Sorted Random Projections for Robust Texture Classification

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Abstract

Goal: Developing a simple, robust, yet highly effective Texture Classification (TC) system

- *Simple*, local feature extraction
- *Universal*, data-independent features
- Low-dimensional features
- Good classification performance
- Robustness to environment changes

Main components:

- **Local features:** SRP random features → simple, universal, informative, fast, illumination invariant, rotation invariant, robust and effective
- **Global representation:** Bag-of-Words model → simple, effective, vector feature
- **Classifier:** Kernel Support Vector Machines (SVMs)

Performance:

- CUReT → 99.37%
- Brodatz → 97.16%
- UMD → 99.30%
- KTH-TIPS → 99.29%
- FMD → 48.2%

Introduction

TC remains a challenge problem:

- The wide range of various natural texture types
- The presence of large intra-class variations → brightness, contrast, rotation, affine, scale, skew, occlusion …
- The demands of algorithms with low computational complexity

Motivations:

- To leverage the sparse nature of texture images
- To Preserve all the advantages of Random Projection (RP) Classifier
- To avoid complex local texture feature extraction
- To increase robustness
- To use a kernel-based learning classifier
- To combine multiple complementary features

Background

Random projection (RP) refers to the technique of projecting a set of points from a high-dimensional space to a randomly chosen low-dimensional subspace. RP, while reducing dimensionality, approximately preserves pairwise distances with high probability :

- Computationally simple and efficient
- Universal, information-preserving, dimensionality reduction
- Plays an important role in both Johnson-Lindenstrauss embedding and compressed sensing

Sorted Random Projections

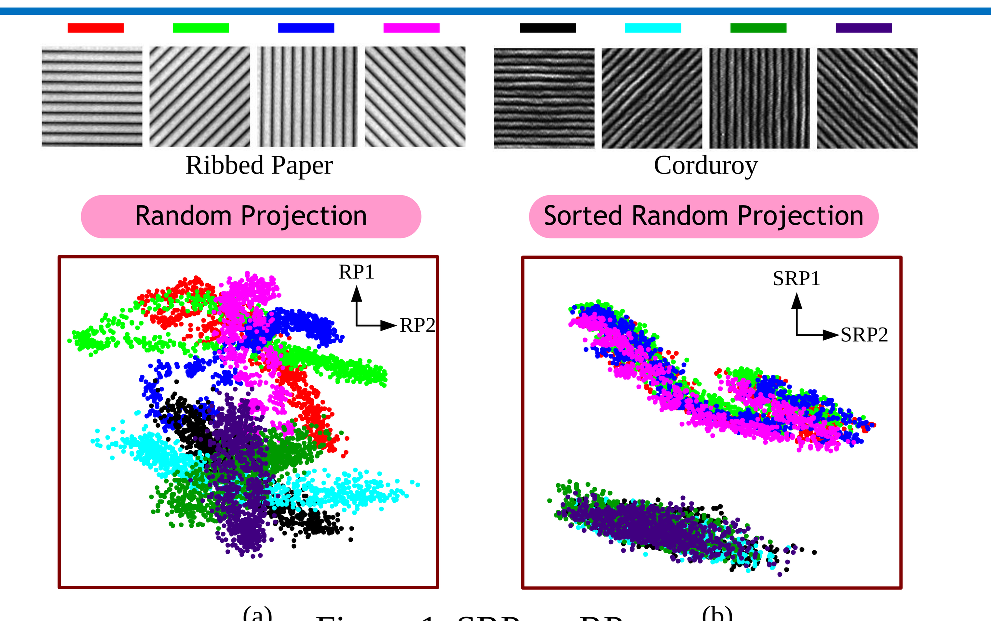
Problems with existing approaches for including rotation invariance:

- Add randomly rotated local patches → much more data points, much greater spread cluster, posing storage and processing challenges, and also creating challenges in clustering
- Estimate the dominant gradient orientation → unreliable, computational expensive
- Compute multilevel histograms → computational expensive, low efficiency

Our solution: Sorting followed by Random Projection → intuitive (Figure 1), computational simple, rotation invariant and Discriminative

We have proposed two types of SRP features (Figure 2):

- Pixel –intensity based
  - SRP Global → globally sorting raw pixel intensities
  - SRP Square → multiscale sorting raw pixel intensities (Square Neighborhood)
  - SRP Circular → multiscale sorting raw pixel intensities (Circular Neighborhood)
- Pixel-difference based
  - SRP Radial-Diff → multiscale sorting radial differences
  - SRP Angular-Diff → multiscale sorting angular differences



