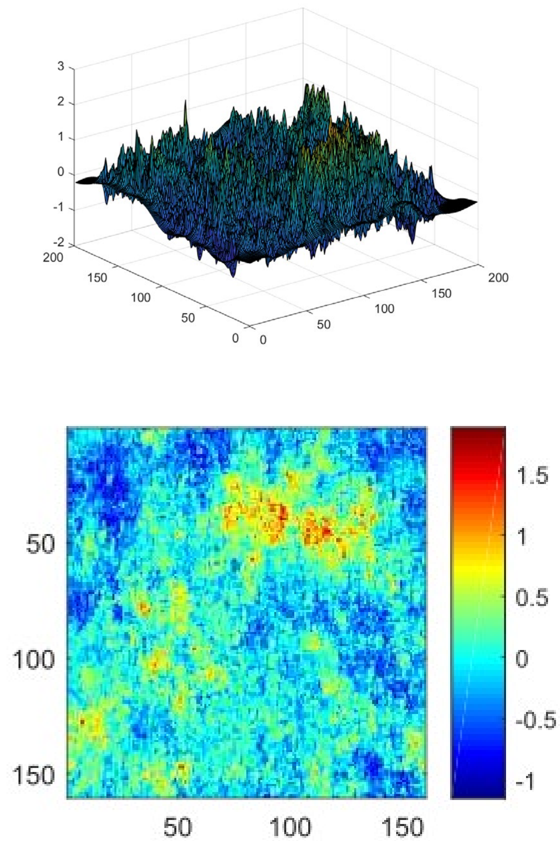
Kovesi, Peter. "Shapelets correlated with surface normals produce surfaces." *IEEE International Conference on Computer Vision*. 2005.

Surfaces From Cameras vs. Confocal Microscope

- Spatial trend in reconstructed surface not similar, but changes in normal direction spatially should be similar.



