Image micro-pattern analysis using Fuzzy Numbers

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***Abstract*—This paper proposes a new methodology for micro-pattern analysis in digital images based on fuzzy numbers. A micro-pattern is the structure of the gray-level pixels within a neighborhood and can describe the spatial context of the image, such as edge, line, spot, blob, corner, texture, and more complex patterns. By treating a pixel neighborhood as a fuzzy set and each pixel gray-level as a fuzzy number, we can evaluate the membership degree of the central pixel to the others. We have called this method the Local Fuzzy Pattern (LFP). Using a sigmoid membership function, we proved that the proposed methodology surpasses the Hit-rate of the Local Binary Pattern (LBP), for texture classification. The LFP proved to be robust to image rotation. Moreover, our proposed formulation for the LFP is a generalization of previously published techniques, such as Texture Unit, LBP, FUNED, and Census Transform.**

***Keywords*-micro-pattern analysis; fuzzy numbers; texture analysis;**

I. Introduction

An image's spatial distribution plays an important role in many computer vision tasks. Visual patterns, however, are ambiguous by nature. Image characteristics are often corrupted and distorted by the acquisition process. Descriptions of objects in scenes are not always well-defined, and the knowledge about the objects in the scene is described in vague terms. The gray-level distribution in an image neighborhood $(3\times3, 5\times5, ...)$ can be defined as an image micro-pattern. This structure can describe the spatial context of the image, such as edge, line, spot, blob, corner, texture, and more complex patterns. The topographical characteristics of micro-patterns are more robust to shift, scale, and changes in illumination. In the computer vision literature, some approaches were developed to extract these characteristics. The Orientation Histogram designs the micro-pattern as a directional line or edge and calculates the histogram of each direction in the region [1] [2] [3] [4]. The Scale Invariant Feature Transform (SIFT) [5] is a method for micro-pattern analysis that extracts some points called key features.

Another method is the design of a bank of filters to extract the micro-structural features, and the regional characteristics are computed from the filter response [6] [7]. The Local Binary Pattern (LBP) [8] was first applied for texture analysis [9] but was later extended to background modeling [10], face detection [11], facial expression analysis [12] and face recognition [13]. The image is first divided into small regions, from which LBP histograms are extracted and concatenated into a single feature histogram to represent the image.

Yang, Gong and Tang [14] have proposed a model-based feature extraction approach, which uses a Markov Random Field to model the micro-structure of the image and design adaptive micro-patterns for feature extraction. The micro-pattern representation was also extended to Gabor magnitude features [15] and Gabor phase features [16] to increase the discrimination capacity. Zhao, Gao and Zhang [17] have conducted a comparative performance evaluation of micro-pattern representations on four Gabor features (real part, imaginary part, magnitude and phase) for face recognition.

However, in all these methods, the micro-patterns are designed by user on the basis of experience, and they are application oriented. Another problem is that in some cases, it is difficult for the user to determine whether the micro-pattern is appropriate, unless he refers to the experimental result.

Zhao, Wu, Liu and Chen [18] extend the LBP to the Completed modeling of Local Binary Pattern (CLBP), which is composed by the center gray level, sign components and magnitude components. The authors concluded that the CLBP has better texture feature extraction capabilities than standard LBP.

The Fuzzy Local Binary Pattern (FLBP) extends the LBP approach by incorporating fuzzy logic in the representation of local patterns of texture [19] [20]. The fuzzification allows the FLBP to contribute to more than a single bin in the distribution of the LBP values used as a feature vector. This methodology assumes that a local neighborhood can be partially characterized by more than one binary pattern as a result of noise-originated uncertainty in the pixel values. The results show that the FLBP leads to improvement in texture classification compared with the original LBP [21]. The Fuzzy Local Texture Pattern - FLTP also incorporates fuzzy logic in the local texture patterns' representations by using fuzzy rules in 3x3 neighborhoods to find a local texture descriptor [22]. The problem with using fuzzy logic is the computational cost.

In contrast with the FLBP and FLTP that use fuzzy logic for the Binary Pattern fuzzification, the objective of this paper is to model the gray-level distribution of an image micro-pattern as a fuzzy set, and based on membership function, generate fuzzy-codes that represent the membership degree of each neighborhood pixel to the central one. We call the proposed methodology the Local Fuzzy Pattern (LFP).

