LBP-Based Edge Information for Color Texture Classification

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Abstract. In this paper, we propose to extract two types of feature from Neighbor-Center Difference Image (NCDI). NCDI is a variant of Local Binary Pattern (LBP) and originally used as input for Convolutional Neural Network (CNN). NCDI is a high dimensional feature and thus histograms are extracted from these NCDI features to mainly store useful information for statistical analysis. Two types of histograms are extracted from NCDI and then concatenated to further capture useful information. Experimental results on several benchmark color texture datasets show that the proposed approaches outperform the original LBP with a large margin (in accuracy) on several benchmark color texture datasets.

Keywords: LBP · Neighbor-Center Different Image · Color texture classification

1 Introduction

Texture analysis is one of the most active area of research in computer vision with a wide range of real-life applications, including industrial inspection, medical magnetic resonance imaging, materials science. In reality, the texture of the same material or object varies in illumination, orientation, scale, and rotation. Therefore, it needs a robust descriptor to characterize and discriminate different classes. Various approaches have been proposed to overcome these drawbacks in illumination, orientation, and other visual appearance problems. There exist many works to propose a new efficiency and discriminant image descriptors. Most approaches are based on local and global techniques.

One simple yet efficient local descriptor is Local Binary Pattern (LBP) introduced by Ojala et al. [1]. LBP is a computational efficiency operator with high discriminative power and robustness against illumination. However, it may not work properly for noisy images due to its threshold function [2]. Various variants of LBP and its extension have been proposed to minimize its limitation [3]. Lu et al. [4] have proposed Neighbor-Center Difference Vector (NCDV) which is extracted by subtracting the center pixel value from its neighboring pixel values. They extract NCDV features of different sizes from several non-overlapped

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blocks of training samples. For NCDV features extracted from each block, they train one projection to map it into a binary feature vector. Then, they cluster these binary codes into a codebook and encode these binary codes within the same face as a histogram feature vector. Finally, an age ranker is trained on these histograms. Their approach has shown to provide very good results on several datasets.

Recently, Wu and Lin [5] have proposed a new descriptor based on NCDV to capture edge information, namely Neighbor-Center Difference Image (NCDI). Normally, Convolutional Neural Network (CNN) model takes RGB images as input. However, Wu and Lin [5] have proposed to feed CNN model with hand-crafted feature NCDI which collects NCDV from all patches to reconstruct the image. This approach has shown to improve the accuracy in the facial expression recognition task. Edge information is useful to a wide range of computer vision tasks but NCDI is a high dimensional feature. Therefore, we propose to extract two types of histogram feature from NCDI to mainly store useful information and use it for texture classification.

The rest of this paper is organized as follows. In Sect. 2, LBP, NCDI, and K-Nearest Neighbors are briefly reviewed. Section 3 introduces the feature extracting methods. Next, four benchmark color texture datasets and experimental results are introduced in Sect. 4. Finally, the conclusion is discussed in Sect. 5.

2 Related Work

2.1 Local Binary Pattern (LBP)

LBP is a powerful local descriptor to deal with texture and related to classification tasks. LBP operator takes values of points on a circular neighborhood, thresholds the pixel values of the neighborhood at the value of the central pixel value. The binary results are then used to form an integer LBP code. The formula to compute the $\mathrm{LBP}_{P,R}$ code from P circular neighbors of radius R is defined as:

$$\mathrm{LBP}_{P,R} = \sum_{i=0}^{P-1} \theta\left(g_i - g_c\right) \times 2^i \tag{1}$$

where g_c is the value of central pixel and g_i is the value of ith neighborhood pixel. The threshold function $\theta\left(.\right)$ is defined as:

$$\theta\left(t\right) = \begin{cases} 1 & \text{if}\, t \geq 0 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

LBP is a computational efficiency descriptor with high discriminative power and robustness against illumination. However, LBP has several disadvantages, it loses intensity information due to the threshold function and may not work properly for noisy images [6]. Many variants of LBP have been proposed to minimize LBP's limitation [3].

