# Combining Sorted Random Features For Texture Classification

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## 1 Abstract

**Goal:** How to combine local texture descriptors for texture classification.

- Features: Sorted random features (SRP) → fast, robust
- Model: Global Bag-of-Words (BoW) → simple, effective orderless histogramming
- Classifier: Multiple kernel SVM → combines multiple features with low computational complexity

## 2 Introduction

**Complementary components of the BoW model:**

- *local* discriminative and robust texture descriptors
- *global* statistical histogram characterization

**Motivations for combining local descriptors:**

- Many possible local descriptors exist
- Past research identifies no clear winner

**So why use SRP features?**

- Universal, simple and low-dimensional
- Even single SRP features offer state-of-the-art performance

## 3 Background

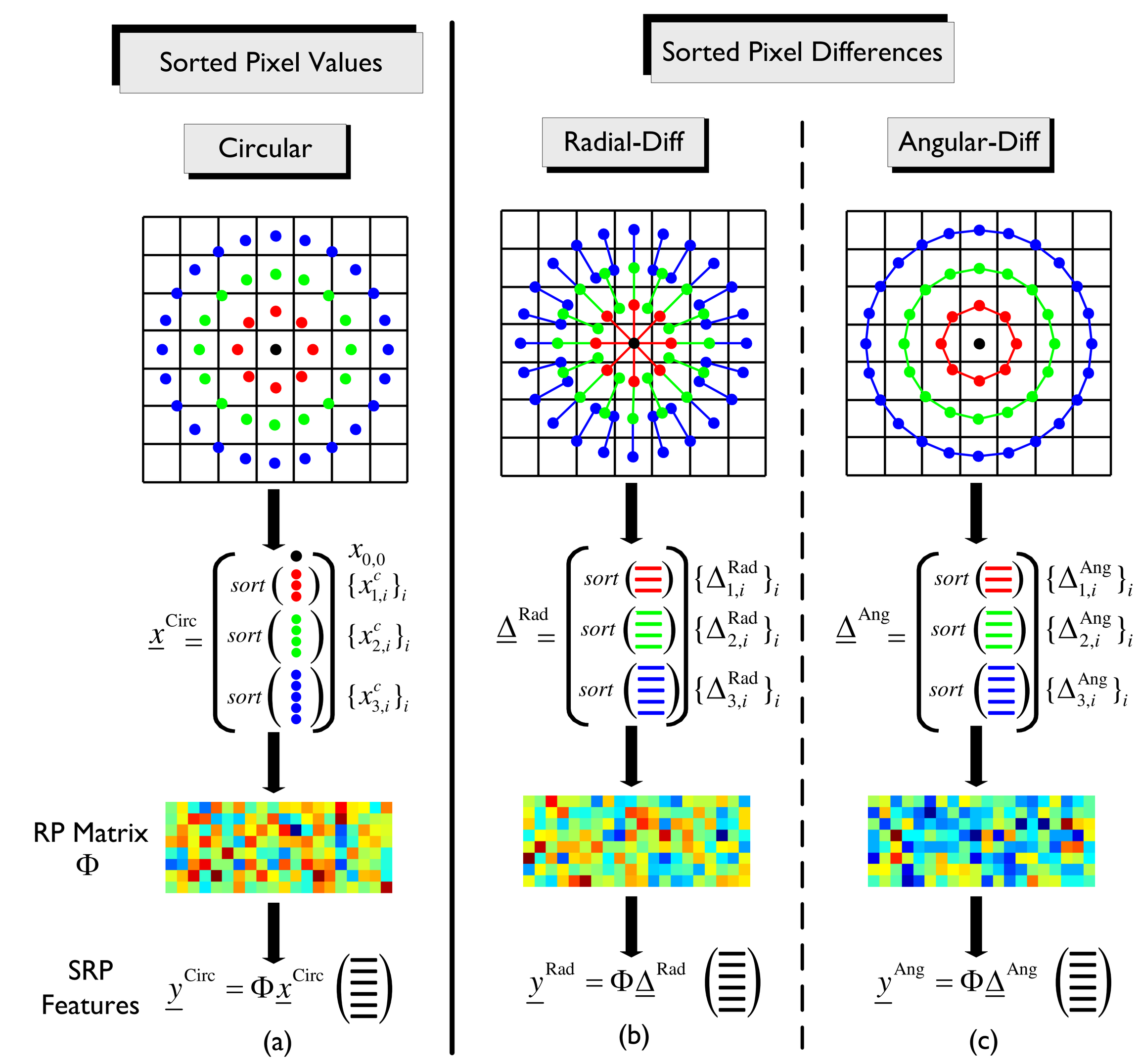
Random projection (RP) refers to the technique of projecting a set of points from a high-dimensional space to a randomly chosen low-dimensional subspace:

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

## 4 SRP Features

We have used three different SRP features (figure)

- SRP circular → sorted raw pixel intensities
- SRP Radial-Diff → sorted radial differences
- SRP Angular-Diff → sorted angular differences




## 5 SRP Based Classification

Given a single SRP feature:

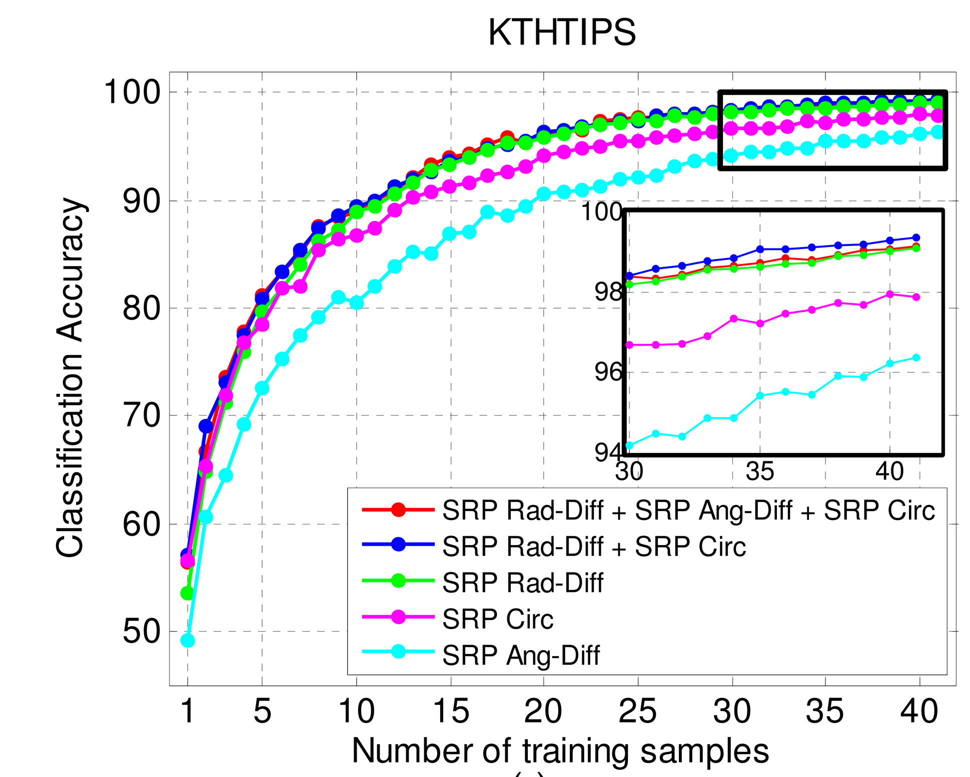
1. Universal texton dictionary learning by clustering
2. Histogram of textons by labeling to closest texton
3. Classification by comparing the $\chi^2$ distances between the $\underline{\boldsymbol{h}}_{new}$ of a novel image and the histogram models learned from the training images

We wish to generalize this mechanism to combined features. Since the descriptors in this paper (especially SRP Rad-Diff) are, on their own, already very discriminative, there may be limitations to applying Multiple Kernel Learning (MKL).