The rest of this paper comprises four sections. Section II presents the proposed LFP methodology. Section III describes the application to texture analysis. Section IV refers to the experimental evaluation and the classification results obtained. The conclusions are provided in the last section.

II. Methodology

When considering gray-levels as fuzzy numbers, the inherent variability of image gray values are incorporated, thus providing a more powerful approach for the treatment of digital images compared with the classic treatment that is based on an analytic formulation.

A. Fuzzy Set and Fuzzy Numbers

A fuzzy set is a pair (U, μ) where U is a set and $\mu : U \rightarrow [0, 1]$. For each $x \in U$, the value $\mu(x)$ is called the membership degree of x in (U, μ). For a finite set $U = \{x_1, x_2, ..., x_n\}$, the fuzzy set (U, μ) is denoted by $\{\mu(x_1)|x_1, ..., \mu(x_n)|x_n\}$. x is called a fuzzy member if $0 < \mu(x) < 1$. The function $\mu(x)$ is called the membership function of the fuzzy set (U, μ).

A fuzzy number is a convex, normalized fuzzy set $B \subseteq \mathbb{R}$ represented by a membership function, whose discourse universe is the real straight line. The concept of fuzzy numbers, as fuzzy subsets of real numbers, is a powerful paradigm for representing imprecision in numerical information. In many aspects, fuzzy numbers depict the physical world more realistically than single-valued numbers. The concept takes into account the fact that all phenomena in the physical universe have a degree of inherent uncertainty.

B. Local Fuzzy Pattern

It is important to note that this fuzzy number representation is quite compact. In addition, the definition of an appropriate membership function is heuristic and, therefore, not unique. Thus, the definitions of different membership functions may be based on the properties of the micro-pattern neighborhood $W \times W$ of a central pixel (i, j) in a digital image. The proposed methodology assumes that each gray-level distribution within this neighborhood is a Fuzzy Set composed of Fuzzy Numbers, that is, because of image generation and preprocessing, there is a degree of uncertainty in the pixel values. We propose that the membership degree of the central pixel $g(i, j)$ to the micro-pattern defined by the neighborhood $W \times W$ should be determined by (1).

$$\hat{\mu}_{g(i,j)} = \frac{\sum_{k=1}^{W} \sum_{l=1}^{W} (f_{g(i,j)} P(k, l))}{\sum_{k=1}^{W} \sum_{l=1}^{W} P(k, l)}, \tag{1}$$

where, $f_{g(i,j)}$ is the membership function and $P(k, l)$ is a weighting matrix for the neighborhood $W \times W$ with the same dimension.

Through (1), it is possible to derive some previously published approaches for micro-pattern analysis. The Fuzzy Number Edge Detector (FUNED) [23] [24] can be obtained using the triangular symmetric membership function shown in (2).

$$f_{g(i,j)} = max(0, 1 - \frac{|g(i, j) - A(k, l)|}{\delta}), \tag{2}$$

where, $A(k, l)$ are the pixels in the $W \times W$ neighborhood, δ is the fuzzy number span, and the weighting matrix has the central value equal to 0 and the other elements equal to 1.

The Local Binary Pattern can be derived from (1) using a crisp function as the Heaviside Step Function shown in (3).

$$f_{g(i,j)} = H[A(k, l) - g(i, j)], \tag{3}$$

where,

$$H[A(k, l) - g(i, j)] = \begin{cases} 0, & \text{if} \quad [A(k, l) - g(i, j)] < 0, \\ 1, & \text{if} \quad [A(k, l) - g(i, j)] \geq 0. \end{cases}$$

Taking into account the basic LBP with a neighborhood of pixels, the weighting matrix will be:

$$P(k, l) = \begin{matrix} 1 & 2 & 4 \\ 128 & 0 & 8 \\ 64 & 32 & 16 \end{matrix}$$

The LBP_{code} (values between 0 and 255) will be obtained by (4):

$$LBP_{code} = \hat{\mu}_{g(i,j)} \sum_{k=1}^{W} \sum_{l=1}^{W} P(k, l). \tag{4}$$

The LBP_{code}, thus, is a particular case of the LFP approach.

