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Local Binary Pattern Regrouping for Rotation Invariant Texture Classification

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ABSTRACT

This paper represents a deep study of the local binary pattern (LBP) method and its variants of patterns regrouping, which is largely used in texture classification as well in other domains. The analysis of LBP's 256 patterns has led the authors to propose a new organization of uniform and no uniform patterns into 28 groups; each group assembled a number of patterns that varied according to specific terms. The principal idea is to preserve the low complexity of LBP and simultaneously increase the method robustness against quality degradation caused by image operations like rotation, grey level changes, illumination, and mirror effects. The experiments are done with the two texture databases Outex and Brodatz; the tests are proving the robustness of Local Binary Pattern Regrouping (LBPG) under circumstances.

KEYWORDS

Heuristic Groupings, Histogram Building, Matching, Non-Uniform Pattern, Rotation Invariant, Uniform Pattern

1. INTRODUCTION

In computer vision or pattern recognition, texture classification is one of the keys of successful systems due to the role that plays in different fields including document image analysis, biomedical image analysis, content-based image retrieval, face analysis and object recognition.

A good texture descriptor gives an efficient texture classification. This efficiency is measured by achieving two goals; the first one is the low computational complexity, the other one is keeping the most rigid texture that can be distinguished with the various image distortions like illumination, rotation, noise, scaling and occlusion (Liu et al, 2017). Until now, most proposed texture descriptor methods have not achieved the needed level for real world textures classification.

There are many methods of texture extraction we can mentioned co-occurrence matrix (Pianpian et al, 2008), wavelet-based (Xavierm et al, 2011), Gabor Features (Kim & JooSo, 2018) and Local Binary Pattern (LBP) and its variants. From the time when Ojala presents the method to these days, many studies prove that it is considered among the most valuable method. It had been used in different fields including; texture classification (Liao et al, 2010), image matching (Heikkilä et al, 2009), image retrieval (Doshi, 2012), biomedical image analysis (Nanni et al, 2010), face image analysis (Ahonen

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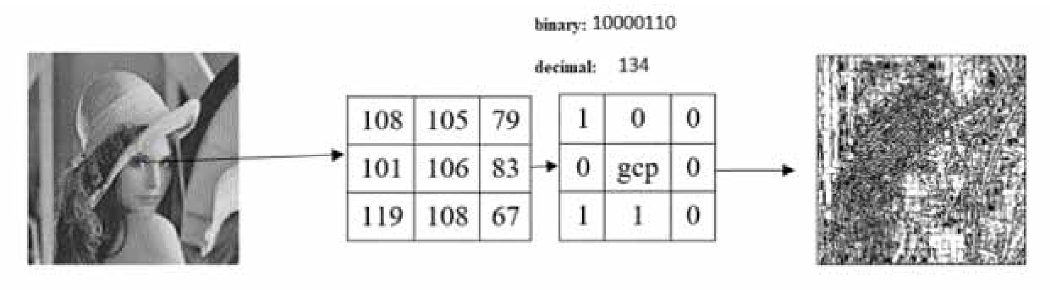
Figure 1. Lena picture under LBP operator



et al, 2006), motion and activity analysis (Kellokumpu et al, 2008), object detection (Satpathy et al, 2014) and back ground subtraction (Heikkilä & Pietikäinen, 2006).

The disadvantages of LBP as enumerated in (Fu & Wei, 2008), is that it produces rather long histograms, which slow down the recognition speed especially on large-scale database. Moreover, Fu & Wei add that under some certain circumstances, the patterns miss the local structure, as they do not consider the effect of the centre pixel, and the binary data produced by them are sensitive to noise.

This work focuses on holding the low computational complexity of LBP, where the majority of its variants increase it. We do decrease the size of histogram from 256 patterns by regrouping them into 28 groups; each one in the proposed group gathered the patterns that represent the same shape in different positions. This regrouping creates a new perspective, which preserves the low complexity of traditional LBP and increases the robustness of the descriptor under changes such as rotation, grey scale level, and mirror effects.

The remainder of this paper is organized as follows.

Section 2 discusses the original LBP method and its variants; Section 3 presents an overview of our pipeline; Section 4 defines our images Dataset; Section 5 discuss the obtained results with comparison to other works; Section 6 provides the conclusion and future work.

