

One-Nearest-Neighbor Classification via Contrast of Local Energy Histograms



Y. DING AND J. NI

Abstract—In this letter, we propose an efficient one-nearest-neighbor classifier of texture via the contrast of local energy histograms of all the wavelet subbands between an input texture patch and each sample texture patch in a given training set. In particular, the contrast is realized with a discrepancy measure which is just a sum of symmetrized Kullback–Leibler divergences between the input and sample local energy histograms on all the wavelet subbands. It is demonstrated by various experiments that our proposed method obtains a satisfactory texture classification accuracy in comparison with several current state-of-the-art texture classification approaches.

Index Terms—Energy histogram, one-nearest-neighbor classifier, symmetrized Kullback–Leibler divergence (SKLD), texture classification, wavelet transform.

I. INTRODUCTION

TEXTURE classification is a fundamental problem in image processing. In this letter, we propose an efficient one-nearest-neighbor classifier of texture via the contrast of local energy histograms of all the wavelet subbands between an input texture patch and each sample texture patch in a given training set. In particular, the contrast is realized with a discrepancy measure which is just a sum of symmetrized Kullback–Leibler divergences between the input and sample local energy histograms on all the wavelet subbands. It is demonstrated by various experiments that our proposed method obtains a satisfactory texture classification accuracy in comparison with several current state-of-the-art texture classification approaches.

Texture classification is a fundamental problem in image processing. In this letter, we propose an efficient one-nearest-neighbor classifier of texture via the contrast of local energy histograms of all the wavelet subbands between an input texture patch and each sample texture patch in a given training set. In particular, the contrast is realized with a discrepancy measure which is just a sum of symmetrized Kullback–Leibler divergences between the input and sample local energy histograms on all the wavelet subbands. It is demonstrated by various experiments that our proposed method obtains a satisfactory texture classification accuracy in comparison with several current state-of-the-art texture classification approaches.

M. Ni received the D.Eng. degree in 2006, and the Ph.D. degree in 2010, from the School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengde, China, in 2011. He is currently an Associate Professor with the School of Information and Communication Engineering, University of Electronic Science and Technology of China, Chengde, China. His research interests include image processing, pattern recognition, and machine learning. He has published several papers in the area of texture classification.

In this letter, we propose an efficient one-nearest-neighbor classifier of texture via the contrast of local energy histograms of all the wavelet subbands between an input texture patch and each sample texture patch in a given training set. In particular, the contrast is realized with a discrepancy measure which is just a sum of symmetrized Kullback–Leibler divergences between the input and sample local energy histograms on all the wavelet subbands. It is demonstrated by various experiments that our proposed method obtains a satisfactory texture classification accuracy in comparison with several current state-of-the-art texture classification approaches.

In this letter, we propose an efficient one-nearest-neighbor classifier of texture via the contrast of local energy histograms of all the wavelet subbands between an input texture patch and each sample texture patch in a given training set. In particular, the contrast is realized with a discrepancy measure which is just a sum of symmetrized Kullback–Leibler divergences between the input and sample local energy histograms on all the wavelet subbands. It is demonstrated by various experiments that our proposed method obtains a satisfactory texture classification accuracy in comparison with several current state-of-the-art texture classification approaches.

II. PROPOSED ENERGY HISTOGRAM-BASED CLASSIFICATION METHOD

A. Local Energy Feature Extraction in Wavelet Domain

For an input texture patch I , we first decompose it into $3L$ subbands $(B_1, B_2, \dots, B_{3L})$ by using a wavelet transform with S scales and S orientations. Let Ω_i^j denote the i -th orientation subband at the j -th scale.

$$E_{Loc}^{i,j}(l, k) = \frac{1}{S^2} \sum_{u=1}^S \sum_{v=1}^S |w_{i,j}(l+u-1, k+v-1)| \quad (1)$$

where $1 \leq l, k \leq \Omega_i^j - S + 1$ and $w_{i,j}(m, n)$ is the local energy histogram of the i -th orientation subband at the j -th scale.

Next, we extract the local energy features by computing the local energy histograms for all the subbands. The local energy histogram $E_{Loc}^{i,j}$ is defined as the number of pixels with local energy values between l and k in the i -th orientation subband at the j -th scale. The local energy features are represented by the local energy histograms of all the subbands.

n

B. Local Energy Histogram (LEH)

1) *Definition*: Given a grayscale image I of size $M \times N$, the Local Energy Histogram (LEH) is defined as the distribution of local energy values e_m over the image. The local energy e_m is calculated as the difference between the maximum and minimum values in a local neighborhood Δ_n of size 2^n . The local energy histogram P is given by $P = (p_1, p_2, \dots, p_N)$, where p_n is the probability of finding a local energy value e_m in the neighborhood Δ_n .

