Generalized Local Binary Patterns for Texture Classification

Li Liu[1]
dreamliu2010@gmail.com
Paul Fieguth[2]
pfieguth@uwaterloo.ca
Gangyao Kuang[1]
kuangyeats@vip.sina.com

[1] School of Electronic Science and Engineering
National University of Defense Technology
Changsha, Hunan, China 410073

[2] Department of System Design Engineering
University of Waterloo
Waterloo, Ontario, Canada N2L 3G1

Recently, the orderless Bag-of-Words (BoW) approach has proven extremely popular and successful in texture classification tasks [1, 2, 3]. Due to its impressive computational efficiency and good texture discriminative property, the BoW-based approach LBP [1] has gained considerable attention. In order to employ the advantages of the method of Zhang *et al.* [3] in combining complementary local features, and those of LBP in computational efficiency and smaller support regions, we developed two intensity-based descriptors CI-LBP and NI-LBP, and two difference-based descriptors RD-LBP and AD-LBP. An overview of the proposed approach is illustrated in Fig. 1.

1. A Brief Review of LBP. Images are probed locally by sampling greyscale values at a central point $x_{0,0}$ and p points $x_{r,0},\ldots,x_{r,p-1}$ spaced equidistantly around a circle of radius r centered at $x_{0,0}$. Formally,

$$LBP_{p,r} = \sum_{n=0}^{p-1} s(x_{r,n}-x_{0,0})2^n, \quad s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{1}$$

The gray values of neighbors which do not lie precisely in a pixel location may be estimated by interpolation.

An important extension of the original LBP operator was made by Ojala *et al.* [1], who proposed the so-called "uniform" pattern $LBP_{p,r}^{riu2}$, merging nonuniform patterns directly into one pattern:

$$LBP_{p,r}^{riu2} = \begin{cases} \sum_{n=0}^{p-1} s(x_{r,n}-x_{0,0}), & \text{if } U(LBP_{p,r}) \leq 2 \\ p+1, & \text{otherwise} \end{cases} \tag{2}$$

where $U(LBP_{p,r}) = \sum_{n=0}^{p-1} |s(x_{r,n}-x_{0,0}) - s(x_{r,mod(n+1,p)}-x_{0,0})|$ The superscript $riu2$ denotes the rotation invariant "uniform" patterns that have U values at most 2. Therefore, mapping from $LBP_{p,r}$ to $LBP_{p,r}^{riu2}$ results in only $p+2$ distinct groups of patterns, leading to a much shorter histogram representation.

2. Intensity-based Descriptors. Inspired by Markov Random Field (MRF) models, we propose to use only local neighborhood distributions, similar to ideas of Varma and Zisserman [2]. In MRF modeling, the probability of a central pixel $\mathbf{I}(x_c)$ depends only on its neighborhood $\mathcal{N}(x_c)$. In this paper we explicitly model the joint distribution of a central pixel and its neighbors, in order to test the significance of the conditional probability distribution for classification.

Inspired by the coding strategy of LBP, we define the following NI-LBP descriptor (see also Fig. 1):

$$NI-LBP_{p,r} = \sum_{n=0}^{p-1} s(x_{r,n}-\mu)2^n, \quad \text{where} \quad \mu = \frac{1}{p}\sum_{n=0}^{p-1} x_{r,n} \tag{3}$$

Similar to $LBP_{p,r}^{riu2}$, the rotation invariant version of $NI-LBP$, denoted by $NI-LBP_{p,r}^{riu2}$, can also be defined to achieve rotation invariant classification. To maintain consistency with the standard binary coding strategy, the central pixels intensity is discretized as $CI-LBP = s(x_{0,0}-\mu_I)$, relative to μ_I, the mean of image $\mathbf{I}$.

3. Difference-based Descriptors. We propose two different descriptors, Radial Difference Local Binary Pattern and Angular Difference Local Binary Pattern (denoted as RD-LBP and AD-LBP respectively and as illustrated in Fig. 1):

$$RD-LBP_{p,r,\delta} = \sum_{n=0}^{p-1} s(\Delta_{\delta,n}^{\text{Rad}})2^n, \quad AD-LBP_{p,r,\delta} = \sum_{n=0}^{p-1} s(\Delta_{\delta,n}^{\text{Ang}})2^n \tag{4}$$

where δ is an integer, and $\Delta_{\delta,n}^{\text{Rad}} = x_{r,n} - x_{r-\delta,n}$ is the radial difference computed with given radial displacement δ, and $\Delta_{\delta,n}^{\text{Ang}} = x_{r,n} - x_{r,mod(n+\delta,p)}$ is the angular difference computed with given angular displacement $\delta(2\pi/p)$, and where $x_{r,n}$ and $x_{r,mod(n+\delta,p)}$ correspond to the gray values of pairs of pixels of δ equally spaced pixels on a circular radius r.

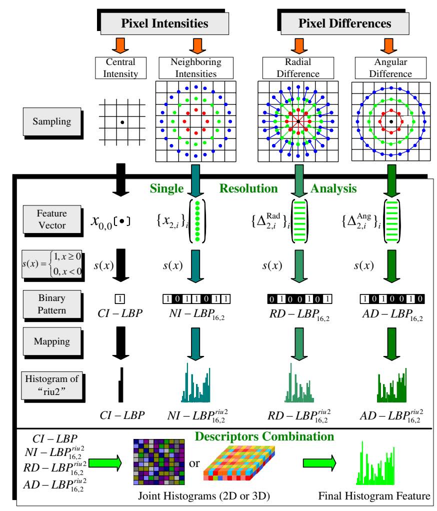

Figure 1: Overview of the proposed approach.

The uniform patterns represent meaningful and fundamental characteristics of the local texture structures; examining the proportions of the uniform patterns for LBP, RD-LBP and AD-LBP clearly demonstrated that the proportions of the uniform patterns of AD-LBP were too small and inadequate to provide a reliable and meaningful description of texture images. Consequently we focus on the RD-LBP descriptor.

Next, there are two ways to combine the NI-LBP and RD-LBP codes: the concatenation of individual histograms, or jointly calculating a two dimensional histogram, represented as NI-LBP / RD-LBP. In this paper, we prefer the latter approach (as illustrated in Fig. 1), which has also been used by Varma and Zisserman [2], and has been shown to produce better results. Following [1], we use only joint distributions of operators that have the same (p,r) values.

Motivated by the idea of [1], we conduct the multiresolution analysis by combining the information provided by multiple descriptors of varying (p,r). The histogram feature vector of multiresolusion analysis is obtained by concatenating the histograms from multiple resolution analysis realized with different (p,r). To perform the texture classification, nearest neighbor classifier (NNC) with χ^2 distance metric is used in this paper.

4. Conclusions. All the four proposed descriptors have the same form as the conventional LBP codes, thus they can be readily combined to form joint histograms to represent textured images. The proposed approach is computationally simple and is training-free: there is no need to learn a texton dictionary and no tuning of parameters. Extensive experimental results on two challenging texture databases (Outex and KTHTIPS2b) show that the proposed approach significantly outperforms the classical LBP approach and other state-of-the-art methods with a nearest neighbor classifier.

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