SOFT HISTOGRAMS FOR LOCAL BINARY PATTERNS

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ABSTRACT

This paper proposes using soft histograms for the Local Binary Pattern (LBP) operator that has been widely applied in different image analysis tasks. This makes the operator more robust to noise and make its output continuous with respect to input. The proposed extension is shown to significantly enhance the performance of the operator with degraded images.

1. INTRODUCTION

The Local Binary Pattern (LBP) [1] is an operator for image description that is based on the signs of differences of neighboring pixels. It is fast to compute and invariant to monotonic gray-scale changes of the image. Despite being simple, it is very descriptive, which is attested by the wide variety of different tasks it has been successfully applied to. The LBP histogram has proven to be a widely applicable image feature for, e.g. texture classification, face analysis, video background subtraction, etc. [2].

A possible drawback of the LBP operator is that the thresholding operation in comparing the neighboring pixels could make it sensitive to noise. Practical experiments with images of good quality have not supported this argument but under difficult conditions or with images taken with noisy special cameras, noise might present a problem to the traditional LBP operator. In this paper we introduce soft histograms for LBP which we show to make the operator more robust to noise.

2. METHODOLOGY

2.1. Local Binary Patterns

The local binary pattern operator [1] is a powerful means of texture description. The original version of the operator labels the pixels of an image by thresholding the 3x3-neighborhood of each pixel with the center value and summing the thresholded values weighted by powers of two. Then the histogram of the labels can be used as a texture descriptor. See Fig. 1 for an illustration of the basic LBP operator.

5	9	1
4	4	6
7	2	3

→ Threshold

1	1	0
1		1
1	0	0

Weights

1	2	4
128		8
64	32	16

LBP code: 1+2+8+64+128=203

Fig. 1. The basic LBP operator.

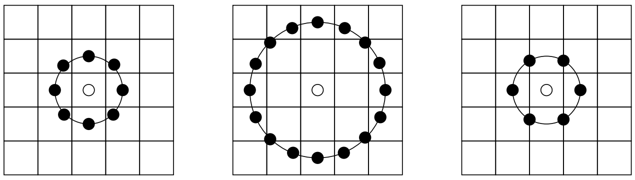

Fig. 2. Three circular neighborhoods: (8,1), (16,2), (6,1). The pixel values are bilinearly interpolated whenever the sampling point is not in the center of a pixel.

The operator can also be extended to use neighborhoods of different sizes [1]. Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood. For neighborhoods we will use the notation (P, R) which means P sampling points on a circle of radius of R. See Fig. 2 for an example of different circular neighborhoods.

Let us denote the gray value of the center pixel by g_c and the gray values of the pixels in the circular neighborhood by $g_0, \dots, g_{P-1}$. Now the LBP label for the center pixel (x, y) is obtained by

$$LBP_{P,R}(x,y) = \sum_{p=0}^{P-1} s(g_c - g_p)2^p, \tag{1}$$

where $s(z)$ is the thresholding function

$$s(z) = \begin{cases} 1, & z \geq 0 \\ 0, & z < 0 \end{cases} \tag{2}$$

The texture is represented by the histogram of the labels,

$$H_{LBP}(i) = \sum_{x,y} \delta\left\{i, LBP_{P,R}(x,y)\right\}, i = 0, \ldots, 2^P - 1 \tag{3}$$

in which δ is the Kronecker delta

$$\delta\left\{i,j\right\} = \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases} \tag{4}$$

2.2. Soft Histograms

A drawback of the local binary pattern method as well as all local descriptors that apply vector quantization is that they are not robust in the sense that a small change in the input image would always cause only a small change in the output. To increase the robustness of the operator, the thresholding function $s(z)$ is replaced by the following two fuzzy membership functions:

$$f_{1,d}(z) = \begin{cases} 0, & z < -d \\ 0.5 + 0.5\frac{z}{d}, & -d \leq z \leq d \\ 1, & z > d. \end{cases} \tag{5}$$

$$f_{0,d}(z) = 1 - f_{1,d}(z). \tag{6}$$

The parameter d controls the amount of fuzzification the function performs. These functions are plotted in Fig. 3.

When the local neighborhood consists of P sampling points, the resulting histogram has bins numbered $0 \cdots 2^P - 1$. Now the contribution of a single pixel (x,y) to bin i of the histogram is

$$\begin{aligned} SLBP(x,y,i) &= \prod_{p=0}^{P-1} [b_p(i) f_{1,d}(g_c - g_p) \\ &+ (1 - b_p(i)) f_{0,d}(g_c - g_p)], \end{aligned} \tag{7}$$

where $b_p(i) \in \{0,1\}$ denotes the numerical value of the p-th bit of binary representation of i. The complete soft histogram H_{SLBP} is computed by summing the contributions of all the pixels in the input image:

$$H_{SLBP}(i) = \sum_{x,y} SLBP(x,y,i), i = 0, \ldots, 2^P - 1. \tag{8}$$

When using the original LBP operator, one pixel always contributes to one bin of the histogram but in case of the soft histogram version, one pixel typically contributes to more than one bin. However, the sum of contributions of the pixel to all bins is always 1.