(a) Figure 1. SRP vs. RP (b)

Description and Classification

Two BoW-based representation schemes:

- **HOGC:** Histogram-Of-Global-Codebook → universal texton codebook learning from all texture classes, histogram + chi square distance
- **SOLC:** Signature-Of-Local-Codebook → local texton codebook learning from each image, signature + EMD distance

Classification:

- **Nearest Neighbor Classifier** → single feature
- **SVMs** → single kernel
- **SVMs** → multiple kernel combination

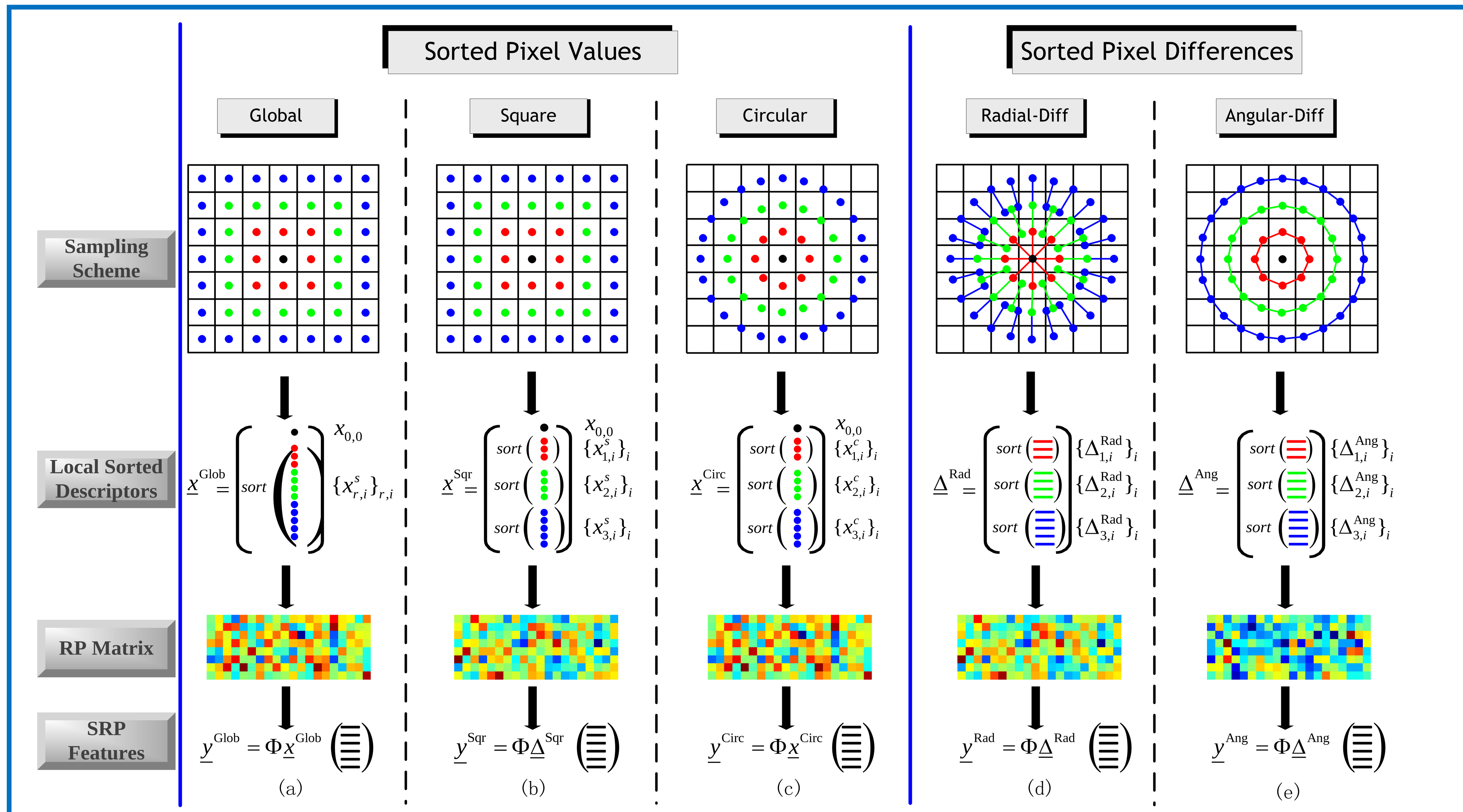
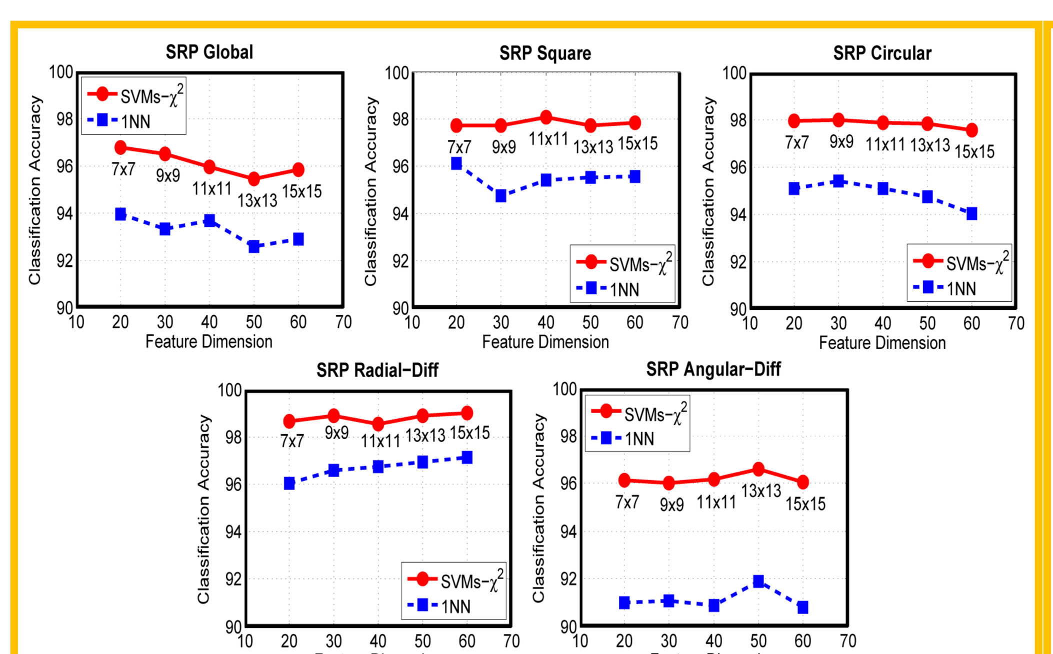