2) *Discrepancy Measure*: On the LEH, the discrepancy measure is defined as the Kullback-Leibler Divergence (KLD) between the LEH H and the target LEH Q . The KLD is given by $KLD(H, Q) = \sum_{n=1}^N p_n \log \left(\frac{p_n}{q_n} \right) + \sum_{n=1}^N q_n \log \left(\frac{q_n}{p_n} \right)$.

The discrepancy measure is used to evaluate the performance of the LEH-based classifier. The discrepancy measure is defined as the Kullback-Leibler Divergence (KLD) between the LEH H and the target LEH Q . The KLD is given by $KLD(H, Q) = \sum_{n=1}^N p_n \log \left(\frac{p_n}{q_n} \right) + \sum_{n=1}^N q_n \log \left(\frac{q_n}{p_n} \right)$.

$$SKLD(H, Q) = \sum_{n=1}^N p_n \log \left(\frac{p_n}{q_n} \right) + \sum_{n=1}^N q_n \log \left(\frac{q_n}{p_n} \right) \quad (2)$$

where p_n and q_n are the probabilities of finding a local energy value e_m in the neighborhood Δ_n for the LEH H and the target LEH Q , respectively.

The LEH is used to classify images. The LEH is compared with the target LEH using the KLD. The KLD is used to evaluate the performance of the LEH-based classifier.

$$TD = \sum_{i=1}^{3L+1} d_i = HD + d_{3L+1} \quad (3)$$

where $HD = \sum_{i=1}^{3L} d_i$, $d_i = SKLD(H_i^{I_1}, Q_i^{I_2})$, and KLD is the Kullback-Leibler Divergence. The LEH $H_i^{I_1}$ and $Q_i^{I_2}$ are the LEHs of the images $B_i^{I_1}$ and $B_i^{I_2}$, respectively, for $i = 1, 2, \dots, 3L+1$.

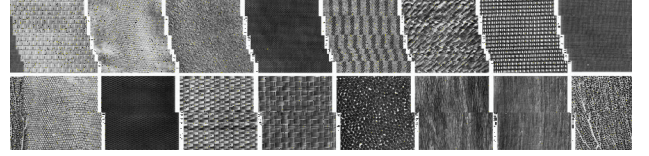


Fig. 1. Test images of size 80×80 pixels.

The LEH is used to classify images. The LEH is compared with the target LEH using the KLD. The KLD is used to evaluate the performance of the LEH-based classifier.

C. One-Nearest-Neighbor Classifier

The One-Nearest-Neighbor Classifier (1-NN) is used to classify images. The 1-NN classifier is based on the LEH. The LEH is compared with the target LEH using the KLD. The KLD is used to evaluate the performance of the 1-NN classifier.

III. EXPERIMENTAL RESULTS

In this section, the performance of the LEH-based classifier is evaluated. The performance is evaluated using the classification accuracy. The classification accuracy is defined as the percentage of images correctly classified. The classification accuracy is used to evaluate the performance of the LEH-based classifier.

A. Classification Performance

The classification performance is evaluated using the classification accuracy. The classification accuracy is defined as the percentage of images correctly classified. The classification accuracy is used to evaluate the performance of the LEH-based classifier.

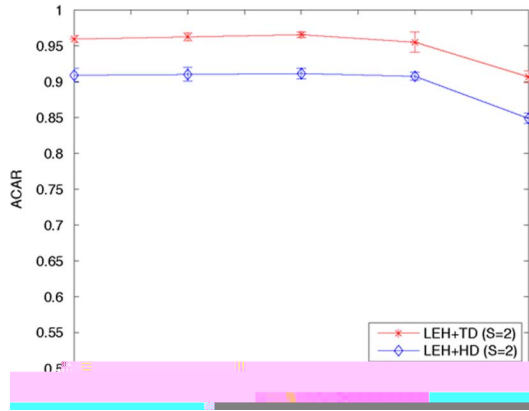


Fig. 2. Comparison of ACAR between LEH+TD ($S=2$) and LEH+HD ($S=2$) for different numbers of training samples (N_{tr}). The error bars represent standard deviation.