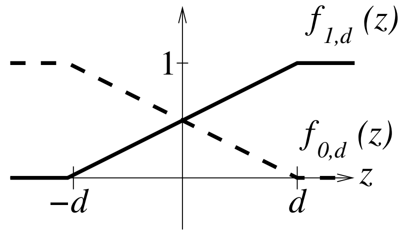

Fig. 3. The functions $f_{0,d}(z)$ and $f_{1,d}(z)$.

When d is set to 0, the resulting fuzzy membership functions $f_{0,0}(z)$ and $f_{1,0}(z)$ are almost equal to the thresholding function $s(z)$, the difference being that $f_{0,0}(0) = f_{1,0}(0) = 0.5$ whereas $s(0) = 1$. Because of this the soft histogram representation differs from that of original LBP even when $d = 0$.

A possible problem of the soft histogram extension is the loss of invariance to monotonic gray-scale changes. The original LBP operator is invariant to monotonic gray-scale changes of the images. This is due to the thresholding operation and as thresholding is replaced by a fuzzy membership function, the resulting histogram is no more completely invariant to such changes. However, as only differences of gray values are considered by the operator, adding a constant to the gray values does not change the soft histogram representation. Moreover, because of the robustness property induced by the fuzzy membership function, a small change of the gray scale causes only a small change in the operator output.

Another possible weakness of the soft histogram representation in comparison with original LBP is the increased computational complexity. When computing the original LBP histogram, only one bin needs to be updated at each pixel location. In the case of soft histogram, the contributions $SLBP(x,y,i)$ needs to be computed for each of the 2^P bins if no optimizations are utilized.

Using soft histograms for image description has been previously introduced by Siggelkov [3]. The soft histograms for local binary patterns outlined in this paper can be seen as a P-dimensional variant of Siggelkov's soft histograms where each dimension, corresponding to one sampling point in the neighborhood, contains two bins ("greater than center pixel" and "less than center pixel"). Also, independently of this work, a similar extension of the texture spectrum operator was recently proposed by Barcelo *et al.* in [4].

3. EXPERIMENTS

To test the performance of the proposed soft histograms, we used the supervised texture classification test images by Randen and Husøy [5]. This test set consists of 12 images

Table 1. List of test images and previously reported classification errors

Image	Image source	Num of textures	Best of [5]	Basic LBP [6]
11a	Brodatz	5	7.2	6.2
11b	MIT	5	18.9	18.1
11c	MIT	5	20.6	12.1
11d	MIT	5	16.8	10.0
11e	Meastex	5	17.2	10.9
11f	Brodatz	16	34.7	16.8
11g	MIT	16	41.7	20.8
11h	Brodatz	10	32.3	22.8
11i	MIT	10	27.8	19.2
12a	Brodatz	2	0.7	0.3
12b	Brodatz	2	0.2	1.0
12c	Brodatz	2	2.5	9.9
Mean			18.4	12.3

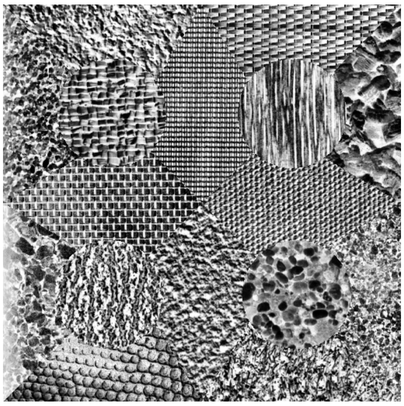

Fig. 4. Test image 11f consisting of 16 Brodatz textures

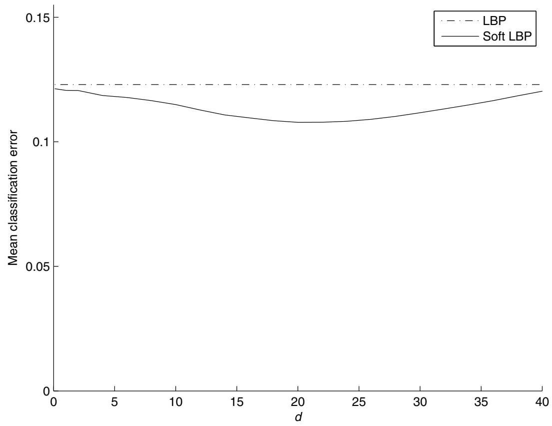

Fig. 5. Mean classification error over all test images.