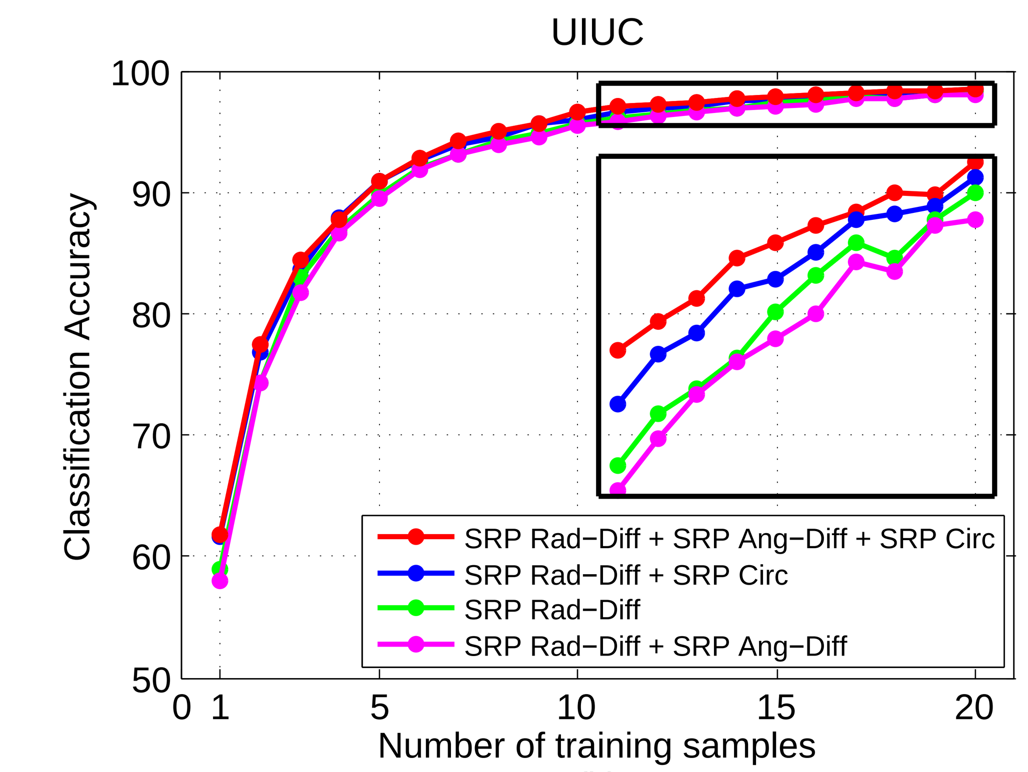
Furthermore, simple kernel combination methods are capable of reaching the same classification accuracy as MKL. Therefore, we propose to combine kernels in a pre-defined deterministic way and use the resulting kernel for SVM training.

To incorporate the $\chi^2$ distance into the SVM framework, we use the kernel $\mathbf{K}(\underline{\boldsymbol{h}}_i, \underline{\boldsymbol{h}}_j) = \exp(-\gamma\chi^2(\underline{\boldsymbol{h}}_i, \underline{\boldsymbol{h}}_j))$.