Figure 2. Extracting SRP features from an example local image patch



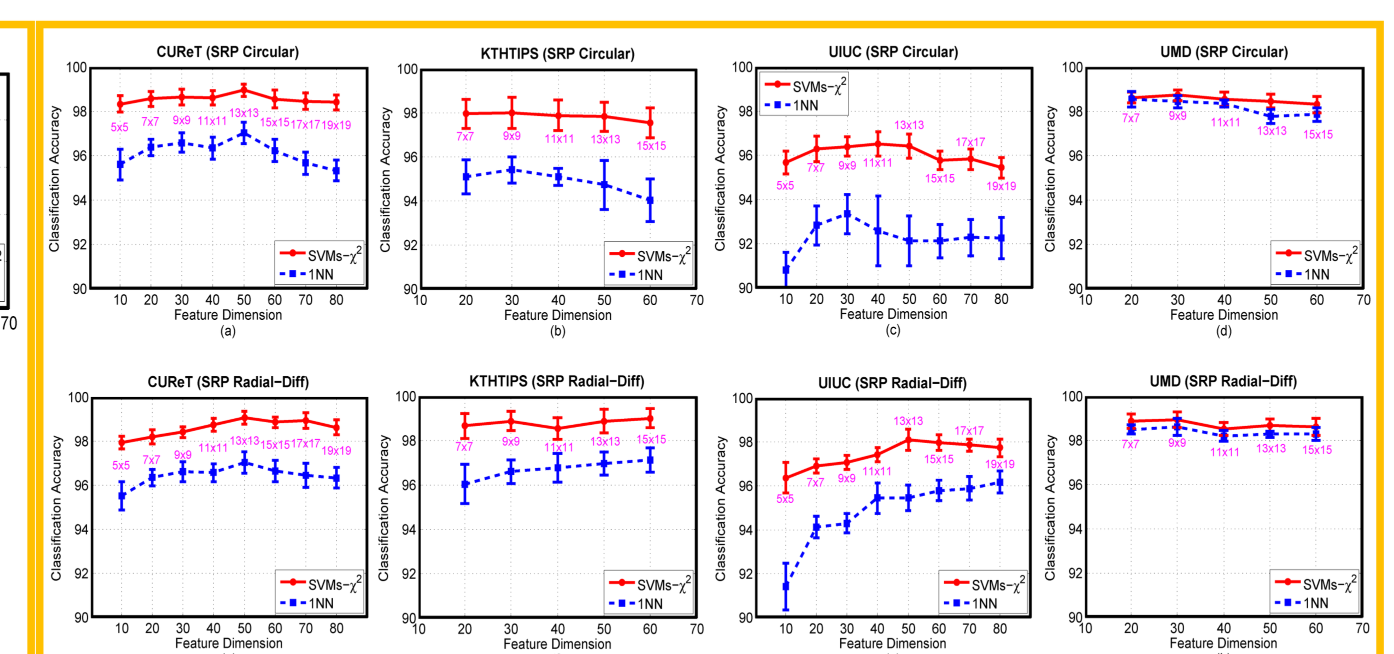
