Texel-based Image Classification with Orthogonal Bases

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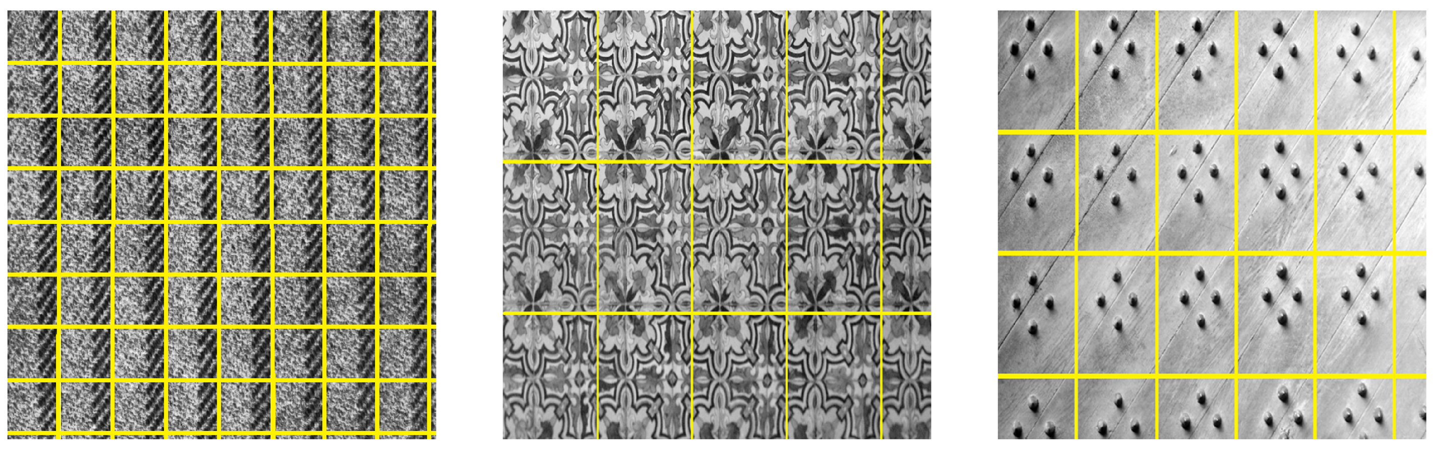
Introduction

Texture is defined as periodic-like behavior patterns within a spatial region and is also a property related to material, roughness, or shape of a surface.
Texel is the smallest window of analysis that captures the fundamental oscillating pattern of a given texture.



Texels computed in different textures

Motivation: Orthogonal bases can characterize textures by projecting an image over a set of functions that describes the behavior of the patterns. However, they present *limitations*:

- Numerical instability in higher-order polynomials
- High computational cost due to the size of texture

Proposal:

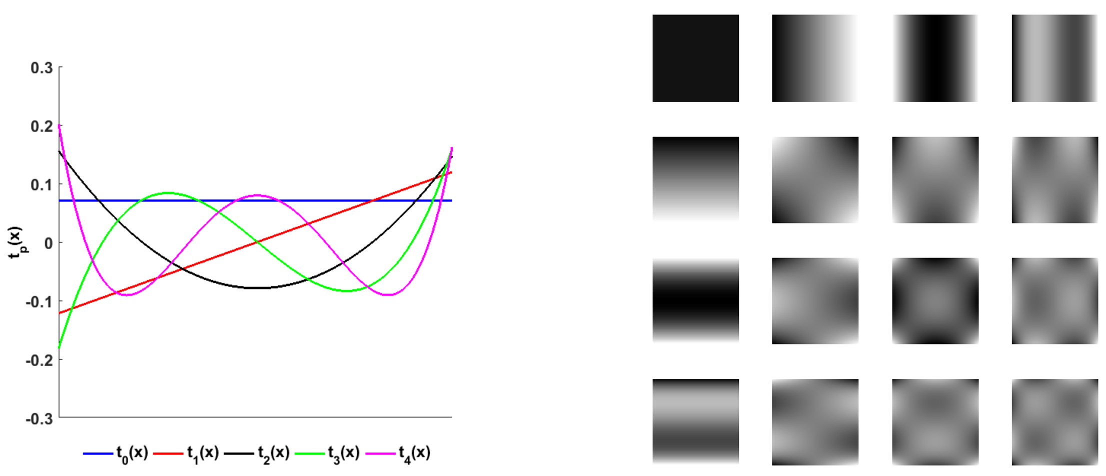
- Novel technique to find the texel that describes the texture
- Feature extraction based on texels
- Feature space reduced
- A suitable model for classification tasks