The Census Transform (CT) proposed by Zabih and Woodfill [25] differs from the LBP by the order of the bit string. Similarly, the CT [26] can be inferred from the LFP using the appropriate weighting matrix:

$$P(k, l) = \begin{matrix} 1 & 2 & 4 \\ 8 & 0 & 16 \\ 32 & 64 & 128 \end{matrix}$$

The Texture Unit proposed by He and Wang [27] can also be derived from the LFP. The membership function must be as in (5).

$$f_{g(i,j)} = 1 + sgn[A(i, k) - g(i, j)], \tag{5}$$

where,

$$sgn(x) = \begin{cases} -1, & \text{if} \quad x < 0, \\ 0, & \text{if} \quad x = 0, \\ 1, & \text{if} \quad x > 0. \end{cases}$$

and

$$P(k, l) = \begin{matrix} 1 & 3 & 9 \\ 2187 & 0 & 27 \\ 729 & 243 & 81 \end{matrix}$$

Using the right membership function, our proposed methodology could extract specific features from the image, based on the micro-pattern processing.

For texture analysis in this work, we propose a smooth approximation to the step function by a logistic function or a logistic curve, a common sigmoid curve membership function, as in (6).

$$f_{g(i,j)} = \frac{1}{1 + e^{\frac{-[A(k,l) - g(i,j)]}{\beta}}}, \tag{6}$$

where β is the curve slope.

Sigmoid functions, whose graphs are "S-shaped" curves, appear in a great variety of contexts, such as the transfer functions in many neural networks. Their ubiquity is no accident: these curves are among the simplest non-linear curves, striking a graceful balance between linear and non-linear behavior.

Because the LBP method uses the "crisp version of the sigmoid curve" for texture analysis, we have performed a comparative performance evaluation of our approach.

III. TEXTURE ANALYSIS USING THE LFP

For the performance evaluation of our method, we used two texture databases fully employed by computer vision researchers: Brodatz's album and the Outex texture database.

Among several classifiers used to compute goodness of fit between two histograms, such as log-likelihood ratio and histogram intersection, we choose the Chi-square distance [28], the same metric used by [29], as the classifier (Equation 7).

$$\chi^2(P_i, Q_i) = \frac{1}{2} \sum_{i=0}^{255} \frac{(P_i - Q_i)^2}{(P_i + Q_i)}, \tag{7}$$

where, Q_i are the gray-level frequencies of the query sample and P_i are the gray-level's frequencies of the compared sample from the set.

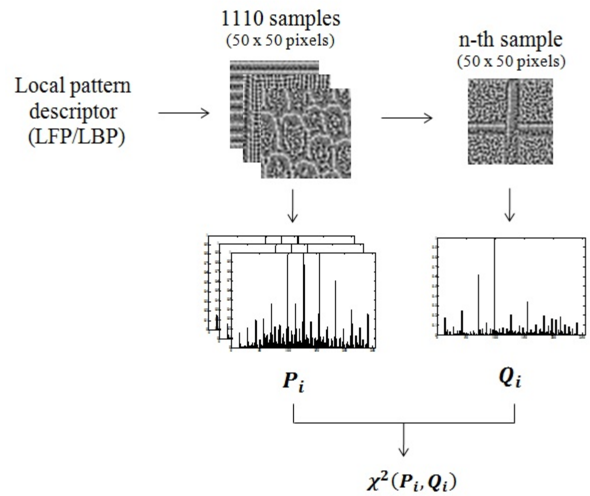


Fig. 1. Discrimination method

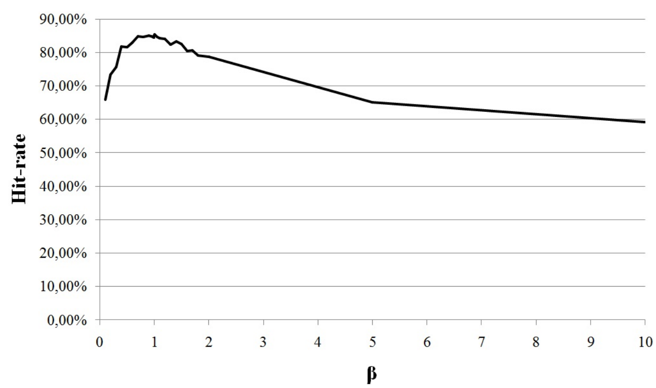


Fig. 2. Slope of sigmoid curve

A. Brodatz's album

For the performance assessment, the proposed approach was tested using 111 images of synthetic and natural textures from Brodatz's album [30]. Brodatz's photo album is a well-known benchmark database for evaluating texture recognition algorithms. Each texture image is considered to be a class, with a dimension of 640×640 pixels. We randomly extracted ten samples with a size of 50×50 pixels from each class, totalizing 1110 samples.