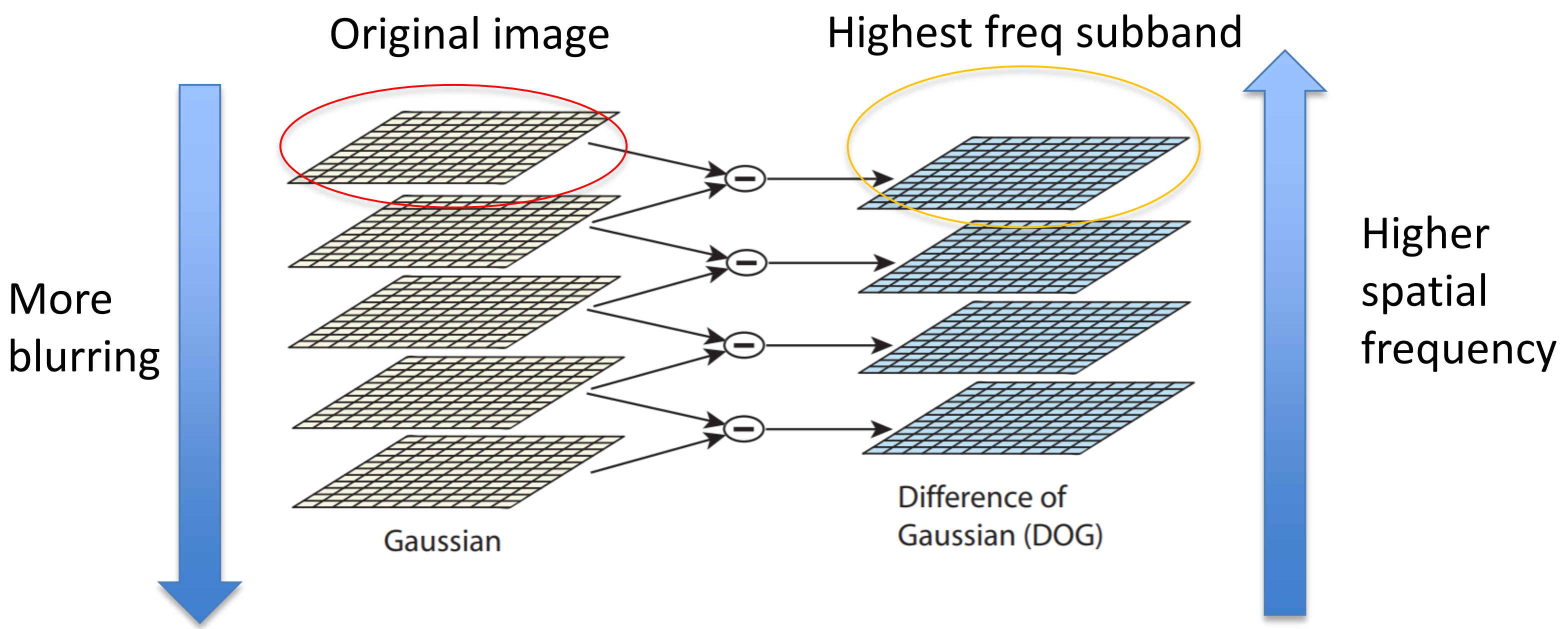
Reconstructed surface from Model 1



Reconstructed surface from confocal

Difference of Gaussian (DoG) Representation

- A DoG representation: take the differences of Gaussian-blurred images. Laplacian pyramids without subsampling.
- Allows separate analysis of the discrimination performance at different spatial frequency subbands.

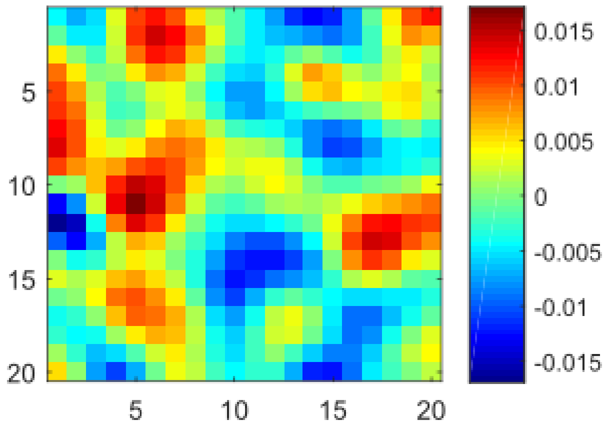


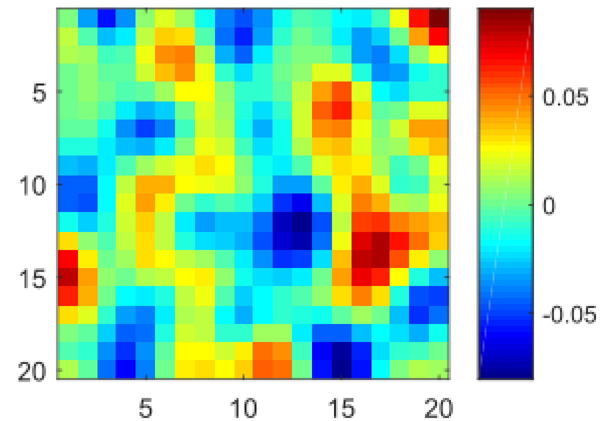
D. G. Lowe. Distinctive image features from scaleinvariant keypoints. International journal of computer vision, 60(2):91–110, 2004

Reconstructed Surfaces at High Spatial Frequency

2nd high frequency subband of:

surface reconstructed from Model 1



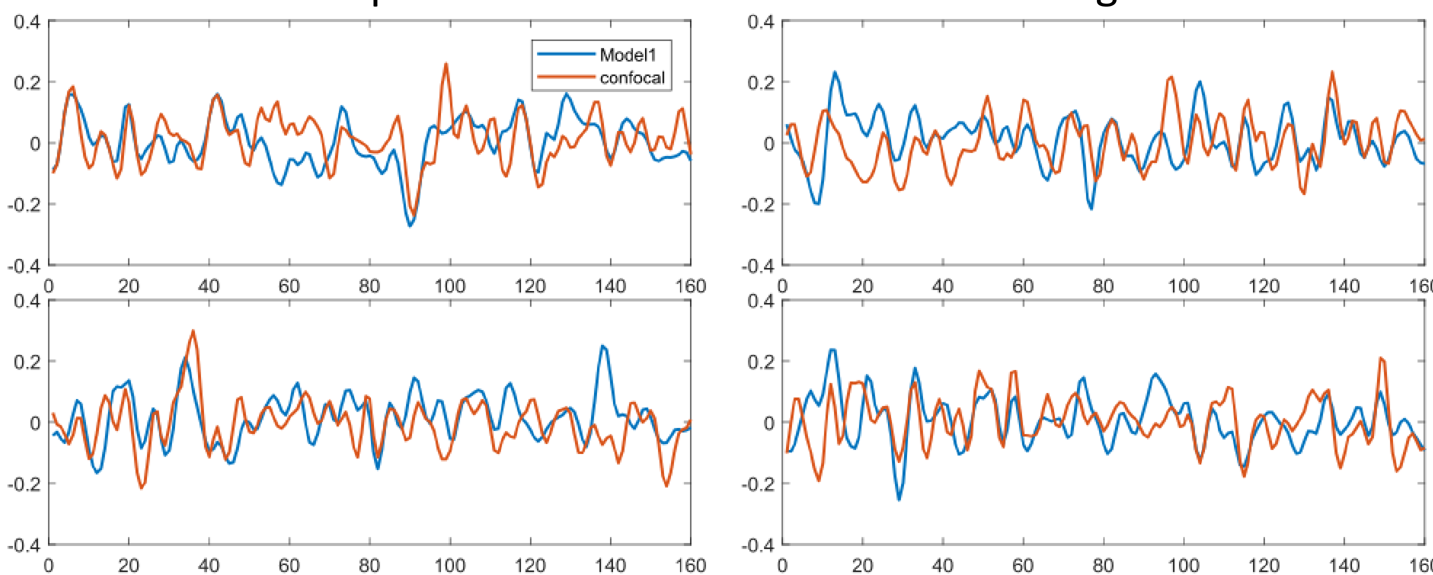


surface reconstructed from confocal microscope

Four representative slices from subband image

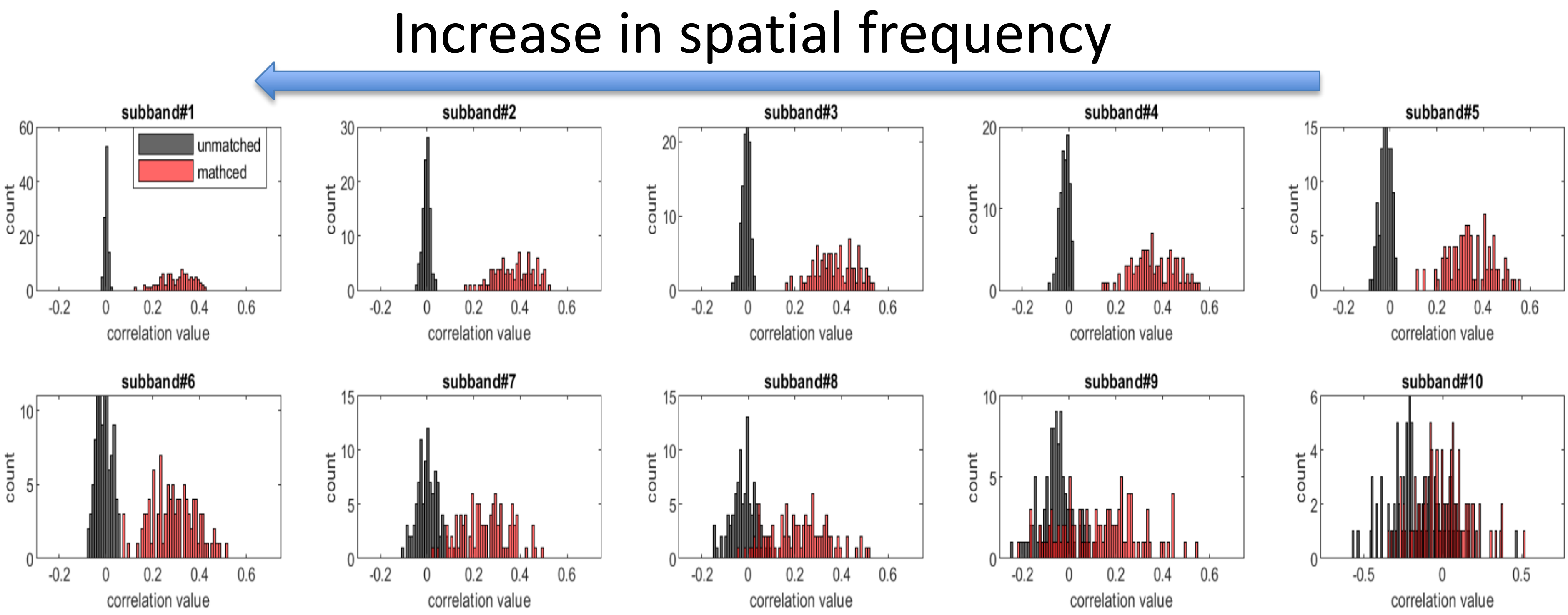
Normalized height

Normalized height