2.2 Neighbor-Center Difference Image (NCDI)

LBP may lose intensity information due to the threshold function $\theta(.)$. In order to tackle this issue, several approaches have been proposed, one of these approaches is NCDI which is proposed by Wu and Lin [5]. NCDI is extracted on a grayscale image by iterating each pixel (x, y) and subtracting its value g_c from P neighboring pixel values $\{g_i\}_{i=1}^{P}$.

$$\mathrm{NCDI}\,(x, y)_i = g_i - g_c \tag{3}$$

Finally, $\mathrm{NCDI}_{i=1}^{P}$ were concatenated to create a multi-channel image. The P-channel of NCDI are extracted from a grayscale image will have edge information in P directions.

2.3 K-Nearest Neighbors Classifier

The K-Nearest Neighbors classifier (K-NN) is among the simplest classifiers of all machine learning algorithms and it is widely used in texture classification. To classify a testing image, firstly, the distance in the feature space between the testing image and each training images is computed. Then, the testing image is assigned to the class that has the highest number of images among K nearest neighbors. K is a user-defined constant. If $\mathrm{K} = 1$, the testing image is assigned as the class of the nearest neighbor in the feature space. The value of K is commonly set to 1 and the distance metric is usually L1 or Euclidean. The L1 distance d_{L1} between two feature vectors a, b is computed as follow:

$$d_{\mathrm{L1}} = \sum_i |a_i - b_i| \tag{4}$$

Where a_i, b_i is the i^{th} value in the feature vector a, b respectively.

3 Proposed Approach

The edge information is useful for several computer vision tasks. The 8-channel NCDI feature has shown to provide better results for facial expression recognition [5]. However, The 8-channel NCDI feature is a very high dimensional feature. Therefore, we investigate to extract two types of NCDI histogram feature to reduce the dimension and apply it for texture classification.

- The first histogram feature is obtained from each NCDI by counting the frequency of each value from -255 to 255. These histograms have information about the intensity of difference between pixel values.
- To further capture the edge information from NCDI, the second histogram feature is extracted from each NCDI by counting the frequency of 256 LBP values. These histograms have information about the correlation of difference between pixel values.

A LBP value at each point only stores information of which neighbor pixel value is larger than the center pixel value. In case of the NCDI, at each pixel, it stores how much each neighbor pixel value larger than the center pixel value. Therefore, the histogram of each NCDIs has more information about the intensity of difference between pixel values. However, the histogram of each NCDI channels does not have correlation information of neighboring values, thus we propose to combine NCDI Histogram and LBP-NCDI histogram to incorporate the intensity of difference and the correlation of difference information.

4 Experiments

4.1 Dataset Description

The proposed approaches are evaluated on four benchmark color texture datasets, including New BarkTex [7], Outex-TC-00013 [1], USPTex [8] and STex. Training and testing set of each dataset is divided by the holdout method (as shown in Table 1).

Table 1. Summary of image datasets used in the experiment.

Dataset name	Image size	# class	# training	# test	Total
New BarkTex	64×64	6	816	816	1632
Outex-TC-00013	128×128	68	680	680	1360
USPTex	128×128	191	1146	1146	2292
STex	128×128	476	3808	3808	7616

4.2 Experimental Setup

In order to evaluate the proposed approaches, experiments are conducted on the same training and testing set of four benchmark color texture datasets by using the nearest neighbor (1-NN) classifier associated with the L1 distance. It is worth to note that the sophisticated classifier might provide a better classification performance (i.e SVM classifier), but at the cost of computing and tuning parameters.

Firstly, the baseline result (LBP RGB) is obtained by extracting three $LBP_{8,1}$ histograms from the three channels of RGB images.

Secondly, two types of proposed histogram feature are evaluated separately. To begin, 8-channel NCDI is extracted from each channel of RGB image. Then, $LBP_{8,1}$ histograms of NCDI and histograms of NCDI are extracted from these NCDIs. Next, 1-NN classifier is used to obtain the accuracy of each type of feature.

