NOISE-ROBUST STATISTICAL FEATURE DISTRIBUTIONS FOR TEXTURE ANALYSIS

Eystratios G. Keramidas, Dimitris K. Iakovidis, Dimitris Maroulis

Dept. of Informatics and Telecommunications, University of Athens,
Panepistimioupolis, 15784, Athens, Greece
emails: e.keramidas@di.uoa.gr, dimitris.iakovidis@ieee.org; d.maroulis@di.uoa.gr

ABSTRACT

A novel image feature extraction methodology is proposed in this study. By incorporating fuzzy logic into the well-established Local Binary Pattern (LBP) approach we derive statistical feature distributions suitable for noise-robust texture representation. The proposed Fuzzy Local Binary Pattern (FLBP) approach is based on the assumption that a local image neighbourhood may be characterized by more than a single binary pattern. The effectiveness of the proposed methodology is demonstrated by classification experiments on noise degraded Brodatz textures. The classification performance obtained with the FLBP features was higher than the one obtained with the original LBP features for various noise levels.

1. INTRODUCTION

Texture analysis has been extensively investigated in the literature for nearly three decades. Although several texture-analysis algorithms have been proposed, a number of challenging problems still need to be addressed.

For most practical applications, noise is a common source of uncertainty to texture characterization. Several texture-analysis approaches have been proposed in the literature [1], however, robust to noise texture description representation still remains an open issue. Studies dealing with this issue have proposed texture representations that include spatial frequency domain features [2]; Gabor features based on multichannel filtering [3]; and bispectrum features [4]. However, the extraction of most of these features involves rather complex computations.

A computationally simple local texture descriptor that has been shown to be effective in the computer vision field is Local Binary Pattern (LBP) [5]. Although the LBP texture representation presents certain important advantages, a major drawback is its sensitivity to noise and small variations of grey scale values. A feature extraction approach incorporating fuzzy logic can minimize noise sensitivity characteristic of the LBP approach. In this paper we propose an LBP-based feature extraction approach that leads to a noise-robust texture representation. This is achieved by incorporating fuzzy logic into the LBP methodology. The proposed approach, called Fuzzy Local Binary Pattern (FLBP), provides an improved texture representation compared to the original LBP that enables more accurate discrimination of textures.

The remainder of this paper is structured as follows. Section 2 describes the original LBP approach and presents the proposed FLBP approach. The results from the experimental evaluation of the proposed approach on the Brodatz texture album are provided in Section 3. Finally, the conclusions of this study are summarised in Section 4.

2. LOCAL BINARY PATTERNS FUZZIFICATION

A suitable approach for the characterization of the texture context of an image is the LBP texture model. According to that, a pattern is represented by a set of nine elements P = { p_{center}, p_0, p_1, . . . , p_7}, where p_{center} represents the intensity value of the central pixel and p_i ($0 \le i \le 7$) represents the intensity values of the peripheral pixels in a 3×3 local neighborhood. Such a neighborhood can be characterized by a set of binary values d_i ($0 \le i \le 7$), as follows:

$$d_i = \begin{cases} 1 & \text{if } \Delta p_i \ge 0 \\ 0 & \text{if } \Delta p_i < 0 \end{cases} \quad (1)$$

where $\Delta p_i = p_i - p_{center}$.

Based on these binary values, for each neighborhood a unique LBP code can be derived as follows:

$$LBP = \sum_{i=0}^{7} d_i \cdot 2^i \quad (2)$$

Thus, out of $2^8 = 256$ possible codes, a single LBP code can describe a binary pattern of 3×3 pixel neighborhood.

For every pixel in a given image region, an LBP code is extracted creating a histogram. Each such histogram is considered as a feature vector, representing the underlying texture.