2. RELATED WORK

The traditional LBP operator appeared in 1994, introduced by Ojala et al. as a local texture descriptor that works on the neighbourhood structure of pixels. It turns each pixel value of the image into a new one, which is the result of the comparison between the centre pixel and its 3*3 neighbours. This comparison is simple; each neighbour gets the value zero or one depending on its grey scale value compared to the one of the central. This is done according to the described thresholding function (**S**) in expression (1), where the p_c is the central pixel's grey value and p_{ni} is one of the ith neighbour's grey value, that applies a subtraction between the two values. The eight obtained binary values are then concatenated in a clockwise order starting from the top-left neighbour to produce the new decimal value of the central pixel. When all pixels' values of the image are transformed by the same way, the next step is to generate the histogram that describes the image and gives the possibility to analyse it:

$$S\left(p_c, p_{ni}\right) = \begin{matrix} 1 \ if \ p_c - p_{ni} > 0 \\ 0 \ if \ p_c - p_{ni} \leq 0 \end{matrix} \quad (1)$$

Despite the low complexity of the method, the basic LBP is sensitive to noise and not invariant to rotation, in addition to other limitations. However, several papers work on improving it, each one focuses on one side or combines a bunch of them. One of the improvements was to extend the range of neighbours (Ojala et al 2002). There are many works that fit these improvements, for more details, we do propose the survey of Li Liu et al (2017), which represents taxonomy of existing works. There classification of the LBP variants is done in the following six classes:

1. **Traditional LBP:** The classic, original method LBP proposed by Ojala et al (1994).
2. **Neighbourhood topology and sampling:** Working on pixel patterns in a certain neighbourhood topology in order to form local feature vectors.
3. **Thresholding and quantization:** Where a threshold is the basic of the quantization operation.
4. **Encoding and regrouping:** Reorganize the patterns into groups, basing of a specific criteria to improve distinctiveness.
5. **Combining complementary features:** It is a current trend in both local image and video descriptors, to associate multiple complementary LBP-like descriptors, or to combine LBP-like with non-LBP.
6. **Methods inspired by LBP:** Supplementary LBP-related approaches.

This work falls within the fourth class. It aims at regrouping the patterns of the original LBP, which are originally two hundred fifty-six. We eliminate the zero pattern to get two hundred fifty-five dividing them into twenty-eight groups, with respect to the rotation and flip effects. However, according to Li Liu et al (2017) study, there are more than one category of encoding and regrouping, and they are based on three criteria:

1. Heuristic groupings
2. Co-occurrence groupings
3. Learning strategies

We are focusing on heuristic grouping, where the changes concern the patterns and the way they get more effective, keeping it all or some that's depending on the point of view weather it is a uniform or not. Ojala et al (2002) defend uniformity:

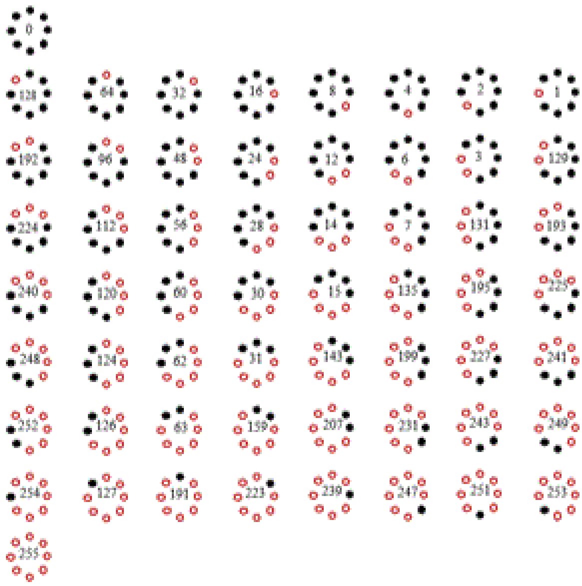
Refers to the uniform appearance of the local binary pattern, i.e. there is a limited number of transitions or discontinuities in the circular presentation of the pattern. These 'uniform' patterns provide a vast majority, sometimes over 90%.

Figure 2 is a visual representation of the 58 uniform LBP patterns, we should mention that not all the uniform patterns are equal in density, it depends on the image type but the most famous uniform pattern is the zero pattern, where the flat areas.

Empty circles correspond to bit values of one and filled circles are zero, the number inside it is the decimal representation.

It is a fact, that uniform patterns are majorities and they are invariant for rotation, this is why several works are using them in different grouping to have a lower feature dimensionality and a higher discriminative ability than LBP, plus to another powerful point of these patterns, which is their ability to catch the edges, the corners and the lings. In some domain, they are exactly the purposes but not in texture classification, where all the patterns are equally important, the more the vector descriptor is rich with information the more effectiveness it well gets. We mention some uniform grouping methods used out of texture domain. There are Symmetric Uniform Local Binary Pattern SULBP (Lahdenoja et al, 2005), for real-time face recognition and detection systems. It does grouping the uniform patterns to 30 groups, same as semantic Local Binary Pattern sLBP (Mu et al, 2008), specialize in human detection and the Complementary Uniform Local Binary Pattern CULBP (Nguyen et al, 2013), for object detection, It divide the 58 uniform patterns to the half as a result 29 groups are used to provide

Figure 2. The Uniform Patterns



the vector descriptor. In figure 3 the illustration of this three uniform grouping pattern behaviour, with the number of group inside the circle.