Finally, two proposed types of histogram feature are concatenated produce the result of the proposed approach.

All experiments are implemented in Matlab-2015b and conducted on a PC with a configuration of a CPU 4 cores 2.2 GHz, 8 GBs of RAM.

4.3 Results

Table 2 shows that the proposed approaches take a longer time to extract features. However, the proposed approach to combine two types of NCDI histograms is still very fast. It takes only 0.068 s to extract features from the three channels of a 128×128 RGB image.

Table 2. The computation time (in seconds) to extract features from a 128×128 RGB image of the proposed approaches compare with the original LBP.

Methods	Computation time
LBP RGB	0.008
LBP NCDI	0.047
NCDI Histogram	0.024
NCDI Histogram & LBP NCDI	0.068

Table 3. Classification accuracy (in %) of the original LBP approach and the proposed approaches on four texture datasets New BarkTex, Outex-TC-00013, USPTex, and STex. LBP RGB stands for LBP histogram feature extracted on three channel of RGB image. LBP NCDI is the approach that uses the LBP histogram feature extracted on NCDIs. NCDI Histogram is the histogram feature extracted by counting the frequency of each value in NCDIs. NCDI Histogram & LBP NCDI is the proposed approach that concatenates two types of histogram features.

Methods	New BarkTex	Outex-TC-00013	USPTex	STex
LBP RGB	76.6	86.0	85.3	85.5
LBP NCDI	74.4	88.9	82.3	87.8
NCDI Histogram	69.4	86.3	80.8	76.9
NCDI Histogram & LBP NCDI	78.3	90.2	88.7	89.1

Table 3 clearly shows that the combination of two proposed feature types outperforms the result of LBP histogram from RGB image. Comparing with features from LBP histograms of RGB image, the proposed approaches achieved significant gain of more than 1.7%, 4%, 3.4% and 3.5% in accuracy on New BarkTex, Outex-TC-00013, USPTex, and STEX dataset respectively.

Table 4. Classification accuracy (in %) of the proposed method compared with other approaches on four texture datasets New BarkTex, Outex-TC-00013, USPTex, and STex.

Methods	New BarkTex	Outex-TC-00013	USPTex	STex
Color ranges LBP [9]	71.0	86.2	79.1	-
Wavelet coefficients [10]	-	89.7	-	77.6
Color contrast occurrence matrix [11]	-	82.6	-	76.7
Soft color descriptors [12]	-	81.4	58.0	55.3
LBP and local color contrast [13]	71.0	85.3	82.9	-
CLBP [14]	72.8	84.4	72.3	-
Mix color order LBP histogram [15]	77.7	87.1	84.2	-
LTP [6]	76.1	90.6	88.4	87.0
LPQ [16]	66.2	81.4	86.6	87.6
TPLBP [17]	61.3	75.0	80.0	71.7
LBP Median [18]	72.3	83.0	84.1	81.9
NCDI Histogram & LBP NCDI	78.3	90.2	88.7	89.1

Table 4 shows that our proposed approach to concatenate two types of feature obtains better results than several other approaches. According to the experiments on STex dataset, the proposed approach outperforms other approaches by a margin of more than 1.5%. The classification results obtained on the USPTex dataset by the proposed method provides slightly better result than other approaches. In the case of Outex-TC-00013 dataset, the Mix color order LBP histogram approach give slightly better accuracy than ours. However, the proposed method outperforms that approach by improving 2.2%, 0.3%, and 2.1% on New BarkTex, USPTex and STex datasets, respectively.

5 Conclusion

In this paper, two types of histogram features are proposed to extract edge information from NCDI. These two types of histograms are then concatenated to further capture useful information from NCDIs. Experimental results on four benchmark color texture datasets show that the concatenation of features from NCDI outperforms the original LBP with a large margin in accuracy. Moreover, the proposed approach has achieved better results compare with several other approaches on four texture datasets.