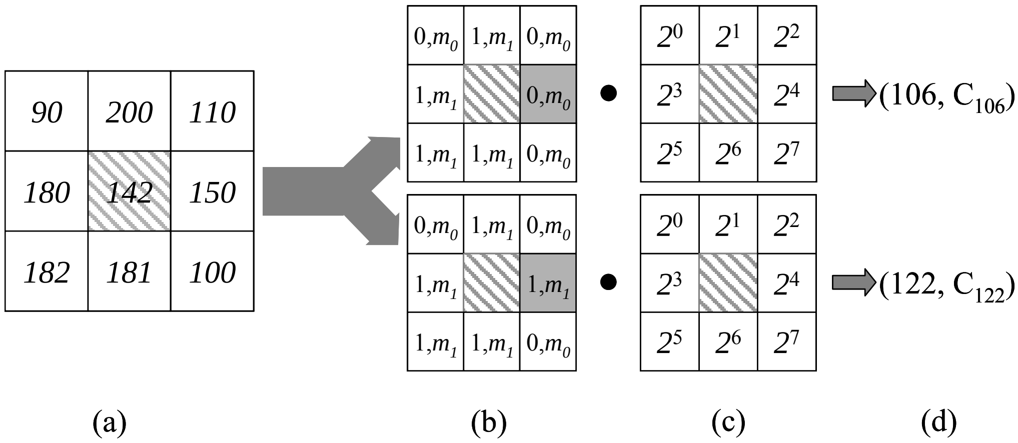


Fig. 1. Example of FLBP computation scheme for a 3×3 neighbourhood for T=10, (a) 3×3 pixels neighbourhood. (b) Fuzzy thresholded values along with corresponding membership values. (c) Binomial weights. (d) LBP codes and corresponding contribution values.

The basic idea behind the LBP approach is the description of a local pattern via a hard thresholding scheme (Eq.1), which makes texture representation sensitive to small grey-level perturbations or noise. By incorporating fuzzy logic in LBP texture extraction scheme, the discrimination power of the original LBP approach can be improved.

A fuzzy texture representation based on the LBP approach could be described by linguistic fuzzy rules. Two fuzzy rules can describe the relation between the intensity values of the peripheral pixels p_i and the central pixel p_{center}, of a 3×3 neighborhood as follows:

Rule R_0: The more negative Δp_i is, the greater the certainty that d_i is 0.

Rule R_1: The more positive Δp_i is, the greater the certainty that d_i is 1.

The linguistic fuzzy rules R_0 and R_1 can be mathematically modelled by two membership functions. Let membership function $m_0()$ define the degree to which Δp_i is negative, and according to Eq. 1 the degree to which d_i is 0. Then function $m_0()$ can be defined as follows:

$$m_0(i) = \begin{cases} 0 & \text{if } \Delta p_i \geq T \\ \dfrac{T - \Delta p_i}{2 \cdot T} & \text{if } -T \leq \Delta p_i < T \\ 1 & \text{if } \Delta p_i \leq -T \end{cases} \tag{3}$$

In a similar manner let function $m_1()$ define the degree to which Δp_i is positive, and according to Eq. 1 the degree to which d_i is 1. The proposed membership function $m_1()$ can be defined as follows:

$$m_1(i) = \begin{cases} 1 & \text{if } \Delta p_i \geq T \\ \dfrac{T + \Delta p_i}{2 \cdot T} & \text{if } -T \leq \Delta p_i < T \\ 0 & \text{if } \Delta p_i \leq -T \end{cases} \tag{4}$$

For both $m_0()$ and $m_1()$, $T \in [0,255]$ represents a parameter that controls the degree of fuzziness.

Although for the original LBP operator a single LBP code characterize a 3×3 neighbourhood, in the proposed FLBP approach, a neighbourhood can be characterized by more than one LBP codes. Figure 1 illustrates FLBP feature extraction scheme, where two LBP codes characterize a 3×3 neighbourhood. The degree to which each LBP code characterizes the neighbourhood, depends on the membership functions $m_0()$ and $m_1()$. For a 3×3 neighbourhood, the contribution C_{LBP} of each LBP code in the FLBP histogram is defined as:

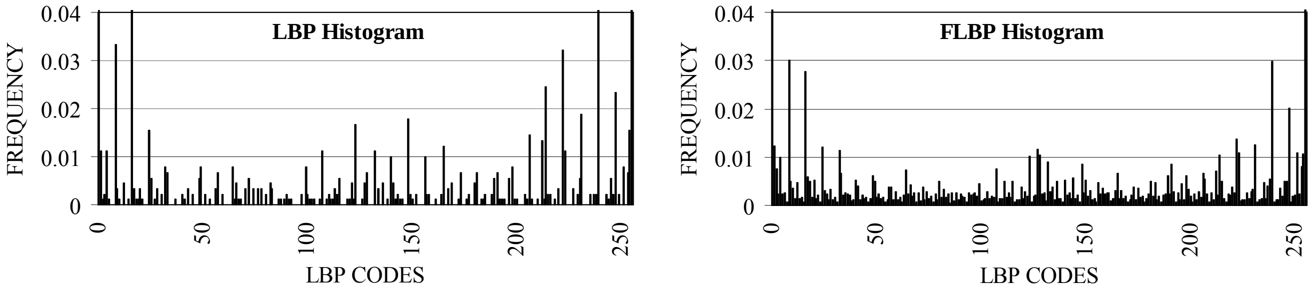
$$C_{LBP} = \prod_{i=0}^{7} m_{d_i}(i) \tag{5}$$

where $d_i \in \{0,1\}$ and LBP code can be obtained from Eq. 2.

In other words, each 3×3 neighbourhood contributes to more than one bins of the FLBP histogram. The total contribution of a 3×3 neighbourhood to the histogram of LBP codes is:

$$\sum_{LBP=0}^{255} C_{LBP} = 1 \tag{6}$$

An LBP histogram created from the bottom image of Fig. 3(b) is presented in Figure 2(a). It can be observed that quite a few bins of that histogram, 105 bins in total, are empty. The corresponding FLBP histogram is illustrated in Fig. 2(b). In this case there are no empty bins and there are more spikes, though limited in magnitude. This indicates that



(a) (b)

Fig. 2. (a) LBP and (b) FLBP normalized histograms obtained from the lower Broadtz image illustrated in Fig. 3(b).

FLBP histograms are more informative than LBP histograms. Based on Shannon's definition of entropy, for a histogram of LBP codes the entropy can be computed as:

$$H = -\sum_{LPB=0}^{255} p_{LBP} \cdot \log(p_{LBP}) \qquad (7)$$

where p_{LBP} is the probability of occurrence of the LBP-th pattern. Thus the less sparse the histogram is, the higher the entropy, and the more the actual information. If all bins have equal probability, the maximum entropy will be reached. On that ground, we can argue that the entropy of the FLBP histograms is greater than or equal to the entropy of the original LBP histograms.