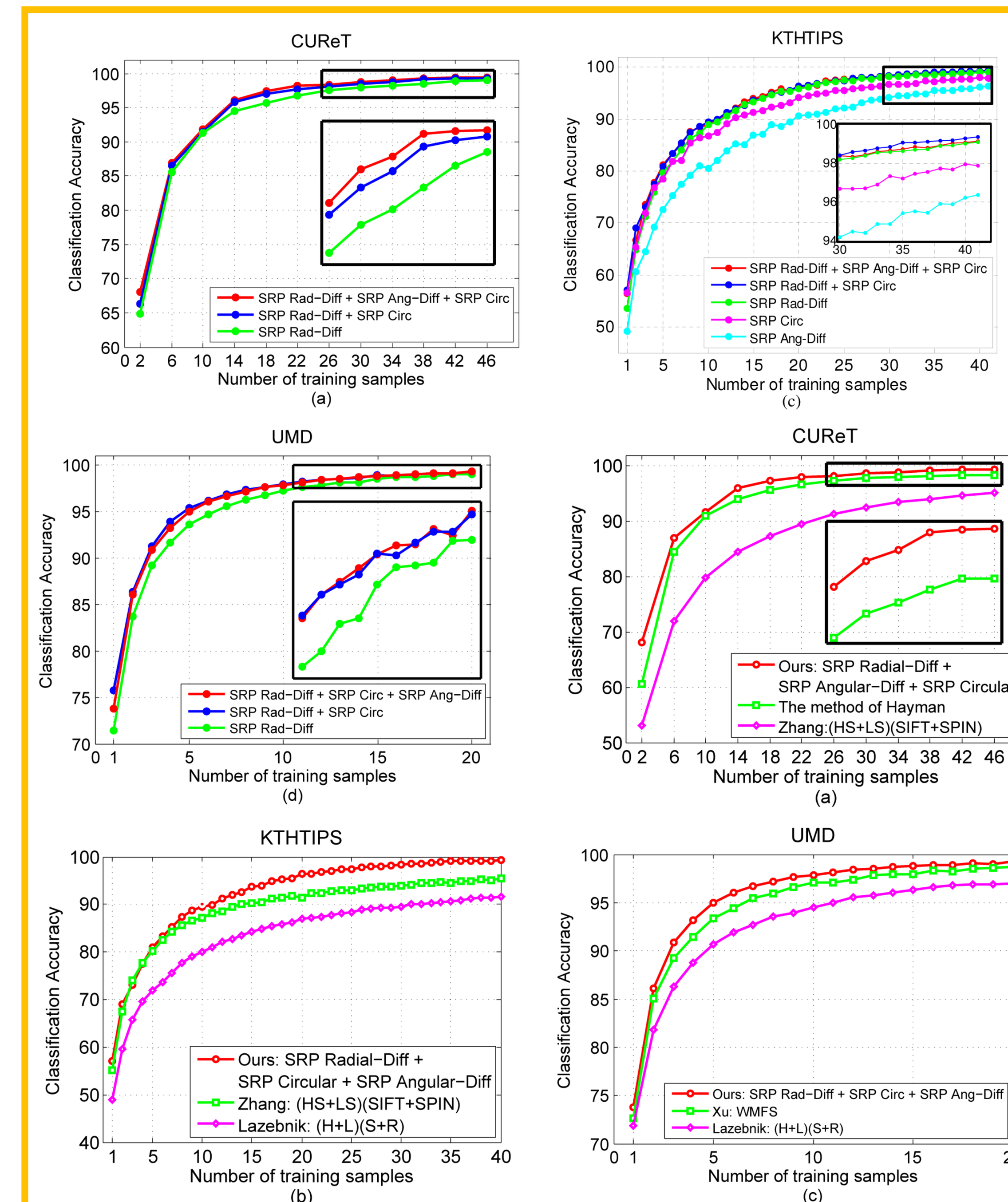


Table 1. Summary of texture datasets used in our experiments.