Orthogonal Bases

Orthogonal basis: Is a set of vectors that satisfies the condition of orthogonality. They are also used to generate a function space.

- Discrete Tchebichef moments (DTM)

$$T_{pq} = \frac{1}{\rho(p,N)\rho(q,N)} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) t_p(x) t_q(y)$$

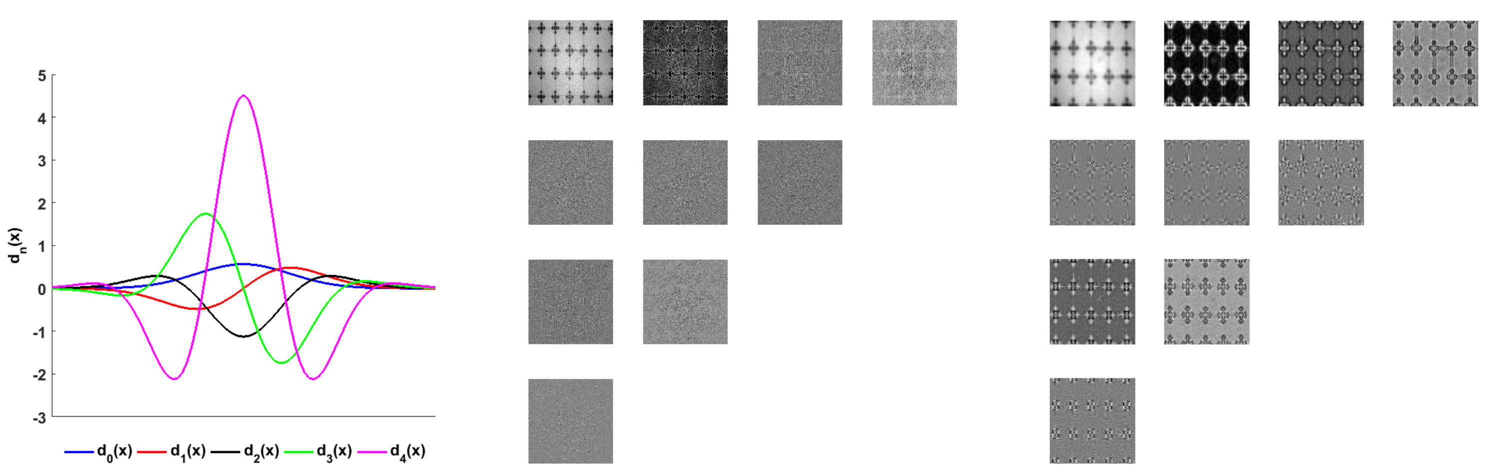


DTM feature extraction:

$$M(s) = \sum_{s=p+q} |T_{pq}|$$

- Steered Hermite transform (SHT)

$$f^{\theta}_{n-m,m}(x_0,y_0,\theta) = \sum_{k=0}^{n} f_{n-k,k}(x_0,y_0)\alpha_{n-k,k}(\theta)$$