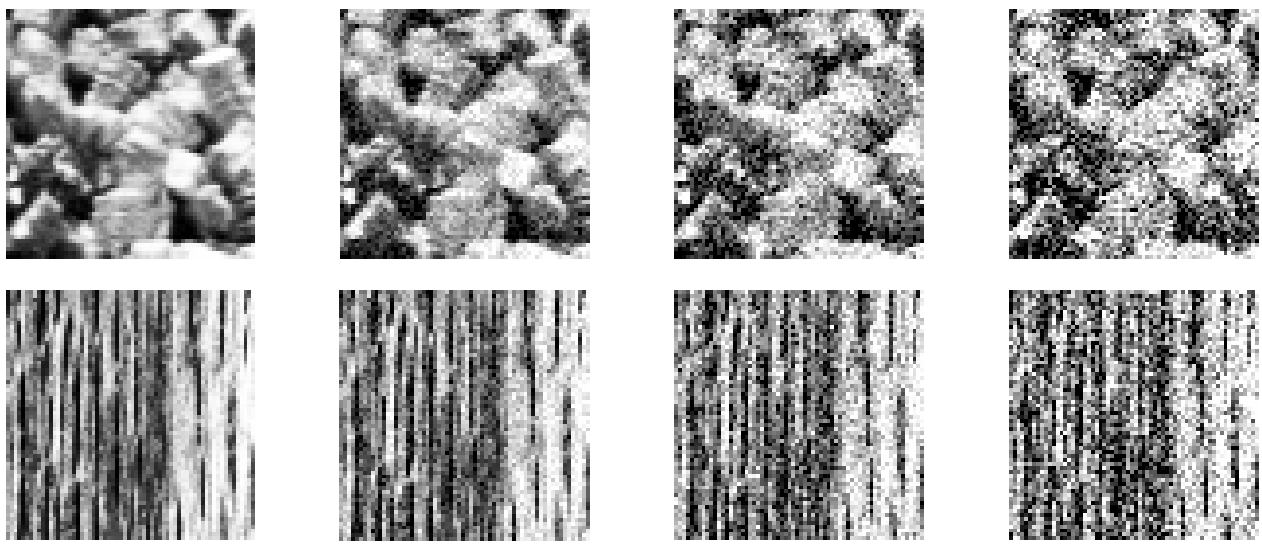
3. EXPERIMENTS AND RESULTS

For the experimental evaluation of the performance of the proposed FLBP approach, classification experiments have been conducted. The dataset used for the experiments include 32 textures classes from the Brodatz album [6]. Each texture used was of 512×512 pixels size and it was divided into 64 non-overlapping blocks of 64×64 pixels.

To allow the investigation of the performance of the FLBP approach an additive noise model has been utilized for degradation of texture images. Additive noise with a zero-mean Gaussian distribution and standard deviation (*SD*) values of 5, 10, 15…60, has been applied to the original dataset, resulting in a total of twelve noise-degraded datasets of 64×64 pixels texture blocks.

A Support Vector Machine (SVM) [7] classifier has been utilized for the classification task. The SVM classifier was implemented using a Gaussian kernel function, well known for its generalization capabilities even for high dimensional spaces [8]. Each dataset was split into two independent sets with the same number of samples used for training and testing respectively. The ranges of the SVM parameters tested in each classification experiment include cost values between 2^{-5} to 2^{15}, and widths of the Gaussian kernel between 2^{-15} to 2^{3}. A grid search approach was followed for parameter selection.

A direct experimental comparison between the proposed FLBP and the original LBP method has been performed on the original noise free dataset. Figure 4 illustrates the best classification results obtained on noise free images for different values of the fuzzification parameter T ranging between 0 and 200. The minimum mean classification error was 2.6%



(a) (b) (c) (d)

Fig. 3. Example of Brodatz images degraded by additive Gaussian noise, of zero mean and standard deviation (a) 0, (b) 20, (c) 40, and (d) 60.

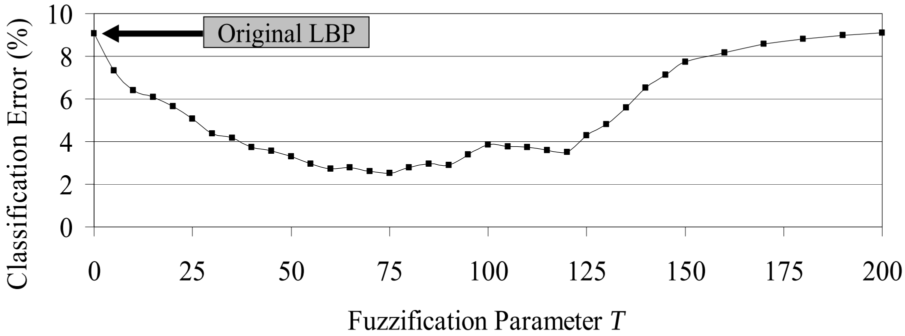
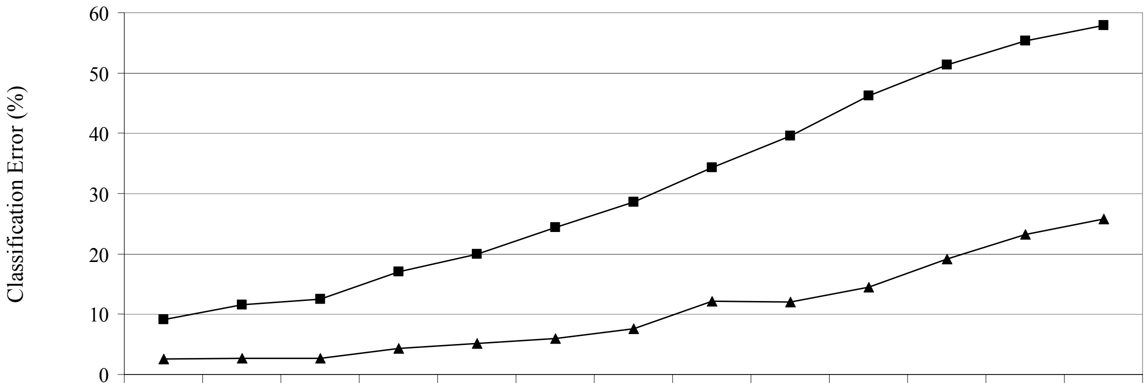