Texture Dataset	Dataset Notation	Image Rotation	Controlled Illumination	Scale Variation	Significant Viewpoint	Texture Classes	Sample Size	Samples per class	Samples in Total
CUReT	$\mathcal{D}^{C}$	√	√			61	200 × 200	92	5612
CUReTRot	$\mathcal{D}^{CRot}$	√	√			61	140 × 140	92	5612
UIUC	$\mathcal{D}^{UIUC}$	√		√	√	25	640 × 480	40	1000
UMD	$\mathcal{D}^{UMD}$	√		√	√	25	320 × 240	40	1000
Brodatz	$\mathcal{D}^{B}$					111	215 × 215	9	999
KTH-TIPS	$\mathcal{D}^{KT}$		√	√		10	200 × 200	81	810

Paradigm	HOGC									SOLC					
Classifier	NNC			SVMs						NNC			SVMs		
Metric	χ^2			RBF	χ^2	RBF	χ^2	RBF	χ^2	EMD			EMD		
Patch size	5 × 5	9 × 9	13 × 13	5 × 5		9 × 9		13 × 13							
$\mathcal{D}^{C}$	95.51	96.61	96.52	95.53	97.92	96.83	98.39	97.72	**99.05**						
Patch size	9 × 9	15 × 15	19 × 19	9 × 9		15 × 15		19 × 19							
$\mathcal{D}^{CRot}$	94.55	94.76	95.01	94.69	96.95	95.76	97.05	96.18	**97.45**						
Patch size	5 × 5	9 × 9	13 × 13	5 × 5		9 × 9		13 × 13		5 × 5	9 × 9	13 × 13	5 × 5	9 × 9	13 × 13
$\mathcal{D}^{UIUC}$	91.40	94.28	95.43	95.66	96.35	96.40	97.06	97.18	**98.08**	78.49	84.58	88.14	88.77	92.40	93.28
Patch size	7 × 7	9 × 9	13 × 13	7 × 7		9 × 9		13 × 13		7 × 7	9 × 9	13 × 13	7 × 7	9 × 9	13 × 13
$\mathcal{D}^{UMD}$	98.48	98.60	98.26	**98.92**	98.86	98.59	**98.92**	98.53	98.67	90.37	91.37	92.97	94.92	95.16	96.08
Patch size	5 × 5	9 × 9	13 × 13	5 × 5		9 × 9		13 × 13		5 × 5	9 × 9	13 × 13	5 × 5	9 × 9	13 × 13
$\mathcal{D}^{B}$	93.13	94.74	94.73	93.07	94.44	94.29	95.77	94.24	**96.04**	84.18	89.30	91.38	87.78	90.72	92.67
Patch size	9 × 9	13 × 13	15 × 15	9 × 9		13 × 13		15 × 15		9 × 9	13 × 13	15 × 15	9 × 9	13 × 13	15 × 15
$\mathcal{D}^{KT}$	97.16	97.35	97.71	98.78	98.95	98.72	99.02	98.65	**99.11**	93.06	95.28	95.27	94.63	95.78	95.20



	$\mathcal{D}^{C}$ (46)	$\mathcal{D}^{B}$ (3)	$\mathcal{D}^{KT}$ (41)	$\mathcal{D}^{UIUC}$ (20)	$\mathcal{D}^{UMD}$ (20)
1. Our Results	**99.37%**	**97.16%**	**99.29%**	**98.56%**	**99.30%**
SRP Radial-Diff	√	RP Rad-Diff	√	√	√
SRP Circular	√	RP Ang-Diff	√	√	√
SRP Angular-Diff	√			√	√
2. VZ-MR8	97.43%				
3. VZ-Patch	98.03%	92.9%(∗)	92.4%(∗)	97.83%	
4. Caputo *et al.*	98.46%	95.0%(∗)	94.8%(∗)	92.0%(∗)	
5. Lazebnik *et al.*	72.5%(∗)	88.15%	91.3%(∗)	96.03%	
6. Mellor *et al.*		89.71%			
7. Zhang *et al.*	95.3%	95.9%	96.1%	**98.7%**	
8. Varma and Ray *et al.*				**98.76%**	
9. Crosier and Griffin *et al.*	98.6%		98.5%	**98.8%**	
10. Xu-MFS *et al.*				92.74%	93.93%
11. Xu-OTF *et al.*				97.40%	98.49%
12. Xu-WMFS *et al.*				**98.60%**	98.68%
13. Liu *et al.*	98.52%	**96.34%**	97.71%	96.27%	**99.13%**