The future of this work is to reduce the dimension of proposed features by feature selection method and apply it to other related computer vision tasks.

References

1. Ojala, T., Maenpaa, T., Pietikainen, M., Viertola, J., Kyllonen, J., Huovinen, S.: Outex - new framework for empirical evaluation of texture analysis algorithms. In: Object Recognition Supported by User Interaction for Service Robots, vol. 1, Quebec City, Quebec, Canada: IEEE Computer Society, pp. 701–706 (2002)
2. Tan, X., Triggs, B.: Enhanced local texture feature sets for face recognition under difficult lighting conditions. In: Zhou, S.K., Zhao, W., Tang, X., Gong, S. (eds.) AMFG 2007. LNCS, vol. 4778, pp. 168–182. Springer, Heidelberg (2007). https://doi.org/10.1007/978-3-540-75690-3_13
3. Liu, L., Fieguth, P., Guo, Y., Wang, X., Pietikäinen, M.: Local binary features for texture classification: taxonomy and experimental study. Pattern Recogn. **62**, 135–160 (2017)
4. Lu, J., Liong, V.E., Zhou, J.: Cost-sensitive local binary feature learning for facial age estimation. IEEE Trans. Image Process. **24**(12), 5356–5368 (2015)
5. Wu, B.-F., Lin, C.-H.: Adaptive feature mapping for customizing deep learning based facial expression recognition model. IEEE Access **6**, 12451–12461 (2018)
6. Tan, X., Triggs, B.: Enhanced local texture feature sets for face recognition under difficult lighting conditions. IEEE Trans. Image Process. **19**(6), 1635–1650 (2010)
7. Porebski, A., Vandenbroucke, N., Macaire, L., Hamad, D.: A new benchmark image test suite for evaluating color texture classification schemes. Multimedia Tools Appl. **70**, 543–556 (2014)
8. Backes, A.R., Casanova, D., Bruno, O.M.: Color texture analysis based on fractal descriptors. Pattern Recogn. **45**(5), 1984–1992 (2012)
9. Ledoux, A., Losson, O., Macaire, L.: Color local binary patterns: compact descriptors for texture classification. J. Electron. Imaging **25**(6), 061404 (2016)
10. El Maliani, A.D., El Hassouni, M., Berthoumieu, Y., Aboutajdine, D.: Color texture classification method based on a statistical multi-model and geodesic distance. J. Vis. Commun. Image Represent. **25**(7), 1717–1725 (2014)
11. Rios, A.M., Richard, N., Fernandez-Maloigne, C.: Alternative to colour feature classification using colour contrast ocurrence matrix, vol. 9534, June 2015
12. Bello, R., Bianconi, F., Fernández, A., González, E., Di Maria, F.: Experimental comparison of color spaces for material classification. J. Electron. Imaging **25**, 061406 (2016)
13. Cusano, C., Napoletano, P., Schettini, R.: Combining local binary patterns and local color contrast for texture classification under varying illumination. J. Opt. Soc. Am. A **31**(7), 1453 (2014)
14. Guo, Z., Zhang, L., Zhang, D.: A completed modeling of local binary pattern operator for texture classification. IEEE Trans. Image Process. **19**(6), 1657–1663 (2010)
15. Ledoux, A., Losson, O., Macaire, L.: Color local binary patterns: compact descriptors for texture classification. J. Electron. Imaging **25**, 061404 (2016)
16. Ojansivu, V., Rahtu, E., Heikkila, J.: Rotation invariant local phase quantization for blur insensitive texture analysis. In: 2008 19th International Conference on Pattern Recognition, Tampa, FL, USA, pp. 1–4. IEEE December 2008

17. Lior, W., Tal, H., Yaniv, T.: Descriptor based methods in the wild. In: Real-Life Images Workshop at the European Conference on Computer Vision (ECCV), October 2008
18. Hafiane, A., Palaniappan, K., Seetharaman, G.: Joint adaptive median binary patterns for texture classification. Pattern Recogn. **48**(8), 2609–2620 (2015)