Table 2. Classification errors for individual test images

Image	LBP(8,1) [6]	Soft LBP(8,1)
11a	6.2	5.8
11b	18.1	9.3
11c	12.1	11.9
11d	10.0	10.9
11e	10.9	8.8
11f	16.8	16.4
11g	20.8	19.2
11h	22.8	19.9
11i	19.2	22.1
12a	0.3	0.3
12b	1.0	1.8
12c	9.9	3.0
Mean	12.3	10.8

containing 2–16 different textures. The performance of the local binary pattern operator on the test images has been reported previously by Mäenpää *et al.* [6]. The test images and the results from [5] and [6] are listed in Table 1. An example of the test images (16-texture test image 11f) is printed in Fig. 4. See [5] for a complete description of the test images.

For every test image in the test set, one training image per texture class present in the test image is provided. The training and testing images are distinct. Following the test setup of [6], we computed a single histogram using (8,1) neighborhood from each training image and used nearest neighbor classifier with Chi square distance. In the testing images we computed the histogram within a disc of radius of 20 pixels and classified the center pixel using this histogram.

In the first experiment we tested the effect of soft histograms in texture segmentation. The 12 testing images were segmented using $LBP_{8,1}$ with thresholding and with soft histograms. The mean classification error over all test images as a function of the fuzzification parameter d is plotted in Fig. 5. The classification errors for individual test images can be found in Table 2. The results in Table 2 were obtained using $d = 20$.

As could be expected, applying soft histograms enhances the performance of the LBP operator especially when images are noisy. The original test images are of rather high quality so we added artificial noise to them in order to test the performance of the method under degraded conditions. Additive white Gaussian noise ($\mu = 0$, $\sigma = 25.5$) was added to the test images and the classification was performed again using the same operator as in the first experiment. The

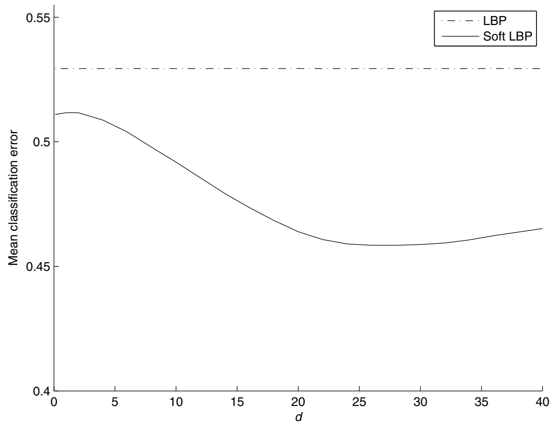

Fig. 6. Mean classification error over test images with additive noise.

Table 3. Classification errors for individual test images with additive noise

Image	**LBP(8,1)**	**Soft LBP(8,1)**
11a	37.5	23.5
11b	52.9	44.6
11c	67.8	51.8
11d	56.9	46.4
11e	60.3	64.2
11f	50.2	46.8
11g	77.8	72.0
11h	59.0	55.9
11i	77.6	74.5
12a	42.3	17.0
12b	3.1	3.3
12c	50.0	50.0
Mean	52.9	45.8

mean classification error over the noisy test images is plotted in Fig. 6 and the results for individual images are in Table 3. Here the optimal results were obtained using $d = 26$ which shows that the optimal value of the fuzzification parameter depends on the amount of noise present in the images.

Examining the effect of fuzzification to the classification error, it can be noted that in both the cases, using fuzzy histograms yields better performance than traditional hard histograms. The actual amount of decrease in the error rate depends on the test images. For the noisy images, the mean error rate dropped by 5.3 percentage units when the fuzzification parameter d was increased from 0.1 to 26.

4. DISCUSSION AND CONCLUSION

In this paper, we introduced soft histograms for the LBP texture operator. Using soft histograms makes the output of the operator continuous and robust, i.e. a small change in the input image only causes a small change in the output of the operator.

The proposed extension was tested using the images by Randen and Husøy which were degraded by additive noise. The main finding of the experiments is that when the images have a high amount of noise, a significant drop in the error rate can be obtained by utilising the soft histograms. Even though the original test images do not contain much noise, applying soft histograms resulted in slightly increased performance for those images as well.

Possible drawbacks of the proposed operator in comparison to original LBP are increased sensitivity to gray-scale changes and computational complexity. Future work includes the study of effect of lighting changes to the performance of the operator and study of faster algorithms for computing the soft histogram.

5. REFERENCES

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