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A Statistical Approach Noise Tolerant Texture Classification

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Abstract: A simple, efficient, yet robust multi resolution approach to texture classification binary rotation invariant and noise tolerant. The proposed approach is very fast to build, very compact while remaining robust to illumination variations, rotation changes, and noise. We develop a novel and simple strategy to compute a local binary descriptor based on the conventional local binary pattern (LBP) approach, preserving the advantageous characteristics of uniform LBP. Points are sampled in a circular neighborhood, but keeping the number of bins in a single-scale LBP histogram constant and small, such that arbitrarily large circular neighborhoods can be sampled and compactly encoded over a number of scales. There is no necessity to learn a texton dictionary, as in methods based on clustering, and no tuning of parameters is required to deal with different data sets. This noise robustness characteristic of the proposed binary rotation invariant and noise tolerant is evaluated quantitatively with different artificially generated types and levels of noise including Gaussian, salt and pepper, and speckle noise in natural texture images.

Keywords: Texture descriptors; rotation invariance; local binary pattern (LBP); feature extraction; texture analysis.

I. INTRODUCTION

Texture is a fundamental characteristic of the appearance of virtually all natural surfaces and is ubiquitous in natural images. Texture classification, as one of the major problems in texture analysis, has received considerable attention during the past decades due to its value both in understanding how the texture recognition process works in humans as well as in the important role it plays in the field of computer vision and pattern recognition. Typical applications of texture classification include medical image analysis and understanding, object recognition, content-based image retrieval, remote sensing, industrial inspection, and document classification.

The texture classification problem is conventionally divided into the two sub problems. It is generally agreed that the extraction of powerful texture features is of more importance to the success of texture classification and, consequently, most research in texture classification focuses on the feature extraction part with extensive surveys. Nevertheless it remains a challenge to design texture features which are computationally efficient, highly discriminative and effective, robust to imaging environment changes (including changes in illumination, rotation, view point, scaling and occlusion) and insensitive to noise.

Recently, the Bag-of-Words (BoW) paradigm, representing texture images as histograms over a discrete vocabulary of local features, has proved effective in providing texture features. Representing a texture image using the BoW model typically involves the following three steps:

(i) Local texture descriptors: extracting distinctive and robust texture features from local regions;

(ii) Texton dictionary formulation: generating a set of representative vectors (i.e., textons or dictionary atoms) learned from a large number of texture features;

(iii) Global statistical histogram computation: representing a texture images statistically as a compact histogram over the learned texton dictionary.

Computationally simple approach, the Binary Rotation Invariant and Noise Tolerant descriptor, which has the following outstanding advantages: It is highly discriminative, has low computational complexity, is highly robust to noise and rotation, and allows for compactly encoding a number of scales and arbitrarily large circular neighborhoods.

At the feature extraction stage there is no pre-learning process and no additional parameters to be learned.

A rotation invariant and noise tolerant local binary pattern descriptor, based on a circularly symmetric neighbor set of 8q members on a circle of radius r. Parameter q controls the quantization of the angular space, and r determines the spatial scale of the Sr,q operator, which produces a histogram feature of constant dimensionality at any spatial scale r with arbitrary large number of sampling points 8q for each texture image

Based on these methods we develop a discriminative and robust combination for multi resolution analysis, which will be demonstrated experimentally to perform robustly against changes in gray-scale, rotation, and noise without suffering any performance degradation under noise-free situations.

II. LOCAL BINARY PATTERN (LBP)

The original LBP method, was proposed by Ojala in 1996.Despite the great success of LBP in computer vision and image processing, the original LBP descriptor has some limitations: producing long histograms which are not rotation invariant; capturingonly the very local texture structure and being unable to exploit long range information; limited discriminative capability based purely on local binarized differences; and lacking noise robustness.On the basis of these issues, many LBP variations have been developed surveys focusing on different aspects of the original LBP descriptor.

Dimensionality Reduction and Rotation Invariance

Most common is to reduce the feature length based on some rules, where influential work has been done by Ojala who proposed three important descriptors: rotation invariant LBP (LBPri), uniform LBP (LBPu2), and rotation invariant uniform LBP (LBPriu2). Of these, LBPriu2, has become the most popular since it reduces the dimensionality of the original LBP significantly and achieves improved discriminative ability.

Discriminative Power

There are two approaches to improve discriminative power: reclassifying the original LBP patterns to form more discriminative clusters, or including other local binary descriptors. Noticeable examples include the Hamming LBP which regroups non-uniform patterns based on Hamming distance instead of collecting them into a single bin as LBPriu2 does, the CLBP approachand the Extended LBP approach which considers the local binary descriptors computed from local intensities, radial differences and angular differences.