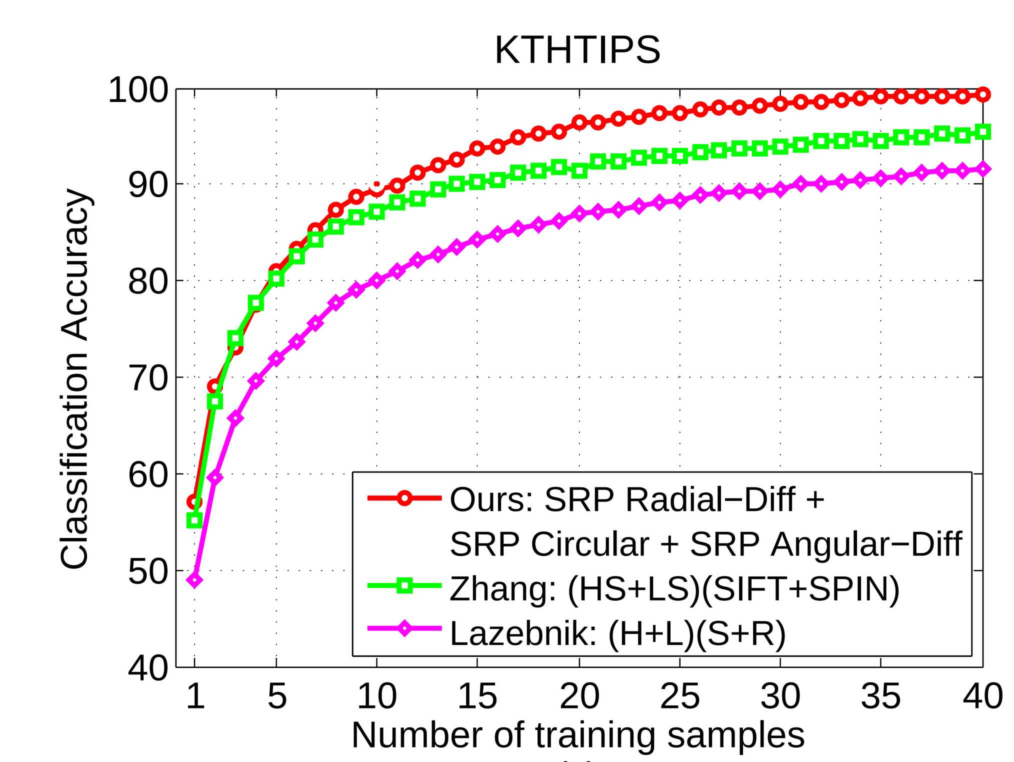
When multiple descriptor types are used, we represent each texture sample using $F$ Bag-of-Words histograms derived from $F$ feature descriptors. The multiple kernel method combines several kernels by multiplication $\mathbf{K}^*(\underline{\boldsymbol{h}}_i, \underline{\boldsymbol{h}}_j) = \prod_{l=1}^{F} \mathbf{K}_l(\underline{\boldsymbol{h}}_i, \underline{\boldsymbol{h}}_j)$.



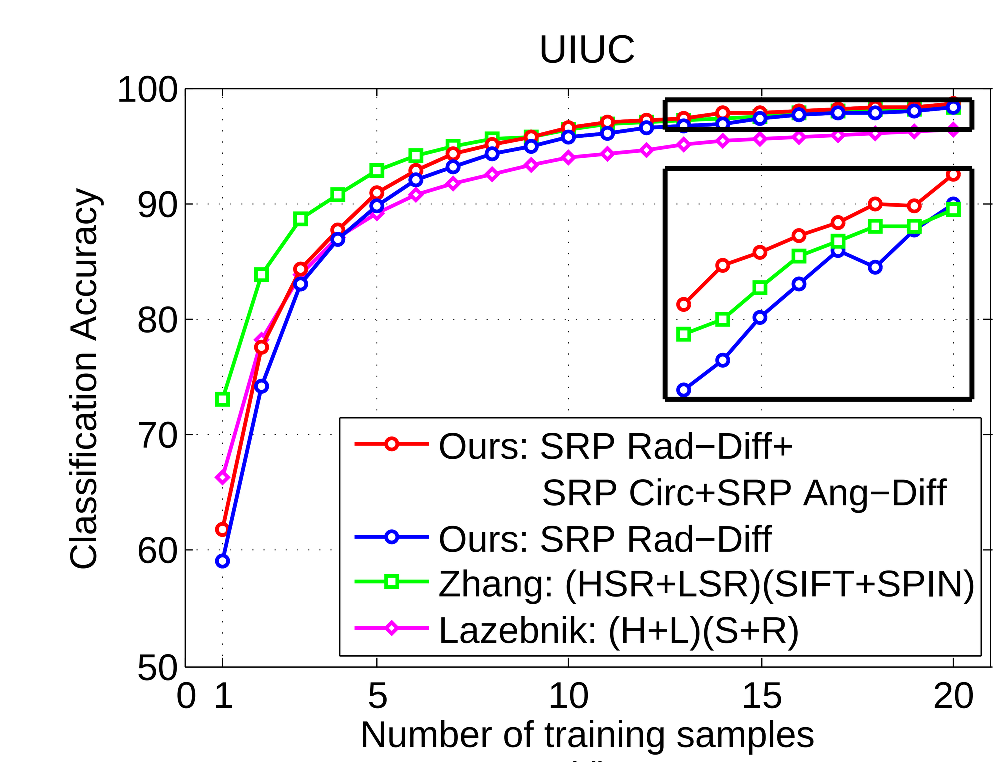
(a)



