RLBP: Robust Local Binary Pattern

Jie Chen
Vili Kellokumpu
Guoying Zhao
Matti Pietikäinen

Center for Machine Vision Research
University of Oulu
Finland

Local binary pattern (LBP) is perhaps the best performing dense descriptor and it has been widely used in various applications, such as texture classification, human detection and face recognition [5]. However, one issue of LBP is that it is not so robust to the noise present in images when the gray-level changes resulting from the noise are not monotonic, even if the changes are not significant. To this end, we propose a new descriptor based on LBP, i.e., robust local binary pattern (RLBP). The idea is to locate the possible bit in LBP pattern changed by the noise and then revise the changed bit of the LBP pattern. The idea is very simple, but it works very well.

An example of how to compute RLBP from LBP is shown in Fig. 1. The neighbors of the pixel x_c would give the LBP pattern string (11010011). However, the pixel value of x_2=124 here is of high probability of being noisy since it results in a (101) substring. If we change the corresponding bit of x_2 in LBP string from 0 to 1, the new LBP string of this pixel (11110011) would denote a local corner, which is a more meaningful pattern for the texture representation.

Let us consider the LBP in the case that P=8 and R=1, i.e., LBP(8,1). In general, any neighboring three-bit substring in an eight-bit LBP pattern string is one in the set Y={y_1=(000), y_2= (001), y_3= (010), y_4= (011), y_5= (100), y_6= (101), y_7= (110), y_8= (111)}. Following the idea of the example in Fig. 1, we assume that the cases of y_3 and y_6 are noisy and change them to a new sub-string: y'_3= (000), and y'_6= (111). Our motivation for RLBP is to develop a descriptor to be robust to point noise (e.g., Gaussian). According to the statistical results [3], the neighboring pixels in an image should be smooth (e.g., LBP=00000000) or disturbed by edges (e.g., LBP=00001111). If one pixel is a noise, the bit in LBP pattern might be changed, e.g, LBP=00001101, where the seventh bit is different from its two neighboring bits, i.e., we have a substring y_6= (101). However, for other patterns, e.g., y_2= (001), the middle bit takes the same bit value as one of its neighboring bits at least, which might describe an edge (e.g., LBP=00001111). In addition, we only mapped those which were non-uniform patterns. In [3], all the non-uniform patterns are mapped to the same bin when building the histogram. By our method, we improve the discriminability of LBP.

Experimental results on the Brodatz [1] and UIUC [2] texture databases show that RLBP impressively outperforms the other widely used descriptors (e.g., SIFT, Gabor, MR8 and LBP) and other variants of LBP (e.g., completed LBP), especially when we add noise in the images (see Fig. 2). In addition, experimental results on human face recognition also show a promising performance comparable to the best known results on the Face Recognition Grand Challenge (FRGC) face dataset [4]. One example face from FRGC data set is shown in Fig.3.

Specifically, the experimental results over Brodatz texture dataset and the noisy Brodatz textures show perfect results. For example, RLBP achieves the accuracy of 98.9% for the dataset without noise and 98.6% with high levels of noise, while LBP gets the accuracy of 91.4% for the dataset without noise and 23.1% with high levels of noise (see Fig. 4). Experimental results on the UIUC texture database also show that RLBP impressively outperforms LBP. In addition, experimental results on FRGC face recognition also show a promising performance comparable to the best known results and reasonably good results for the dataset with added white Gaussian noise. For example, when log(1/SNR) =0.04, *RLBP* achieves the accuracy of 70% compared to 63% of Gabor, 48% of CLBP and 44% of LBP.