Noise Robustness

Ahonenintroduced Soft LBP (SLBP) method which allows multiple local binary patterns to be generated at each pixel position, to make the traditional LBP approach more robust to noise; however, SLBP is computationally expensive and is no longer strictly invariant to monotonic illumination changes. Tan and Triggs introduced local ternary patterns (LTP), where the binary LBP code is replaced by a ternary LTP code. The LTP method is more resistant to noise, but no longer strictly invariant to gray-scale changes. Liao proposed to use dominant LBP (DLBP) patterns which consider the most frequently occurred patterns in a texture image.

The Median Binary Pattern (MBP) proposed in claims increased robustness to impulse noise such as salt-and-pepper noise, but MBP was only explored in a local 3 × 3-patch. Fathi proposed a noise tolerant method based on the traditional LBP by combining a circular majority voting filter and a new LBP variant which regroups the non-uniform LBP patterns in order to gain more discriminability.Raja proposed Optimized Local Ternary Patterns (OLTP) based on LTP in order to reduce feature dimensionality, however the authors did not extend OLTP to multi-scale analysis. Ren proposed a much more efficient Noise Resistant Local Binary Pattern (NRLBP) approach based on the SLBP method, but it is computationally expensive to generalize to larger scales with a bigger number neighboring points.

Combining with Other Approaches

Ojalaproposed a local contrast descriptor to combine with LBP. It was recommended in that Gabor filters and LBP-based features are mutually complementary because LBP captures the local texture structure, whereas Gabor filters extract global texture information. Ahonenproposed an approach named LBP histogram Fourier features (LBP-HF), which combines the LBP and the discrete Fourier transform (DFT).Khellah introduced a Dominant Neighborhood Structure (DNS) method which extracts global rotation-invariant features from the detected image dominant neighborhood structure to complement LBP.

III. COMPLETE LOCAL BINARY PATTERN (CLBP)

Completed Local Binary Patterns (CLBP) consist of three LBP-like descriptors: CLBP_C, CLBP_S and CLBP_M which include information on the center pixel, signeddifferences, and magnitudes of differences, respectively, with the variants tested to improve the discriminative power of the original LBP operator.

IV. A BINARY ROTATION INVARIANT AND NOISE TOLERANT DESCRIPTOR

Motivation

Although the original LBP approach is attractive for its conceptual simplicity and efficient computation, a straightforward application of the original LBPr,p histogram features is limited:

(1) The original LBP operator produces rather long histograms (2p distinct values), overwhelmingly large even for small neighborhoods, leading to poor discriminant power and large storage requirements.
(2) The LBP operator captures only the very local structureof the texture, appropriate for micro-textures but notfor macro-textures. Because the LBP dimensionality becomes intractable as the sampling radius increases, it is difficult to collect information from a larger area.
(3) The original LBP codes computed are sensitive to image rotation.
(4) LBP codes can be highly sensitive to noise:the slightestfluctuation above or below the value of the central pixel is treated the same way as a major contrast.
All of the discussed descriptors share one or more weaknesses of noise sensitivity, high dimensionality, and/or information insufficiency.

Though all of the LBP-based approaches are computationally simple at the feature extraction step, except for LBPriu2r,p the other descriptors are all computationally expensive at the classification stage due

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to the high dimensionality of the histogram feature vector. The inherent difficulty in extracting suitable features for robust texture classification lies in balancing the three competing goals of discriminativeness, low computational requirements, and robustness to noise.

The goal of this paper was to build on the advantageous characteristics of LBP, developing an approach which achieves a better balance among these three competing requirements, in particular increasing robustness to noise. Our concern with the reduced approaches of LBPriu2 and CLBP_CSM lies with the use of only the uniform LBP patterns, which appear to lack texture discriminability. Instead, the LBPri, although having large dimensionality, possesses meaningful texture features and strikes us as a more promising starting point.

BRINT: Proposed Approach

The construction of the local BRINT descriptor is similar to the sampling scheme in the original LBP approach.

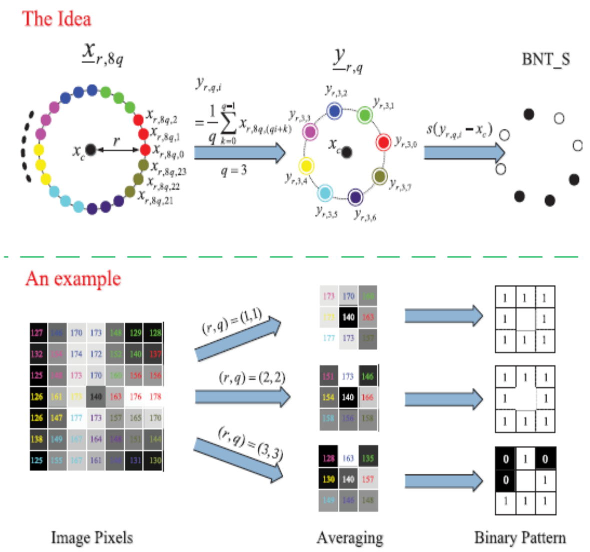

Fig1: Binary Rotation Invariant and Noise Tolerant Texture (BRINT) descriptor.