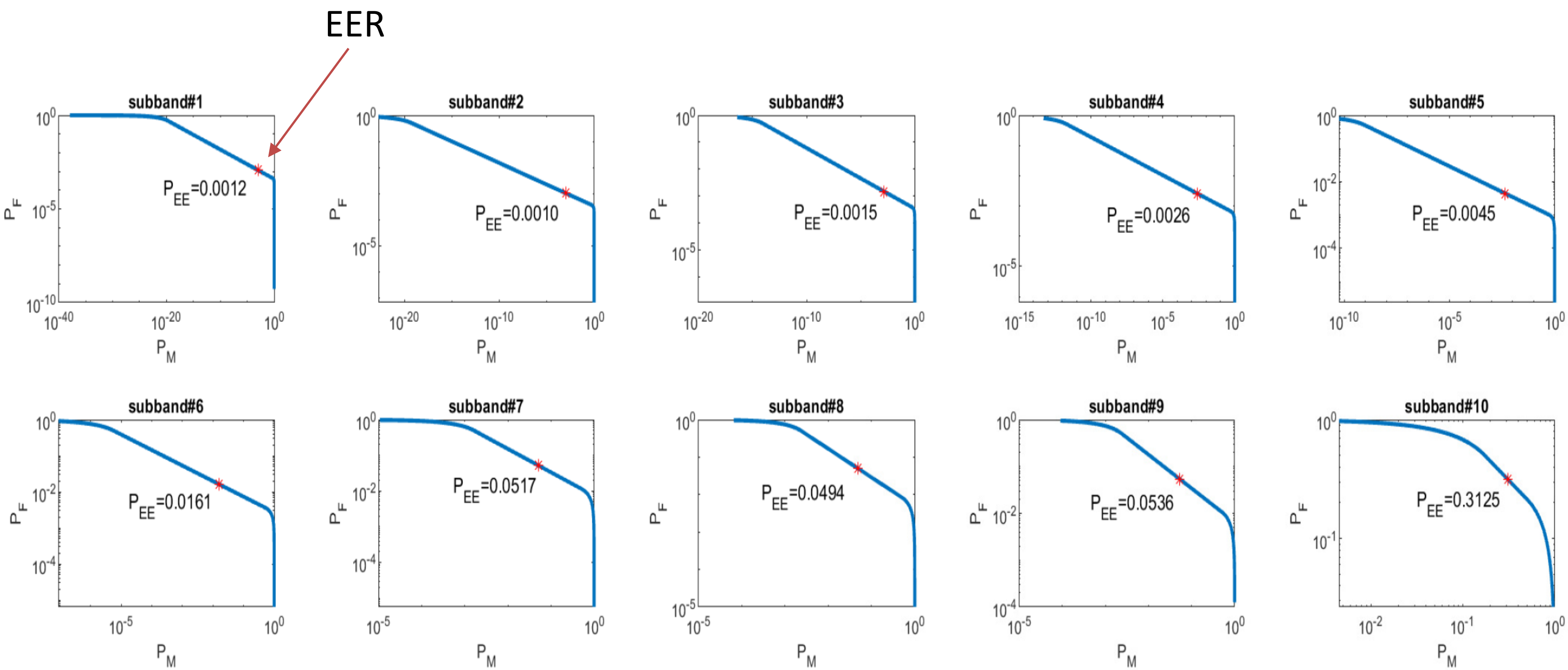


Correlations for Matched and Unmatched Cases

- Estimate norm maps with mobile phones,
- Reconstruct surfaces,
- Obtain the subbands,
- Compare with references from confocal microscope.



ROC and Equal Error Rate (EER)