However, it does not mean that the non-uniform are not effective or non-useful, they have been used in texture classification, we mentioned NTLBP (Fathi & Nilchi, 2012), CLBC (Zhao et al, 2012) and NLBP (Ma, 2011), where they had decide to make better use of the non-uniform patterns instead of discarding them.

- **NLBP:** Number Local Binary Pattern for texture analysis, they divide the patterns according to the uniformity standard after that the non-uniform patterns are grouped according to the number of "0" bits and "1" bits, in figure 4, the visual demonstration.

Figure 3. Uniform LBP Patterns Regrouping Methods (Empty circles correspond to bit values of one and filled circles are zero, the number inside the circles is the number of the group)

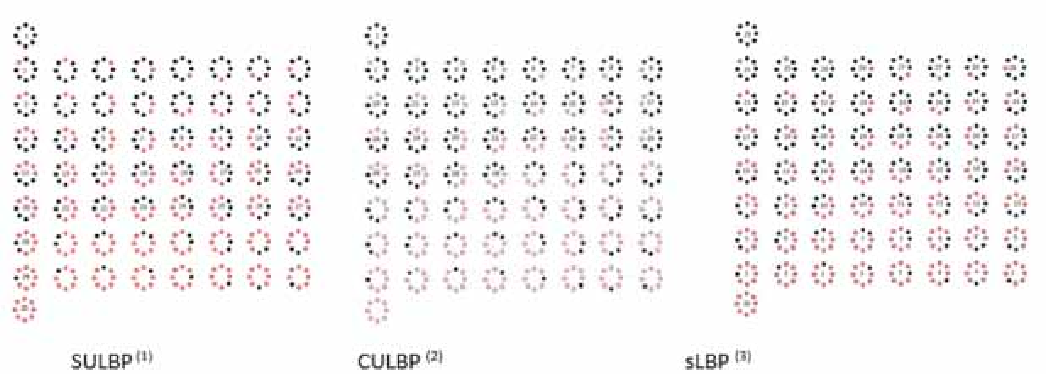
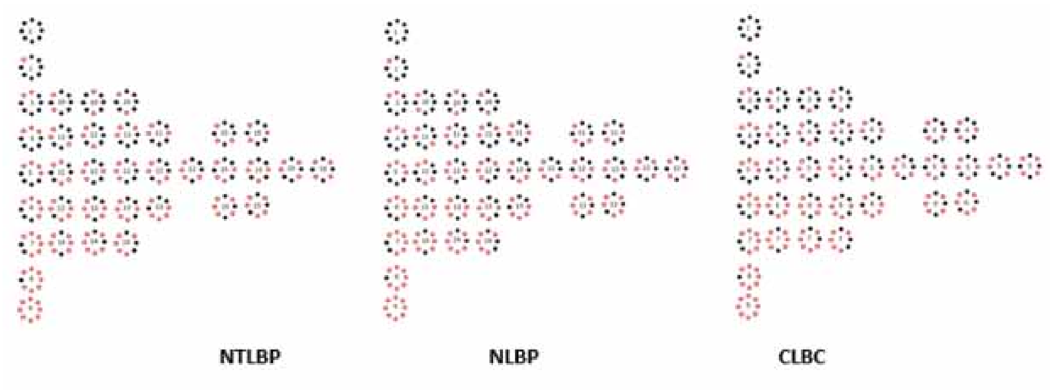