Fig. 4. Classification error obtained with the proposed FLBP features for different values of the fuzzification parameter *T* on noise free image dataset.



	0	5	10	15	20	25	30	35	40	45	50	55	60
FLBP	2.52	2.65	2.65	4.3	5.12	5.99	7.64	12.15	11.98	14.5	19.18	23.22	25.74
LBP	9.07	11.55	12.46	17.01	19.92	24.39	28.6	34.37	39.58	46.22	51.39	55.34	57.86

SD

Fig. 5. Best classification results obtained with FLBP and LBP features at various noise levels that correspond to different values of the standard deviation (SD) of the Gaussian additive noise.

and it was obtained with the FLBP features for *T*=75. On the other hand for the original LBP feature extraction method (*T*=0) the minimum mean classification error obtained was 9.1%.

For the comparison of original LBP and proposed FLBP method further classification experiments were conducted on the noise-degraded image datasets. The best results obtained for different noise levels for both approaches are illustrated in Fig.5. It can be noticed that the proposed FLBP approach outperforms the original LBP for every noise level tested. Evidently the advantage of the FLBP over the LBP approach gets greater as the noise level increases. For the higher noise level tested (*SD*=60), minimum mean classification error for the original LBP features was 57.8%, whereas for FLBP features was 25.7%.

4. CONCLUSIONS

In this study we proposed a noise-robust representation of texture by means of statistical distributions of fuzzy local binary patterns. The experimental results presented in the third section of this study demonstrate the superior performance of the FLBP features as compared with the performance obtained by using the original LBP features not only in noise free images but also in the presence of additive Gaussian noise.

Further experimental evaluation in larger datasets with different types and levels of noise will be included in future works. Also it would be interesting to investigate the performance of the proposed FLBP approach in various kinds of natural noise degraded images, and to compare the performance of the FLBP with other texture representation approaches.

ACKNOWLEDGMENTS

This work was supported by the Greek General Secretariat of Research and Technology (25%), the European Social Fund (75%), and private sector, under the framework of Measure 8.3 of E.P. Antagonistikotita – 3rd European Support Framework - PENED 2003 (grant no. 03-ED-662). This work is also co-funded by the European Social Fund and National Resources - (EPEAEK II)

REFERENCES

[1] T. Wagner, “Texture Analysis”, in B. Jahne, H. Haussecker, P. Geisser, (Eds.), Handbook of Computer Vision and Application, Academic Press, San Diego, pp. 275-308, 1999.
[2] S. Liu, and M. E. Jernigan, “Texture analysis and discrimination in additive noise”, Comput. Vision Graph. Image Process. Vol. 49, pp. 52-67, 1990.
[3] T.N. Tan, “Noise Robustness of Texture Features”, Im. & Vis. Comp., vol. 15, no. 11, pp. 815-817, 1997.
[4] K. B. Hilger, M. B. Stegmann, and R. Larsen, “A noise robust statistical model for image representation”, Medical Image Computing and Computer-Assisted Intervention, Tokyo, Japan, vol. 2488, pp. 444-451, 2002.
[5] T. Ojala, M. Pietikäinen, and D. Harwood, “A comparative study of texture measures with classification based on featured distribution”, Pattern Recognition, vol. 29, pp.51-59, 1996.
[6] P. Brodatz, "Texture: A Photographic Album for Artists and Designers", Dover Publications, New York, USA, 1996.
[7] LIBSVM: A Library for Support Vector Machines http://www.csie.ntu.edu.tw/~cjlin/libsvm
[8] N. Cristianini and J. Shawe-Taylor, "Support Vector Machines and other kernel-based learning methods", Cambridge University Press, 2000.