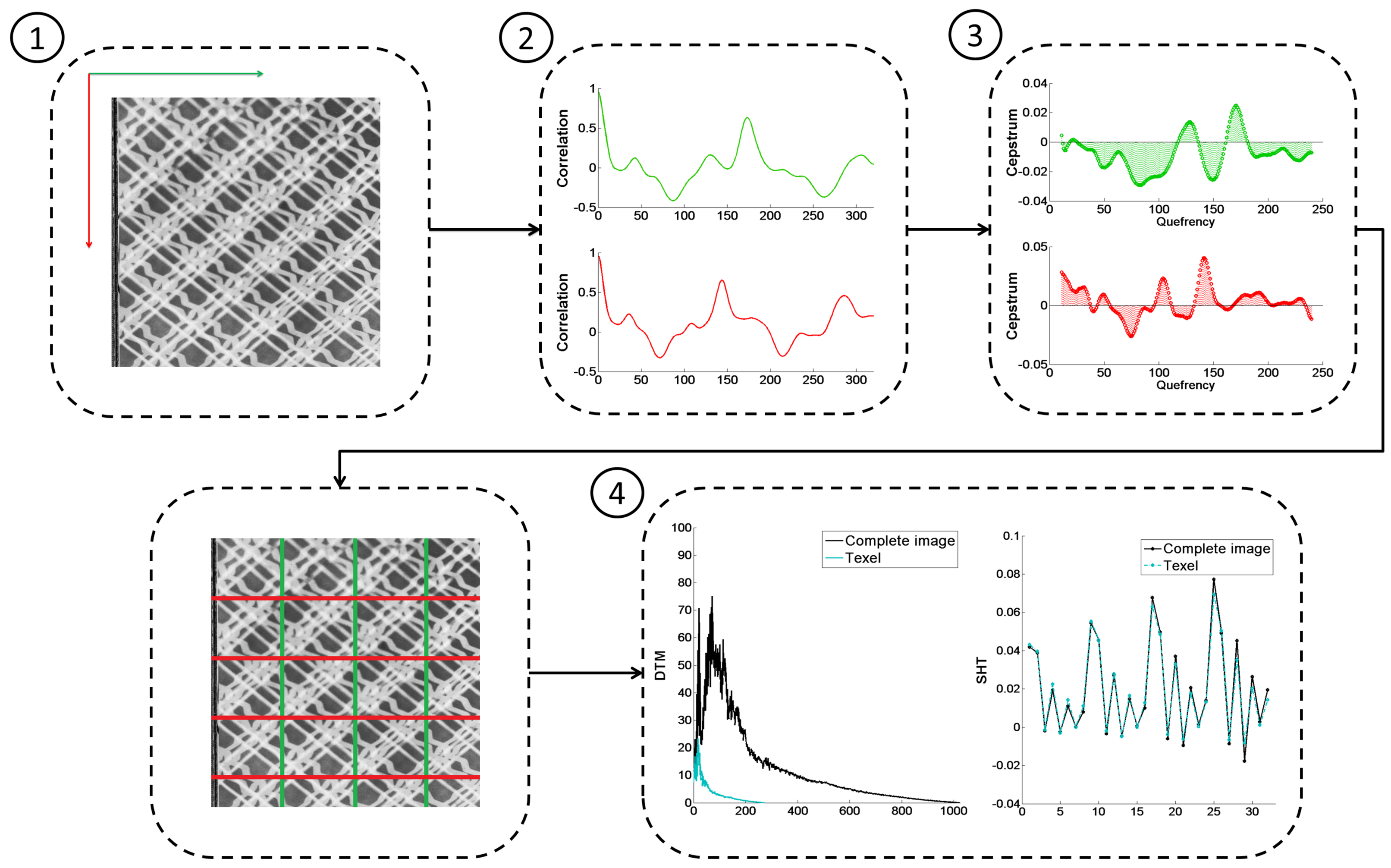


Multiscale-SHT feature extraction:

$$F = \{\mu_n^{H_\sigma}, \sigma_n^{H_\sigma} | n = 0, \ldots N; H_\sigma = n \ldots, N\}$$

