

# Energy-Based One-Nearest-Neighbor Classifier in Wavelet Domain

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**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 computer vision. In the past few decades, many methods have been proposed for texture classification, such as the Gabor-based method [1], [2], the local binary pattern (LBP) [3], [4], the local binary patterns with uniformity [5], [6], the local binary patterns with orientation [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100].

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. The rest of the letter is organized as follows. Section II describes the proposed energy-based one-nearest-neighbor classifier. Section III discusses the experimental results. Section IV concludes the letter.

## II. PROPOSED ENERGY-BASED ONE-NEAREST-NEIGHBOR CLASSIFICATION METHOD

### A. Local Energy Feature Extraction in Wavelet Domain

For local energy feature extraction in wavelet domain, we first decompose the input texture patch  $I$  into  $3L$  wavelet subbands  $(B_1, B_2, \dots, B_{3L})$  by using the wavelet transform  $T$  with  $(N-1)$  levels of decomposition. The local energy histogram  $E_{Loc}^{i,j}$  of the  $i$ -th wavelet subband  $B_i$  is defined as

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

where  $1 \leq l, k \leq \Omega_i^j - S + 1$ ,  $w_{i,j}(m, n)$  is the local energy histogram of the  $i$ -th wavelet subband  $B_i$  at the  $j$ -th scale, and  $E_{Loc}^L$  is the local energy histogram of the  $L$ -th wavelet subband  $B_{3L}$ .

Next, we compare the local energy histogram  $E_{Loc}^{i,j}$  of the input texture patch  $I$  with the local energy histogram  $E_{Loc}^{i,j}$  of each sample texture patch  $P$  in the training set. The discrepancy measure  $D$  between  $E_{Loc}^{i,j}$  and  $E_{Loc}^{i,j}$  is defined as

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**B. Local Energy Histogram (LEH)**

1) *Definition:*  $G = (e_1, e_2, \dots, e_M)$

$$E = (e_1, e_2, \dots, e_M),$$

$$\Delta_n = [2^a(n-1), 2^a n), n = 1, 2, \dots, N,$$

$$N = 2^{N_0-a}, 0 \leq a \leq N_0,$$

$$[0, 2^{N_0}) = \bigcup_{n=1}^N \Delta_n.$$

$$p(\Delta_n) = p_n = m_n/M,$$

$P = (p_1, p_2, \dots, p_N)$

2) *Discrepancy Measure:*

$$P = (p_1, p_2, \dots, p_N)$$

$$p_n = 0$$

$$n^* = \arg \max_n p_n$$

$$p'_n = p_n + \eta / (N-1) \quad n \neq n^*,$$

$$p'_{n^*} = p_{n^*} - \eta.$$

$$P' = (p'_1, p'_2, \dots, p'_N)$$

(KLD) 4

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

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

$$HD = \sum_{i=1}^{3L} d_i, \quad d_i = SKLD(H_i^{I_1}, Q_i^{I_2})$$

$$B_i^{I_1}, B_i^{I_2}, \quad i = 1, 2, \dots, 3L+1.$$

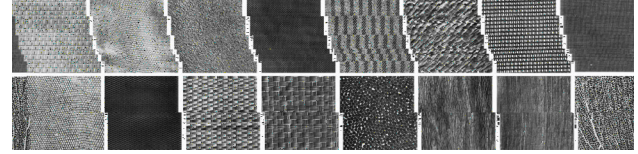


Fig. 1. 80 B

$$B_i^{I_1}, B_i^{I_2},$$

$$TD, HD,$$

$$TD, HD.$$

**C. One-Nearest-Neighbor Classifier**

$$TD,$$

$$k > 1$$

$$TD,$$

$$k > 1$$

$$k > 1$$

$$k > 1$$

**III. EXPERIMENTAL RESULTS**

I

I

D

1, 4

$N_0 = 10$

$2^{10}$

$N_0 = 10$

$N_0$

**A. Classification Performance**

80, 640 x 640

80, 14, 17

160 x 160

1280, 80,  $N_{tr}$

2, 3, ..., 8.  $N_{tr} =$

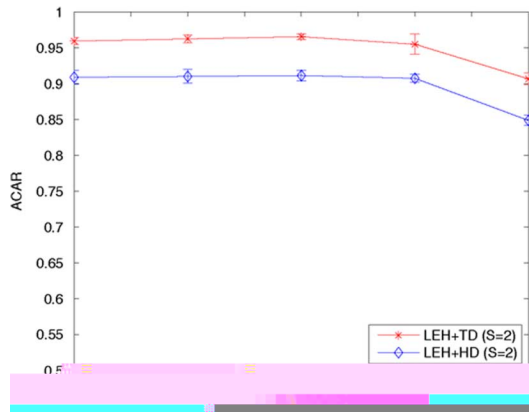


Fig. 2. Comparison of the classification accuracy of LEH+TD ( $S = 2$ ) and LEH+HD ( $S = 2$ ) with the number of training samples ( $N_{tr} = 8$ ).