... (ACA) ...
 N_{tr} .
 From ...
 TD LEH+D, ...
 HD (3) LEH+HD. Fig. 2. ...
 LEH+D and LEH+HD ...
 $(a=0, 1, \dots, 4)$...
 2×2 ($S=2$) ...
 $N_{tr} = 8$.
 ...
 Fig. 2. ...
 LEH+D ...
 LEH+HD 5.00% 6.00%, ...
 TD ...
 HD ...
 In ...
 ACA $a=0$ to $a=4$...
 5.00% 6.50%, ...
 N_{tr} ...
 a ...
 LEH ...
 ACA ...
 $(S=2, 3, 4)$. Fig. 3 ...
 LEH+D ...
 LEH+HD ...
 LEH+D 4.00% 6.00% ...
 N_{tr} ...

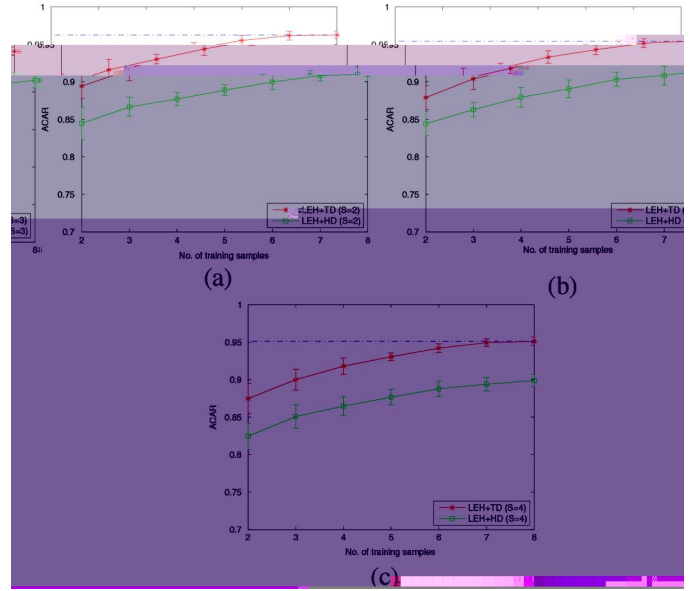


Fig. 3. Comparison of ACAR between LEH+TD and LEH+HD for different values of S : (a) $S=2$; (b) $S=3$; (c) $S=4$.

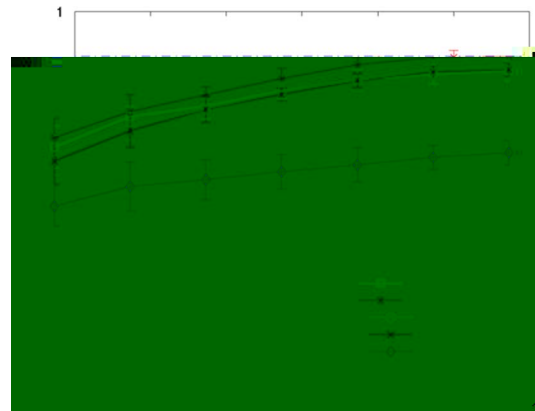


Fig. 4. Comparison of ACAR between LEH+D ($S=2$) and LEH+D ($S=4$) for different numbers of training samples (N_{tr}). The error bars represent standard deviation.

TD ...
 HD ...
 ...
 LEH+D, ... (BP) ...
 ...
 Fig. 4. ...
 ACA ...
 N_{tr} . In ...
 Fig. 4. ...
 BP M ...
 LEH+D ($S=2$) ...
 LEH+D ($S=1$), LEH+D ($S=3$) and LEH+D ($S=4$) ...
 1.00%, ...
 N_{tr} , ...
 $S=2$. M ...
 LEH+D ($S=2$) ...
 $N_{tr} = 8$. ACA ...
 LEH+D ($S=2$) 93.44% and 96.25%, r

TABLE I
THE ACAR (%) AND CLBP (IN SECOND) OF THE HE HE ME HOD

| | LEH+TD ($S = 2$) | CLBP_S | CLBP_S/M/C |
|------|--------------------|--------|------------|
| ACAR | 95.29 | 92.46 | 98.08 |
| TTC | 140.99 | 138.36 | 144.37 |

, LEH+TD ($S = 2$) \approx GMM M. 2.81%.
 A. n. n. LEH+TD \approx
 N_{tr} \approx 0.90%,
 \approx BPM, 1.48%. In \approx ,
 LEH+TD \approx
 LEH+TD.