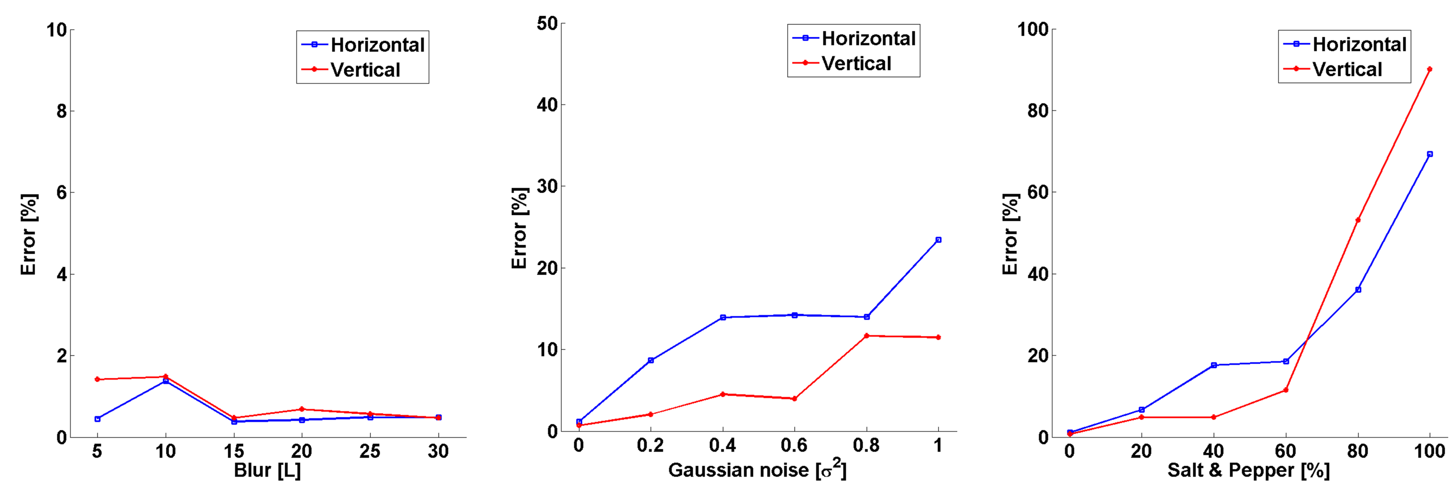
Methodology

1. **Gray-level co-occurrence matrix (GLCM)**. On X- and Y-axes with distances $d = [2, ..., N/2]$.
2. **Correlation values (CV)**. Dependence measure among **GLCMs**.
3. **Cepstral Analysis (CA)**. Transformation of the magnitude spectrum of **CV** into a more suitable scale for periodicity detection.
4. **Feature extraction**. Orthogonal basis to characterize texels.