Figure 4. Other methods regrouping use both Uniform and Non-Uniform LBP patterns



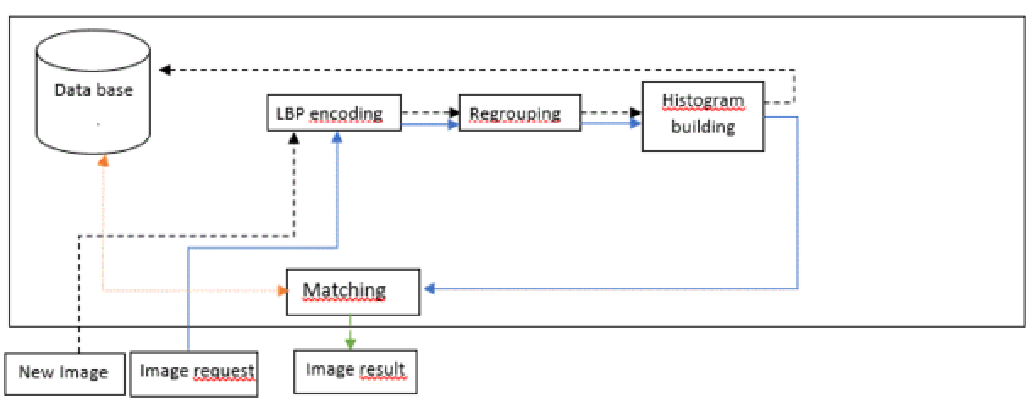
- **CLBC:** Completed Local Binary Count for texture classification, no difference between the uniform patterns and the non-ones, where all the patterns are grouped based on the number of the '1' bits.
- **NTLBP:** Noise Tolerant Local Binary Pattern for texture analysis, the regrouping is done in two steps, first one using the uniformity standard, to get 9 groups from all the uniform patterns, the second it is related to non-uniform patterns, where a calculation of uniformity and the number of "1" bits is done, Sven groups are the results of this steps. The outcome is a vector of both uniform and non-uniform patterns, to have more robustness to noise.

Inspired by their work, we did keep all the patterns except the uniform zero pattern, which is the complementary of all the others patterns, we did grouped the LBP patterns to twenty-eight groups using the uniformity standard and the number of "0" bits and "1" bits.

3. SYSTEM OVERVIEW

The bases of the method are described in figure 5; the different steps are detailed in the following, except LBP encoding which has been explained in section 2.

Figure 5. An illustration of the architecture of the system



Starting by the LBP encoding, the results are the patterns they will be grouped with respect to three criteria, rotation invariant, grey level changes and mirror effects; in the follow, more detailed description is given. After that, histogram building according to our classification, size of 28, it preforms as a texture descriptor. The matching step is the final where the request image goes throw the same procedures already mentioned, a calculation of distance is done between the histogram of requested image and the database histograms, we did use the histogram equalization, who ever have the minimum distance value will considered as the best match.

3.1 Regrouping

We did separate the classification into two parts according to uniformity stander, the 8 bits give us 2^8 possible combinations that equal to 256, the first part is the 58 uniform patterns; we did eliminate the zero pattern and classify the 57 rest into eight groups according to the number of "1" bit. The second part of 198 non-uniform patterns we divide it into twenty groups a cording to simple measures, which is the number of "1" bits and "0" bits between them:

- Uniform pattern (Ojala et al, 2002), where the changes from "0" to "1" (or the opposite) is not greater than two. They do not change their shape even in case of rotation, no matter the angle of rotation is. The sequence of bits will always guaranty that, also the mirror effect robustness, the figure 6 clarify the regrouping behaviour.
- The Non_Uniform patterns where the changes between zero to one or the opposite are more than two.

The number of ones goes from two to six separated by a number of zeros, we distinct twenty groups. Table 1 introduces all the groups with their patterns respecting the point of rotation and mirror effects invariantly.

Figure 6. The Uniform Patterns Regrouping (empty circles correspond to bit values of one and filled circles are zero, the number inside the pattern is the group number)

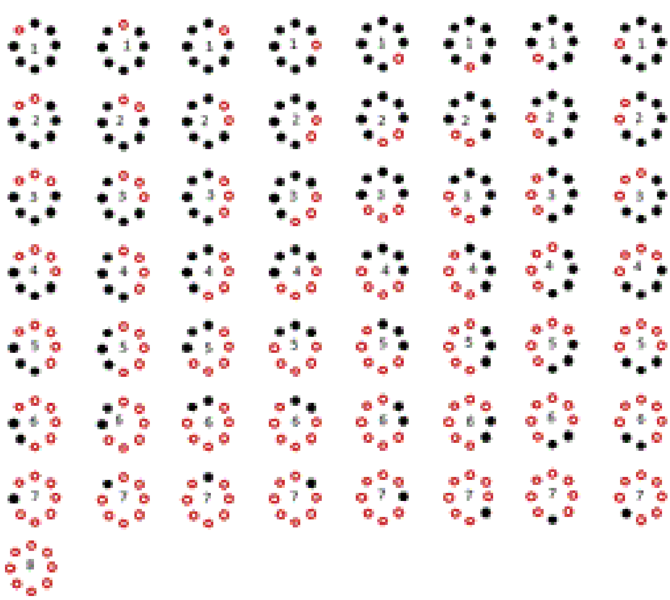


Table 1. The Non-Uniform Patterns Regrouping (Empty circles correspond to bit values of one and filled circles are zero, the number inside the pattern is its decimal value)