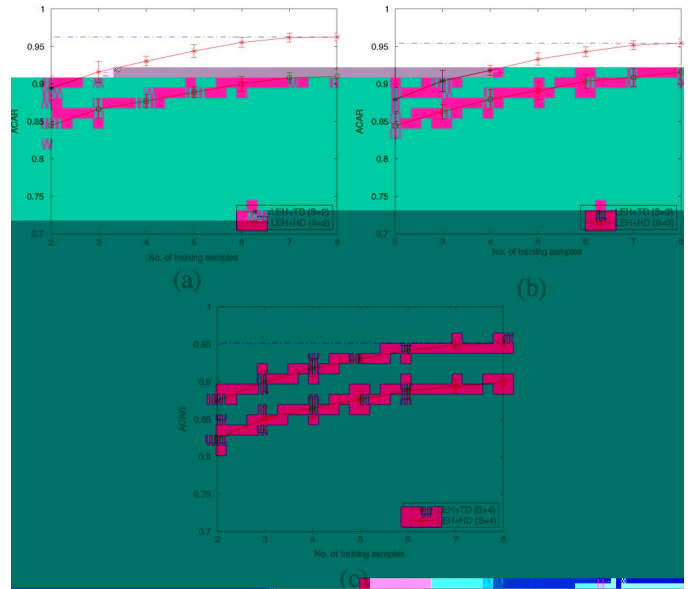


Fig. 3. Comparison of the classification accuracy of LEH+TD and LEH+HD with the number of training samples ( $N_{tr} = 8$ ): (a)  $S = 3$ ; (b)  $S = 4$ .

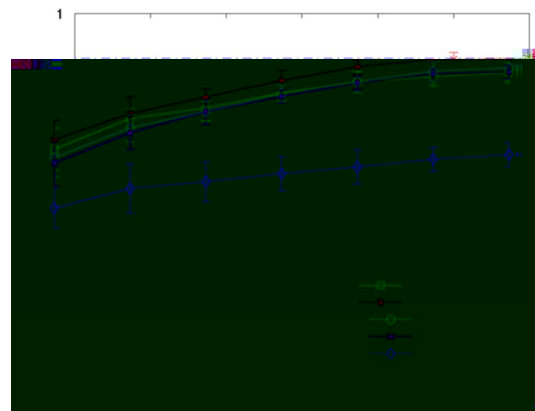


Fig. 4. Comparison of the classification accuracy of LEH+TD and LEH+HD with the number of training samples ( $N_{tr} = 8$ ) against the baseline method (BP M).

(ACA)  $N_{tr}$ .  $F$   $TD$  LEH+D,  $LEH$   $HD$  (3) LEH+HD. Fig. 2. ACA  $LEH+D$   $LEH+HD$  ( $a = 0, 1, \dots, 4$ )  $2 \times 2$  ( $S = 2$ )  $N_{tr} = 8$ .  $N$

Fig. 2. Comparison of the classification accuracy of LEH+TD and LEH+HD with the number of training samples ( $N_{tr} = 8$ ): (a)  $S = 3$ ; (b)  $S = 4$ ; (c)  $S = 2$ .  $TD$   $HD$   $ACA$   $a = 0$   $a = 4$   $a$   $5.00\%$   $6.00\%$   $5.00\%$   $6.50\%$   $ACA$   $a = 0$   $a = 4$   $a$   $3$   $0$   $ACA$   $N$   $TD$   $HD$   $LEH+D$   $LEH+HD$  (BP M)  $BP M$   $ACA$   $N_{tr}$   $I$   $ACA$   $LEH+D$   $BP M$   $LEH+D$  ( $S = 2$ )  $LEH+D$  ( $S = 1$ ),  $LEH+D$  ( $S = 3$ )  $LEH+D$  ( $S = 4$ )  $1.00\%$   $BP M$   $6.00\%$   $8.00\%$   $N_{tr}$   $S = 2$   $M$   $LEH+D$  ( $S = 2$ )  $G$   $17$   $GMM$   $M$   $N_{tr} = 8$   $ACA$   $GMM$   $M$   $LEH+D$  ( $S = 2$ )  $93.44\%$   $96.25\%$

$ACA$   $LEH+D$   $LEH+HD$   $LEH+HD$   $4.00\%$   $6.00\%$   $N_{tr}$   $ACA$   $LEH+D$   $LEH+HD$   $93.44\%$   $96.25\%$

$ACA$   $LEH+D$   $LEH+HD$   $93.44\%$   $96.25\%$

TABLE I  
THE ACA (%) AND CLBP (IN SECOND) OF THE HE METHOD

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

B. Comparisons With the Other Existing Methods

I LEH+TD ( $S = 2$ )  
 B 14 111 640 × 640 ( -  
 -2), BPM  
 (ICA) (A  
 ICA M ) 16 . E 25  
 128 × 128 10  
 ACA LEH+TD ( $S = 2$ ),  
 BPM ICA M 85.80%, 74.90%, 80.7%,  
 LEH+TD ( $S = 2$ )  
 BPM ICA M  
 B  
 LEH+TD  
 ( $S = 2$ ), LEH+TD ( $S = 2$ )  
 (CLBP), CLBP CLBP /M/C 18',  
 15' 30 512 × 512  
 18' 19'. O  
 3'.  
 A  
 I ( ) C ( M ) 5 CP,  
 (3.2 GH ) M I ACA  
 ( C ) A  
 LEH+TD ( $S = 2$ )  
 CLBP 2.83% , CLBP /M/C  
 LEH+TD ( $S = 2$ ) 2.79%. ACA  
 G 3', 88.1%. A  
 C , LEH+TD ( $S = 2$ )  
 CLBP /M/C. LEH+TD ( $S = 2$ )  
 CLBP /M/C

I. CONCLUSION

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