B. Comparisons With the Other Existing Methods

In n, LEH+TD ($S = 2$) n
 Br [14] $111\ 640 \times 640$ (-
 -2), n BPM n n -
 (ICA) n (n
 ICA M) [16]. E n 25
 128×128 n- n, 10 n n
 n n
 ACA LEH+TD ($S = 2$),
 BPM, n ICAM, \approx 85.80%, 74.90%, n 80.7%,
 LEH+TD ($S = 2$) \approx r -
 BPM n ICAM n
 n r Br
 LEH+D
 ($S = 2$), \approx LEH+D ($S = 2$) \approx
 n n n n
 (CLBP), n CLBP n CLBP /M/C n [18],
 [15] $30\ 512 \times 512$ n
 n n
 [18] n [19]. O r r n n
 n [3]. n r n n
 n n n. A n r
 n n \approx In () C r (M) 5 CP
 (3.2 GHz) n M n n. Ir r ACA
 n (C) n. A
 n, r LEH+D ($S = 2$) r
 CLBP 2.83%, CLBP /M/C r
 n LEH+D ($S = 2$) 2.79%. ACA r
 n r n r n
 G n n [3], \approx 88.1%. A r
 C n m, LEH+D ($S = 2$) r n
 CLBP /M/C r r, r LEH+D ($S = 2$)
 r r n - - r CLBP n
 CLBP /M/C r

I. CONCLUSION

n r n n
 \approx n n n n

n r n n n n n r
 n \approx K L r n n
 n n n n r n n
 n, n n n -n r -n r r
 r r n n n r r
 r n - - r r

REFERENCE

- [1] n n n, D- n n r n, *IEEE Trans. Image Process.*, 16, n. 11, 2688-2696, N. 2007.
- [2] M.N.D n M. r, n r r r n, n r - G n n K L r n, *IEEE Trans. Image Process.*, 11, n. 2, 146-158, F. 2002.
- [3] K.C n C. n, n r r n n n r r n r, G n n, *J. Math. Imag. Vis.*, 29, n. 1, 35-47, 2007.
- [4] L.L.C. n n. K.C. r r n n r n, *IEEE Trans. Image Process.*, 19, n. 5, 1371-1378, M. 2010.
- [5] K.C n C. n, n r r n n r n, *IEEE Trans. Image Process.*, 17, n. 8, 1399-1405, A. 2008.
- [6] M.H.P, C. n, K.C. n H. n, A n n r r n, *IEEE Trans. Image Process.*, 15, n. 10, 3078-3088, O. 2006.
- [7] K.C n C. n, n n r r n n n r r, *IEEE Trans. Image Process.*, 19, n. 2, 281-289, F. 2010.
- [8] A.L n n J.F n, n n n n, *IEEE Trans. Pattern Anal. Mach. Intell.*, 15, n. 11, 1186-1191, N. 1993.
- [9] n n n J.H.H. n, F. n r r n: A n r, *IEEE Trans. Pattern Anal. Mach. Intell.*, 21, n. 4, 291-310, A. r. 1999.
- [10] M. n, n n n n n n, *IEEE Trans. Image Process.*, 4, n. 11, 1549-1560, N. 1995.
- [11] G. r, P. n r, n D. D n r r n r n, *IEEE Trans. Image Process.*, 8, n. 4, 592-598, A. r. 1999.
- [12] C.K n n J.K n, n n n n n n, *Pattern Recognit.*, 40, n. 4, 1207-1221, A. r. 2007.
- [13] L. n D.L. n, n n n n, *IEEE Trans. Image Process.*, 12, n. 6, 661-670, J. n. 2003.
- [14] [On n. A : [On n. A : ://% % . n / r n n / r .
- [15] [On n. A : [On n. A : :// . . . / . . . / n r /
- [16] H.L B n n, A.G.D, n N.E.O'C n n r, L n n, *IEEE Trans. Circuits Syst. Video Technol.*, 17, n. 3, 286-297, M. r. 2007.
- [17] H.L n, n Gr, n n. A, r n n n n n n, *IEEE Trans. Image Process.*, 19, n. 6, 1548-1557, J. n. 2010.
- [18] H.G, L. n, n D. n, A n n n, *IEEE Trans. Image Process.*, 19, n. 6, 1657-1663, J. n. 2010.
- [19] H.G, L. n, n D. n, n n n r n, *Pattern Recognit.*, 43, n. 3, 706-719, M. r. 2010.