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Sorted random projections for robust rotation-invariant texture classification

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ABSTRACT

This paper presents a simple, novel, yet very powerful approach for robust rotation-invariant texture classification based on random projection. The proposed sorted random projection maintains the strengths of random projection, in being computationally efficient and low-dimensional, with the addition of a straightforward sorting step to introduce rotation invariance. At the feature extraction stage, a small set of random measurements is extracted from sorted pixels or sorted pixel differences in local image patches. The rotation invariant random features are embedded into a bag-of-words model to perform texture classification, allowing us to achieve global rotation invariance. The proposed unconventional and novel random features are very robust, yet by leveraging the sparse nature of texture images, our approach outperforms traditional feature extraction methods which involve careful design and complex steps. We report extensive experiments comparing the proposed method to six state-of-the-art methods, RP, Patch, LBP, WMFS and the methods of Lazebnik et al. and Zhang et al., in texture classification on five databases: CUReT, Brodatz, UIUC, UMD and KTH-TIPS. Our approach leads to significant improvements in classification accuracy, producing consistently good results on each database, including what we believe to be the best reported results for Brodatz, UMD and KTH-TIPS.

1. Introduction

Texture is an important characteristic of the appearance of objects in natural scenes and is a powerful visual cue, used by both humans and machines in describing and recognizing real world object surfaces. Texture analysis is an active research area spanning image processing, pattern recognition, and computer vision, with applications to medical image analysis, remote sensing, object recognition, industrial surface inspection, document segmentation and content-based image retrieval. Texture classification has received significant attention with many proposed approaches, as documented in comprehensive surveys [1,2].

The texture classification problem is conventionally divided into the two subproblems of feature extraction and classification [1,2]. To improve the overall quality of texture classification, either the quality of the texture features or the quality of the classification algorithm must be improved. This paper focuses on the improvement of texture feature quality, extending earlier preliminary work published in [3] and the work in [4].

There has been longstanding interest in developing robust features for texture classification with strong invariance to rotation, illumination changes, view point variations, perspective projection changes, nonrigid deformations and occlusions [5–12,16]. In other words, the major challenge is to develop texture features which not only are highly discriminative to inter-class textures, but are also robust to one or more intra-class variations. This paper focuses on the important problem of robust gray-scale and rotation invariant texture features.

Rotation invariant feature extraction is usually a complex process, with some steps treated with special care and being computationally demanding [17,18]. Our research is motivated by the concluding remark—"a very useful direction for future research is therefore the development of powerful texture measures that can be extracted and classified with a low computational complexity" in the recent excellent comparative study of Randen and Husøy [2]. Remarkable work along these lines is the LBP set of features [8], the filtering features of Schmid [19] and Leung and Malik [20], and the recent work of Varma and Zisserman [11] who showed that raw image pixel features from local image patches can outperform popular filter bank features such as the rotation-invariant MR8 features.

The dimensionality of patch features can cause severe limitations in the applicability of the patch method of Varma and Zisserman [11]. In order to circumvent this problem, Liu and Fieguth [4] introduced the use of random projections (RPs), a universal, information-preserving dimensionality-reduction technique, to project the patch vector space to a compressed patch

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space without a loss of salient information, claiming that the performance achieved by random features can outperform patch features, MR8, and LBP features.

Even though impressive classification performance was obtained in [4] using RP features, the approach is sensitive to image rotation. Fig. 1 serves as a motivational example for the exploration of the proposed rotation invariant scheme, contrasting the distributions of sorted and unsorted random projections. A texture image produces a cluster in the random feature space, and rotating the texture causes the cluster to be spread along some curve in panels (a,c). Sorting the patches before taking a random projection (b,d) limits the extent to which the cluster is spread along a path, leading to an impressive improvement in class locality and separability. This proposed approach will be referred to as sorted random projection (SRP).