To analyze the LFP approach performance, the 1110 random samples were compared with the LBP descriptor. We generated the histogram (with the LFP codes) from each sample and used the Chi-square distance for histogram comparison, as illustrated in Fig. 1.

We applied the LFP approach proposed in (1), considering the sigmoid function of (6). Fig. 2 shows the sigmoid's curve slope (β) performance for Brodatz's album.

We choose $\beta = 1.005$ as the best-trained value, and the weighting matrix as:

$$P(k,l) = \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$$

This weighting matrix represents the non prevalence position for any pixel. The intention is to become the LFP, which is rotation invariant.

For each sample, we generated its LFP histogram with the membership degree ranging in the 0-1 interval. Aiming to generate gray level images and histograms from each sample processed by the LFP descriptor, we have performed a conversion to an 8-bit gray level scheme by multiplying each membership degree value by 255 and rounding the result. Fig. 3 shows the LFP code generation. Therefore, each image sample histogram has 256 bins (integer values from 0 to 255), the same as the original LBP approach.

By leave-one-out cross-validation, we compared the histograms from each sample with the rest of those from the sample set (1109 samples) using the Chi-square distance.

One query sample is correctly classified if it has the lowest distance value to one of the 9 samples of the same class.

B. Outex database

The $Outex\_TC\_00010$ (TC10) test case [31] has 24 classes of textures digitized under incandescent illumination in nine rotation angles $(0^o, 5^o, 10^o, 15^o, 30^o, 45^o, 60^o, 75^o, 90^o)$. For

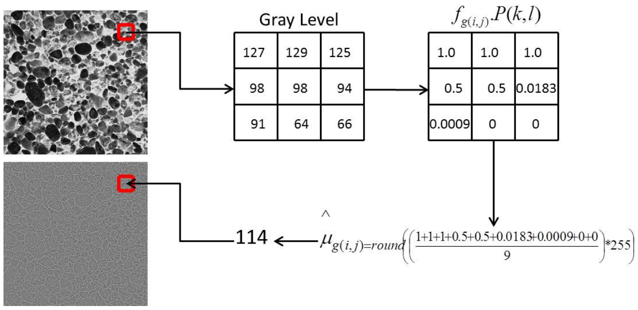


Fig. 3. The LFP code

each angle, there are 20 non-overlapping samples with 128×128 pixels, in a total of 4320 samples. Fig. 4 shows some of these texture samples.

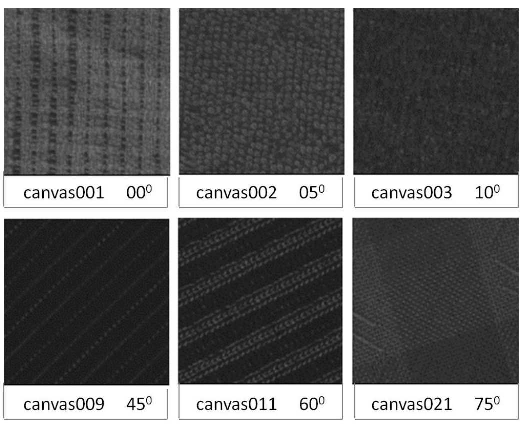


Fig. 4. Texture samples from the Outex database

We built the training set with 480 samples from the 20 non-overlapping images at 0^o of the 24 classes, and we built the test set with the remaining 3.840 samples from the other eight rotation angles. To remove the effect of global first-and-second order grayscale properties in intensity images, each intensity image was individually normalized to have an average intensity of 128 and a standard deviation of 20.

We applied the LFP methodology considering the sigmoid function of (6) and the same curve slope trained for Brodatz's album ($\beta = 1.005$). The histogram dissimilarity was compared using the Chi-square distance.

We compared the LFP with the original LBP which is not rotation invariant due to the weighting matrix having different values for each pixel position, and the two rotation invariant derived methods [29], the $LBP_{8,1}^{ri}$ which rotates the pixel neighborhood aiming the lowest LBP_{code} value, and the $LBP_{8,1}^{riu2}$ where a uniformity measure was introduced [32] in order to reduce the number of LBP codes.