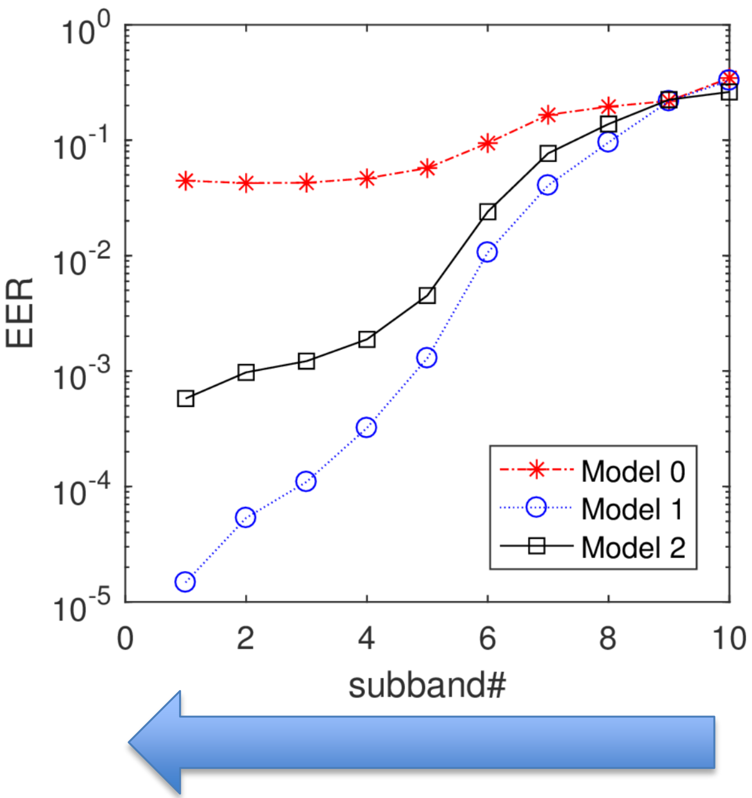


Distributions of correlation values modeled as Laplacian

Comparison of Models

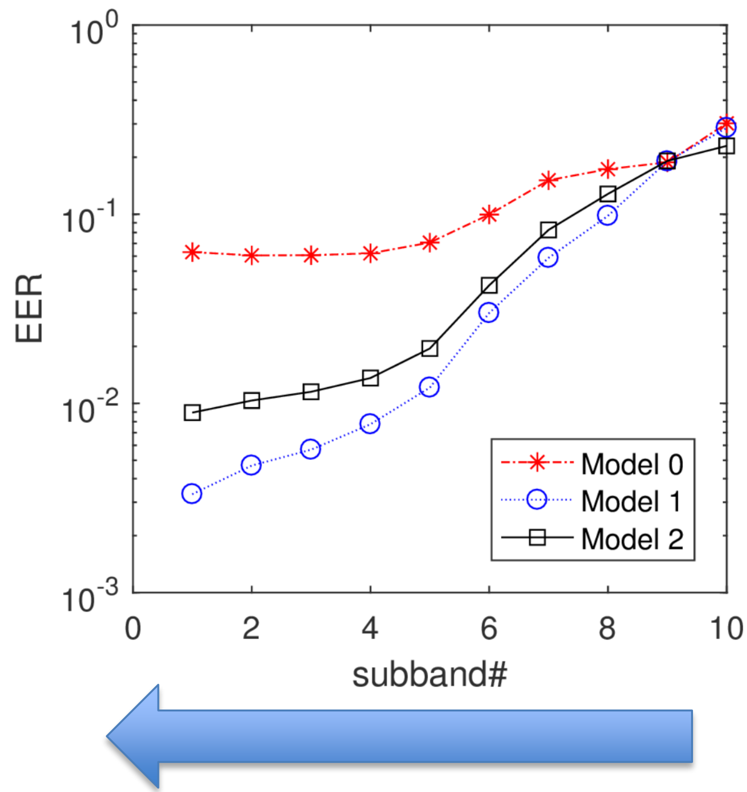
Reference is confocal

Correlations assumed to be Gaussian



Increase in spatial frequency

Correlations assumed to be Laplacian

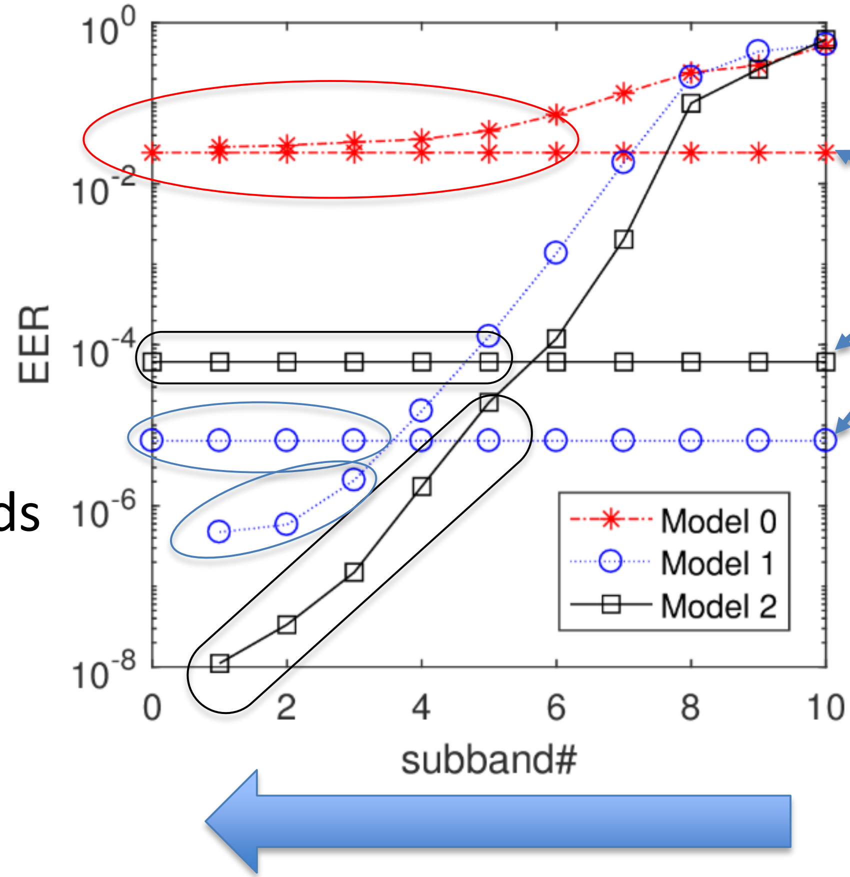


Increase in spatial frequency

Benefits of Using High-Freq Subbands Instead of Norm Maps

Reference is scanner

High frequency subbands are not more discriminative for Model 0



anchor when using norm maps

High frequency subbands are more discriminative when using proposed models

Increase in spatial frequency

Conclusions and Future Work

- Proposed models taking into account the effect of ambient lights and cameras' brightness/contrast adjustment processes: better modeling accuracy
- High-frequency subbands: better discriminative features than norm map for proposed models
- Future work:
  - large dataset: confocal measurements, scanner images, and camera images;
  - different paper types, camera models, and acquisition conditions.