Texel-based Image Classification with Orthogonal Bases

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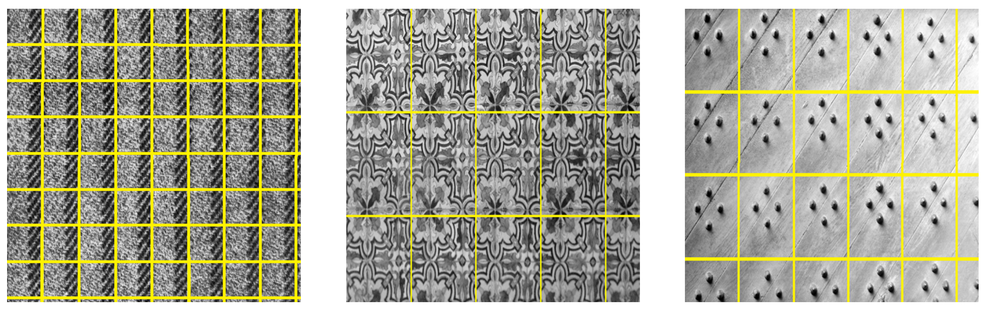
Introduction

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 the texture

Proposal:

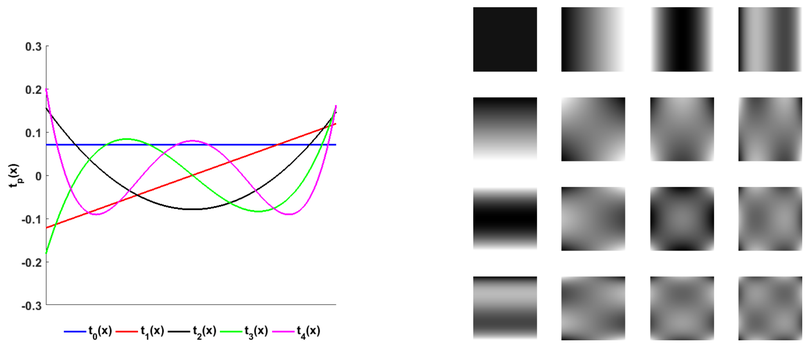
- Novel technique to find the texel that describes the texture
- Feature extraction based on texels
- Reduced feature space
- A suitable model for classification tasks

Orthogonal bases

An ***orthogonal basis*** is a finite set of vectors that satisfies the condition of orthogonality and can be used to describe an object by approximations

- Discrete Tchebichef moments (DTM)

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

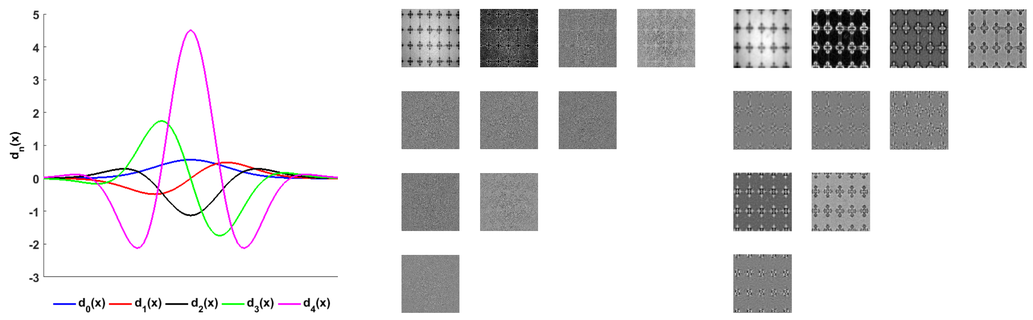


DTM feature extraction:

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

- Steered Hermite transform (SHT)

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

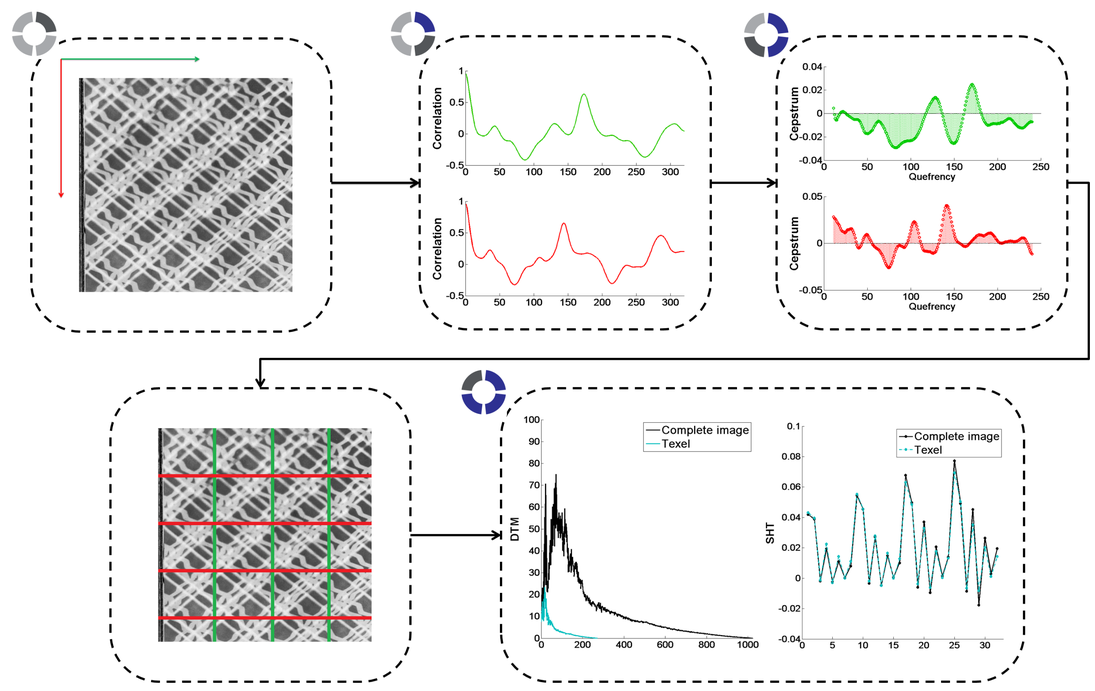


Multi-scale SHT feature extraction:

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

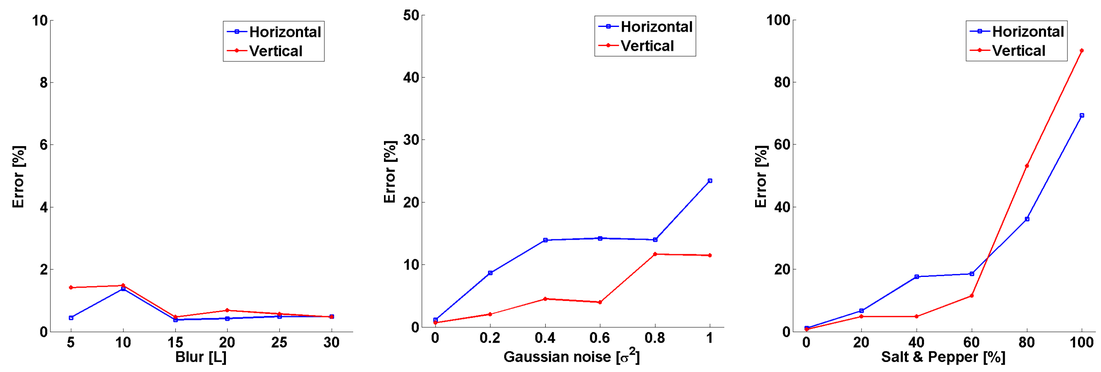
Methodology

- **GLCM**. On X- and Y-axes with $\theta = [0, \frac{\pi}{2}]$ and $d = [2, \ldots, N/2]$.
- **Correlation values (CV)**. Dependence measure among **GLCMs**.
- **Cepstral Analysis (CA)**. Magnitude spectrum of **CV** $\Rightarrow$ a more suitable scale for periodicity detection.
- **Feature extraction**. Multi-scale SHT to characterize texels.

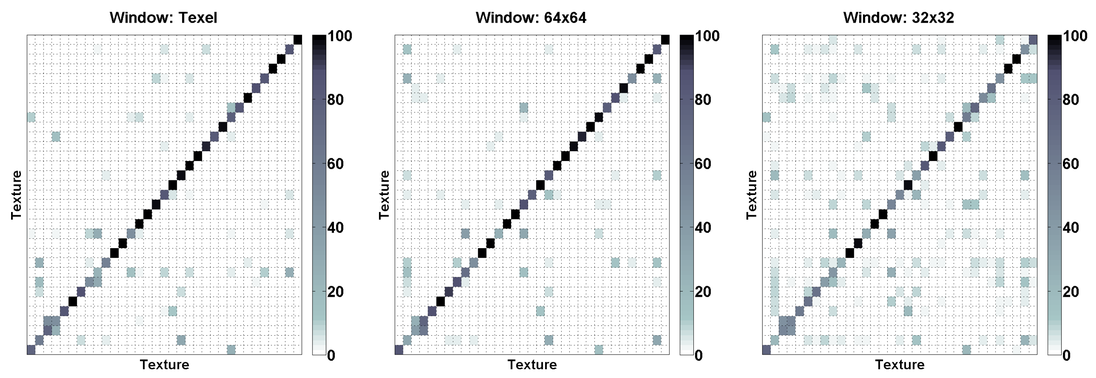


Results

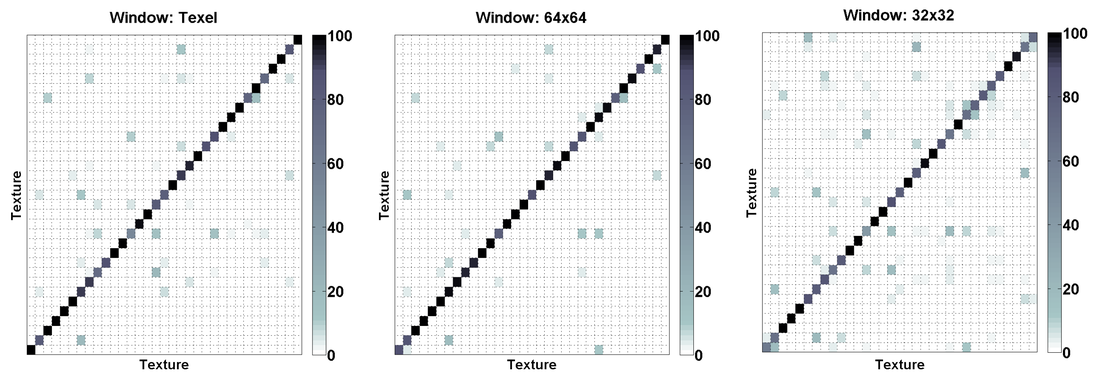
Texel size validation: A dataset of 40 textures from Brodatz, Klette, and Vistex $\Rightarrow$ synthetic textures $\Rightarrow$ Computation of texels by **CA** under three degradations$\Rightarrow$ Error assessment.



Classification results: Two independent datasets from 34 Brodatz textures $\Rightarrow$ Texel calculation $\Rightarrow$ Features extraction with DTM and SHT $\Rightarrow$ k-NN classifier with $k = 1$ $\Rightarrow$ Correct classification rate (CCR)



Evaluation of CCR for DTMs



Evaluation of CCR for SHT

Conclusions

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

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