We have published two works about using fuzzy sets for texture analysis. In the first one [33] we have used a triangular membership function and we have tested in forty texture images. In the second one [34], we have compared the performance of two membership functions, triangular and sigmoid. Both have been tested only over the Brodatz's album.

IV. Results

For the two set of images (Brodatz and Outex), we generated confusion matrices with True Positives (TP), or the number of correctly classified samples, and False Negatives (FN), or the wrongly classified samples, for all of the query samples. The Hit-rate or Sensitivity was calculated as (8).

$$S = \frac{TP}{TP + FN}. \tag{8}$$

We also performed an analysis of the computational effort, comparing our approach with the LBP method.

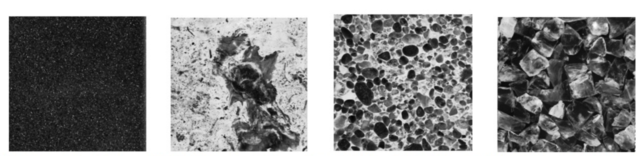
A. *Brodatz's album*

The LFP performance was first evaluated for texture analysis using the 1110 samples from Brodatz's images. The Hit-rate is shown in Table I, considering the two compared methodologies. The LFP surpassed the original LBP by nearly 5%. Most likely, this occurs because the LBP is a crisp version of the LFP, and thus, some texture was better represented as a micro-pattern by our methodology.

TABLE I
Result comparison for Brodatz's album

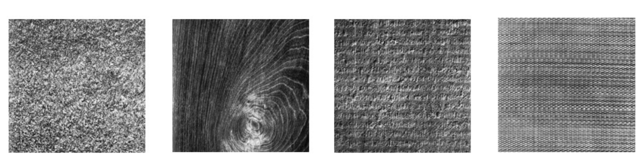
Method	Hit-rate
LFP	85.05%
LBP	80.18%

By analyzing the confusion matrix, we verified that some samples were much better classified by the LFP than by the LBP. The number of True Positives for some of those images showed a superior performance for our approach, as observed in Fig. 5. For these samples, the LFP surpassed the LBP by 6 correct classifications. Otherwise, when the LBP has a better performance than the LFP, as shown in Fig. 6, the number of correct classifications is not higher than 2. That is, the performance comparison showed that some types of texture were very well evaluated with the LFP approach, and some others can be analyzed either by the LBP or LFP.



(a) LFP = 10, LBP = 4 (b) LFP = 9, LBP = 3 (c) LFP = 8, LBP = 2 (d) LFP = 7, LBP = 1

Fig. 5. Better performance for the LFP



(a) LFP = 8, LBP = 10 (b) LFP =7, LBP =8 (c) LFP = 8, LBP = 9 (d) LFP = 9, LBP = 10

Fig. 6. Better performance for the LBP

Table II and the graph in Fig. 7 show the amount of success considering the 10 samples classified by the two compared methodologies. Of all the 111 classes, 48 of them are from the LFP, and 49 are from the LBP with the 10 samples correctly classified. However, the LFP methodology surpasses the LBP approach in classifying 8 correct samples for 17 classes, while the LBP approach only achieves 8 hits in 7 classes. Another result is that the LFP do not have less than 3 hits for a class. For some classes, the LBP performs poorly. It classifies no samples for one class, one sample for two classes and two samples for one class (the last three lines of the Table II). Our recent investigations have shown that if a texture has high frequencies, the best membership function could be the triangular shape [34].

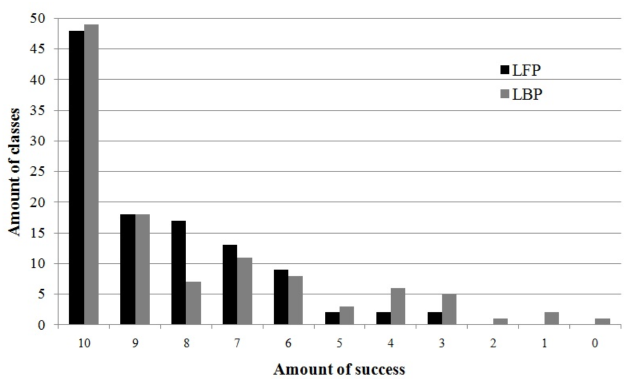


Fig. 7. General comparison of LFP x LBP

TABLE II
GENERAL COMPARISON OF LFP X LBP

Number of correctly classified samples	Number of classes	
	LFP	LBP
10	48	49
9	18	18
8	17	7
7	13	11
6	9	8
5	2	3
4	2	6
3	2	5
2	0	1
1	0	2
0	0	1
Total of classes	111	111