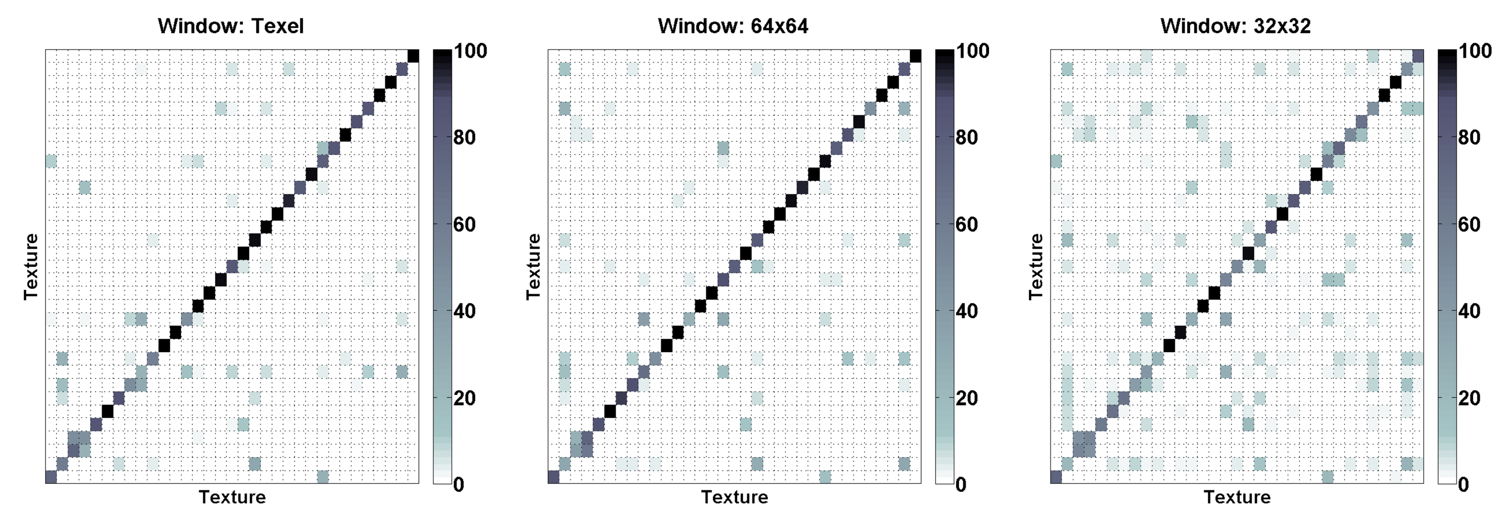


Results

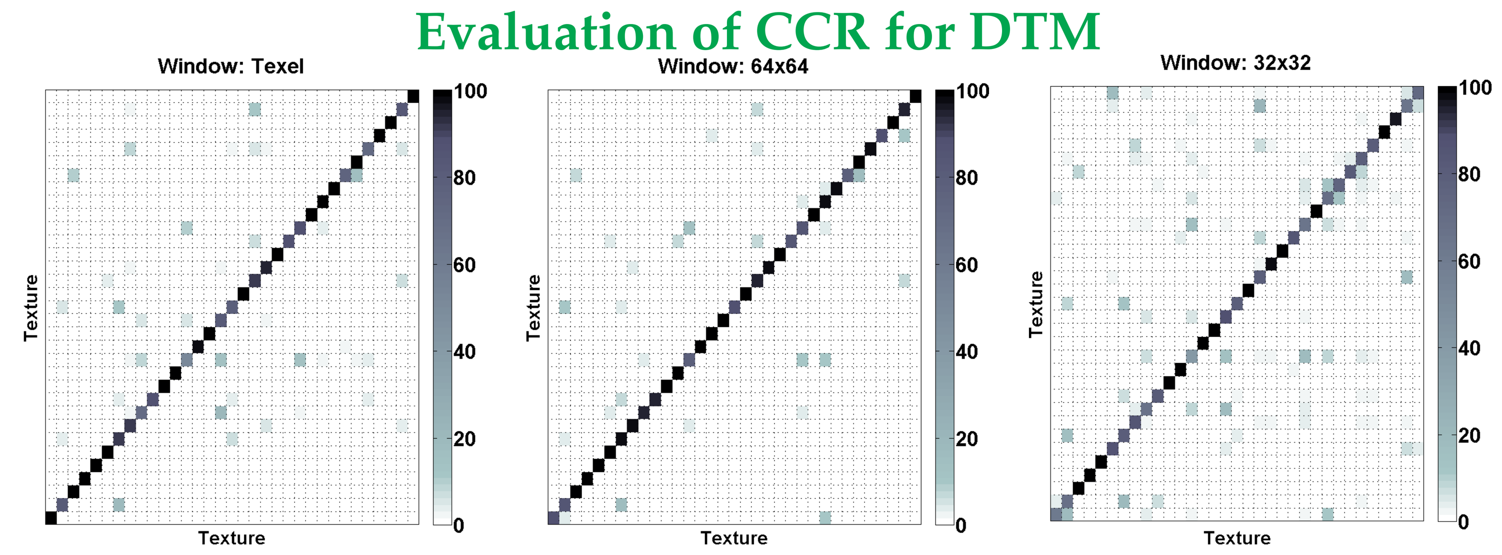
Texel size validation: A dataset of 40 textures from Brodatz, Klette, and Vistex ⇒ Pattern extraction to create synthetic textures ⇒ Computation of texels by **CA** under three degradations ⇒ Error assessment.



Classification results: A set of 34 textures from Brodatz ⇒ Independent subsets for training and testing ⇒ Texel calculation ⇒ Features extraction with DTM and SHT ⇒ *k*-NN classifier with *k = 1* ⇒ Correct classification rate (CCR)



Evaluation of CCR for DTM



Evaluation of CCR for SHT

Conclusions

- Texel size estimation based on **CA** has proven to be a robustness model against degradations.
- Texel-based feature vectors keep a close relationship with full-based texture feature vectors.
- Texels capture the minimum amount of information for describing a texture and achieve good rates in classification tasks.

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