(b)



(c)



(d)

(a) **CUReT (92 samples per class in total)**

| Features | | | Number of training samples per class | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Diff | Circ | Ang | 2 | 10 | 18 | 26 | 34 | 38 | 46 |
| √ | √ | √ | **68.07**% | **91.77**% | **97.45**% | **98.31**% | **98.98**% | **99.31**% | **99.37**% |
| √ | √ | | 66.33% | 91.44% | 96.97% | 98.13% | 98.78% | 99.13% | 99.28% |
| √ | | | 64.88% | 91.30% | 95.71% | 97.57% | 98.22% | 98.53% | 99.05% |

(b) **KTHTIPS (81 samples per class in total)**

| Features | | | Number of training samples per class | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Diff | Circ | Ang | 5 | 10 | 20 | 25 | 30 | 35 | 40 |
| √ | √ | √ | **81.18**% | 88.99% | 96.10% | **97.74**% | 98.38% | 98.71% | 99.06% |
| √ | √ | | 80.90% | **89.49**% | **96.40**% | 97.32% | **98.40**% | **99.07**% | **99.29**% |
| √ | | | 79.72% | 88.93% | 95.81% | 97.45% | 98.22% | 98.62% | 99.01% |

(c) **UIUC (40 samples per class in total)**

| Features | | | Number of training samples per class | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Diff | Circ | Ang | 1 | 5 | 10 | 13 | 15 | 18 | 20 |
| √ | √ | √ | **61.82**% | 90.84% | **96.61**% | **97.42**% | **97.89**% | **98.30**% | **98.56**% |
| √ | √ | | 61.62% | **90.96**% | 96.00% | 97.14% | 97.59% | 98.13% | 98.42% |
| √ | | √ | 58.15% | 89.55% | 95.53% | 96.53% | 97.10% | 97.72% | 98.08% |
| √ | | | 59.00% | 89.84% | 95.67% | 96.69% | 97.31% | 97.75% | 98.30% |

| | $\mathcal{D}^{\mathrm{C}}$ | $\mathcal{D}^{\mathrm{KT}}$ | $\mathcal{D}^{\mathrm{UIUC}}$ |
|---|---|---|---|
| SRP Radial-Diff | √ | √ | √ |
| SRP Circular | √ | √ | √ |
| SRP Angular-Diff | √ | | √ |
| **1. Our Results** | **99.37**% | **99.29**% | **98.56**% |
| 2. VZ-MR8 | 97.43% | | |
| 3. VZ-Patch | 98.03% | 92.4%(∗) | 97.83% |
| 4. Hayman *et al.* | 98.46% | 94.8%(∗) | 92.0%(∗) |
| 5. Lazebnik *et al.* | 72.5%(∗) | 91.3%(∗) | 96.03% |
| 6. Mellor *et al.* | | 89.71% | |
| 7. Zhang *et al.* | 95.3% | 96.1% | **98.7**% |
| 8. Brodhurst | **99.22**% | | |
| 9. Varma and Ray | | | **98.76**% |
| 10. CG | 98.6% | 98.5% | **98.8**% |
| 11. Xu-OTF *et al.* | | | 97.40% |
| 12. WMFS[18] | | | **98.60**% |
| 13. Liu *et al.* | 98.52% | 97.71% | 96.27% |