B. Outex database

This collection of image textures was used to measure the robustness of the LFP considering rotation. For the LFP versus LBP comparison using the Outex database, we also measured the sensitivity or Hit-rate, that is, the proportion of True Positives. The results obtained for each method are shown in Table III.

The original LBP is not rotation invariant because the weighting matrix has different values for each pixel position. This limitation was surpassed by the $LBP_{8,1}^{ri}$ that rotates the pixel neighborhood while aiming at the lowest value. The $LBP_{8,1}^{riu2}$, where a uniformity measure was introduced in order to reduce the number of LBP codes, performs better, with 84.82% sensitivity.

TABLE III
RESULT COMPARISON FOR THE OUTEX DATABESE

Method	Hit-rate
Basic LBP	50.21%
$LBP_{8,1}^{ri}$	78.80%
$LBP_{8,1}^{riu2}$	84.82%
LFP	92.94%

The LFP results show that our approach is rotation invariant and that the Hit-rate has been raised to 92.94%, surpassing all other methodologies.

C. Computational effort analysis

In order to verify the computational effort required by our approach, we measured the execution time for the LFP and LBP code generation.

We choose the Outex_TC_00010 due to it is a more comprehensive image test suite than the Brodat'z album; it has more image samples and enables the use of rotation invariant versions. The tests were performed on a 2.00 GHz Intel Core2 Duo P7350 computer with 4.00 GB of RAM.

Both LBP and LFP operators were implemented in Matlab_R11, and the LBP reference code was downloaded from Outex site (http://www.outex.oulu.fi). The test ran 10 times, and the average times are presented in Table IV.

TABLE IV
AVERAGE TIMES FOR OUTEX_TC_00010

Method	Average time (code generation)
Basic LBP	8.99s
$LBP_{8,1}^{ri}$	21.33s
$LBP_{8,1}^{ri2}$	20.90s
LFP	27.56s

The basic LBP uses a simple crisp function, and it performs faster than LFP, that uses a sigmoid function. However, the rotation invariant derivatives for the LBP code, show execution times similar to the LFP approach.

We believe that by optimizing the LFP algorithm and by reducing the number of histogram bins (less than 256), we could increase the time performance of our method.

V. CONCLUSIONS

In this paper, we have shown a new methodology for micro-pattern analysis. We have formulated a new equation based on membership functions of fuzzy numbers. We have assumed that the neighborhood of a pixel in digital images should be modeled as a fuzzy set, taking in account the pixel's gray levels. The Local Fuzzy Pattern (LFP) has been defined, and it has been proven that it is a generalization of some previously published methods. Using a sigmoid function for calculating the membership degree of a central pixel of a neighborhood, we have applied our approach for texture analysis. Brodatz's album with 111 classes was randomly sampled, generating 10 samples of each class. After processing these images by the LFP and LBP approaches, we have compared the Hit-rate reached using the Chi-square distance. Our results showed that the LFP surpasses the LBP by 5% in terms of correct classifications. This result is justified because the LBP is a particular case the LFP; that is, if we adopt a crisp membership function for the LFP formulation, we obtain the LBP approach.

To test the LFP robustness for textures rotated at different angles, we have taken the Outex database and have applied the same methodology to Brodatz's album. The Hit-rate for the LFP has reached 92.94% correct classifications when using the images without rotation (0^o) as the query images, searching for similarity within the rest of the 3.840 image samples for 8 different angles.

The proposed methodology is a robust method for micro-pattern analysis. Using the correct membership function, it is possible to codify and to note the representative feature of the analyzed pixel neighborhood. Therefore, micro-patterns, such as texture, edges, and corners, should be better extracted by the LFP.

However, as concluded by [35], to achieve the best performance in image pattern classification, it is necessary to use a combination of several descriptors together with a classifier that can make effective use of diverse types of information contained in them.

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