[1] P. Brodatz. *Textures: A Photographic Album for Artists and Designers*, Dover Publications, New York, 1966.
[2] S. Lazebnik, C. Schmid, and J. Ponce. A Sparse Texture Representation Using Local Affine Regions. *IEEE TPAMI,* 2005.
[3] T. Ojala, M. Pietikäinen, and T. Mäenpää, Multiresolution Gray-scale and Rotation Invariant Texture Classification with Local Binary Patterns, IEEE *TPAMI*, 2002.
[4] P. J. Phillips, P. J. Flynn, T. Scruggs, K.W. Bowyer, J. Chang, K. Hoffman, J. Marques, J. Min, and W. Worek, Overview of the Face Recognition Grand Challenge, *CVPR*, 2005.
[5] M. Pietikäinen, A. Hadid, G. Zhao, and T. Ahonen. *Computer Vision Using Local Binary Patterns*. Springer, 2011.

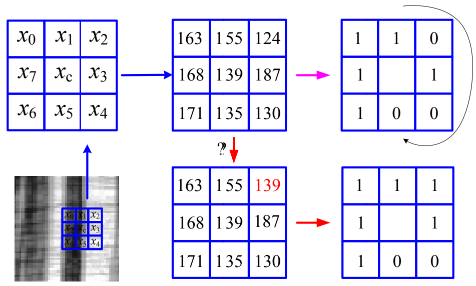

Fig. 1. Robust local binary pattern

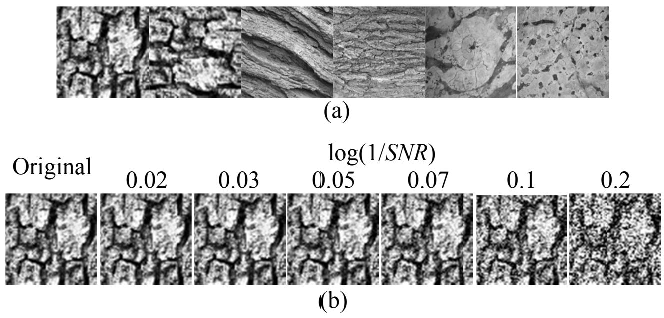

Fig. 2. (a) Example images from Brodatz and UIUC texture datasets. (b) An example from Brodatz by adding white Gaussian noise.

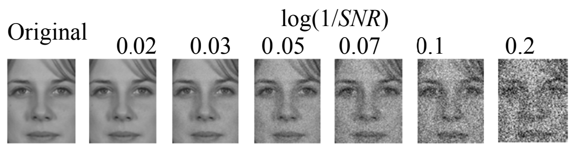

Fig. 3. An example from FRGC data set, with added white Gaussian noise.

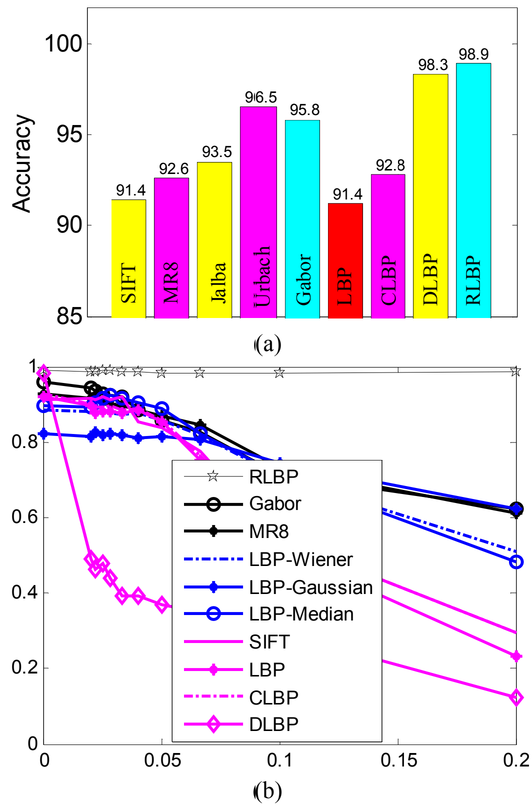

Fig. 4. Performance comparison with existing methods over Brodatz textures, (a) the original textures, (b) white Gaussian noise.