The proposed SRP classifier preserves all of the computational simplicity, universality, and high classification performance advantages of the basic RP classifier. We will show the SRP features to be robust, invariant to image rotation locally, yet very discriminative, allowing us to take advantage of the powerful BoW model [5,6,11] for global rotation invariant texture classification. Furthermore, our method avoids the careful design steps and expensive computational cost involved in some local feature descriptors such as RIFT [5,6], SPIN [5,6] and SIFT [6].

The rest of this paper is organized as follows. Section 2 reviews the background literature for rotation invariant texture classification. Sections 2 and 3 respectively review the RP classifier and develop the proposed SRP classifier. In Section 5, we evaluate the capabilities of the proposed features with extensive experiments on *seven* popular texture datasets, summarized in Table 1, and present comparisons with current state-of-the-art classifiers on each dataset.

2. Background

2.1. BoW and texture classification

There has been a great interest in using a "Bag of Words" (BoW) approach for texture classification [5,6,8,9,11,20,22]. The BoW model, representing texture images statistically as histograms over a universal texton dictionary learned from local features, has proven widely effective for texture classification. This BoW model encompasses two popular paradigms for texture classification, dense and sparse, summarized in Fig. 2.

The dense approach uses local features pixel by pixel over the image, requiring feature extraction, texton selection, image histogram learning and classification (see the upper arrows in Fig. 2). Noticeable work along these lines includes [8,9,11,20,22]. In contrast, the sparse approach uses local features at a sparse set of interest points, with a corresponding sequence of key point detection, feature extraction at key points, texton selection, signature representation of image and classification (lower arrows in Fig. 2) [5,6].

There are three reasons why the BoW approach is popular for invariant texture classification. First, the representation is built on powerful local texture feature descriptors, which can be made insensitive to local image perturbations such as rotation, affine changes and scale. Second, the use of histogram as the statistical characterization for each image is globally invariant to these same changes. Third, the representation can be compared using standard distance metrics, allowing robust classification methods such as support vector machines to be employed.

2.2. Rotation invariant texture features

The general approach to developing rotation invariant techniques has been to modify successful non-rotation invariant techniques,

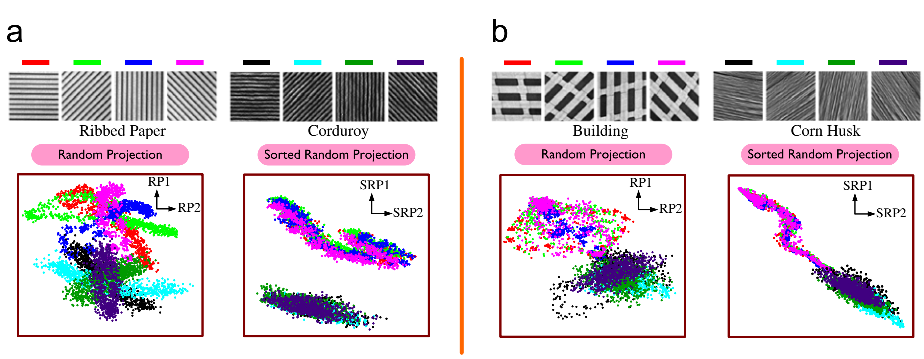

Fig. 1. Consider random projections of four different textures at varying orientations. The scatter plots in the bottom row show the random projections for a large number of extracted texture patches. Relative to random projections (a,c), it is clear that the sorted random projections in (b,d) offer superior class separability and compactness.

Table 1
Summary of texture datasets used in the 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
Brodatz	$\mathcal{D}^{B}$					111	215 × 215	9	999
CUReTRot	$\mathcal{D}^{CRot}$	√	√			61	140 × 140	92	5612
BrodatzRot	$\mathcal{D}^{BRot}$	√				111	128 × 128	9	999
UIUC	$\mathcal{D}^{UIUC}$	√		√	√	25	640 × 480	40	1000
UMD	$\mathcal{D}^{UMD}$	√		√	√	25	320 × 240	40	1000
KTH-TIPS	$\mathcal{D}^{KT}$		√	√		10	200 × 200	81	810