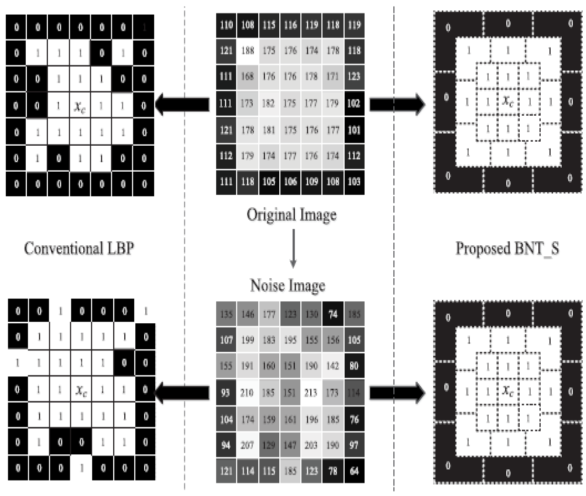

Fig.2: A motivation example for noise robustness.

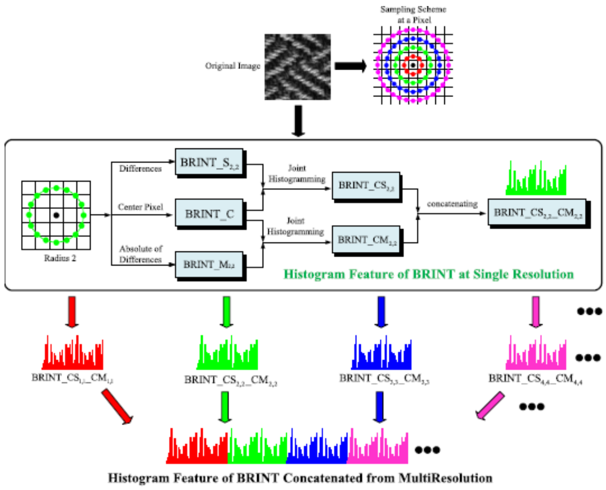

Fig.3: The framework of the BRINT approach.

The proposed BRINT descriptors were, so far, extracted from a single resolution with a circularly symmetric neighbor set of 8q pixels placed on a circle of radius, r. Given that one goal of our approach is to cope with a large number of different scales, by altering r we can create operators for different spatial resolutions, ideally representing a textured patch by concatenating binary histograms from multiple resolutions into a single histogram, as illustrated in Fig.3, clearly requiring that the histogram feature produced at each resolution be of low dimension.

Classification

The actual classification is performed via one of two popular classifiers:

1) The Nearest Neighbor Classifier (NNC) applied to the normalized BRINT histogram feature vectors hi and hj, using the $\chi 2$ distance metric.
2) The nonlinear Support Vector Machine (SVM) where the benefits of SVMs for histogram-based classification have clearly been demonstrated. Kernels commonly used include polynomials,Gaussian Radial Basis Functions and exponential Chi-Square kernel.

V. EXPERIMENTAL RESULTS

Performing classification on the entire database is challenging due to the relatively large number of texture classes, the small number of examples for each class, and the lack of intra-class variation. Each texture sample is preprocessed: normalized to zero mean and unit standard deviation. For the CUReT and Brodatzdatabases, all results are reported over 100 random partitioningsof training and testing sets. For SVM classification, we use the publicly available LibSVM library.The novel “averaging before binarization” scheme turns out to be a very powerful representation of image texture. The use of multiple scales offers significant improvements over single-scale analysis and consistent. The approach is making effective use of interactions between the center pixel and more distant pixels.

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The preceding discussion allows us to assert that the proposed multi-scale BRINT2 approach outperforms the conventional multi-scale CLBP approach on the Outex test suites.We now wish to examine the robustness of our method against noise to test applicability to real-world applications, thus the original texture images have been subject to added Gaussian noise. The classification performance of our proposedescriptor with several recent state-of-the-art methods in the presence of salt-and-pepper noise and multiplicative noise respectively.

VI. CONCLUSION

The proposed descriptor is shown to exhibit very good performance on popular benchmark texture databases under both normal conditions and noise conditions. The robustness of the proposed approach to image rotation and noise has been validated with extensive experiments on six different texture datasets. This noise robustness characteristic is evaluated quantitatively with different artificially generated types and levels of noise including Gaussian, salt and pepper and multiplicative noise in natural texture images. The proposed approach to produce consistently good classification results on all of the datasets, most significantly outperforming the state-of-the-art methods in high noise conditions. The propose work had focus on exploiting the domain of face recognition and object recognition and on texture classification.

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BIOGRAPHY

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