Groups	Patterns							
09	160	80	40	20	10	5	130	65
10	144	72	36	18	9	132	66	33
11	136	68	34	17				
12	208	104	52	26	13	134	67	161
	176	88	44	22	11	133	194	97
13	200	100	50	25	140	70	35	145
	196	98	49	152	76	38	19	137
14	148	74	37	146	73	164	82	41
15	138	69	162	81	168	84	42	21

continued on following page

Table 1. Continued

Groups	Patterns
16	232 116 58 29 142 71 163 209 226 113 184 92 46 23 139 197
17	228 114 57 156 78 39 147 201
18	216 108 54 27 141 198 99 177
19	204 102 51 153
20	210 105 180 90 45 150 75 165 202 101 178 89 172 86 43 149 212 106 53 154 77 166 83 169
21	170 85
22	242 121 188 94 47 151 203 229 244 122 61 158 79 167 211 233

continued on following page

Table 1. Continued

Groups	Patterns
23	236, 118, 59, 157, 206, 103, 179, 217, 230, 115, 185, 220, 110, 55, 155, 205
24	234, 117, 186, 93, 174, 87, 171, 213
25	214, 107, 181, 218, 109, 182, 91, 173
26	250, 125, 190, 95, 175, 215, 235, 245
27	246, 123, 189, 222, 111, 183, 219, 237
28	238, 119, 187, 221

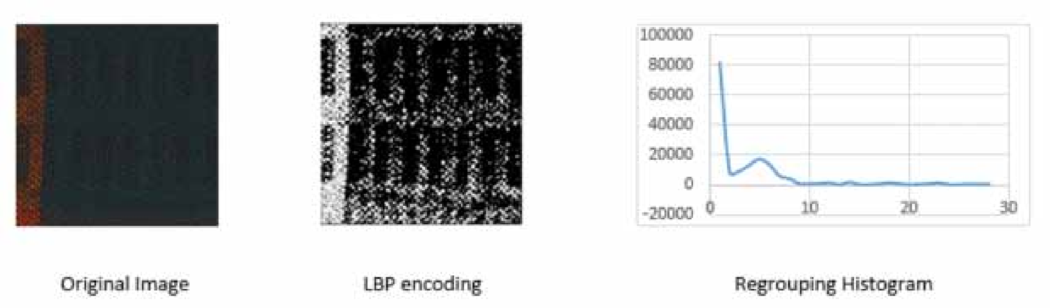
3.2 Histogram Building

After the regrouping operation, a 28 length histogram is built for each image, where all the decimal values of the patterns group are counted together to represent its value in the histogram, in figure 7 we can see the image at left goes throw the LBP encoding and transformed to a histogram which is the vector descriptor.

3.3 Matching

The final step aims to classify the texture images using the vector descriptor (histogram). An off-ling process is applied on all images dataset to produce histograms, than the request image goes throw the same way already mentioned, the matching task is done between those histograms of dataset and the one of the requested image by calculating the distance between two vectors. The operation return the minimal results to define the best match. Many distance measurement is proposed in the theory, chi-square distance used for texture classification (Guo et al, 2016), Euclidean distance in (Fu & Wei, 2008) for facial expression recognition, otherwise other researches do use classifiers like support vector machines (SVM) in (Cimpoi et al, 2015) or nearest neighbour classifier (NNC) in (Chan et al, 2015).

Figure 7. The histogram of an image of Outex dataset



As well, various studies offer a cooperation between distance measurement and classifiers as the case of (Wang et al, 2018), where JRLP do use both of chi-square distance and nearest neighbourhood classifier. The time costs of the method is related to the choice of this operation, the classifiers are more expensive than distance measurement.

For our proposed method, chi-square distance is applied to measure the match between histograms; our training samples and test samples give us the Histograms H and h respectively. Then, distance measurement formula indicated clearly as following:

$$D_i\left(H,h\right)=\sum_{j}^{N}\frac{H_j-h_j}{H_j+h_j+1} \tag{2}$$

where D_i is the i[th] distance associated to the i[th] histogram of the training samples, $j \in \{1, N\}$ and N is the number of groups (N=28). The best match related by finding the image i with the minimal D_i.

4. DATASET

The experiment was applied on two separated datasets, the Outex Texture Dataset (Outex Oulu University) and the Brodatz textures dataset (Southern California University, 2018).

For the Outex Texture Dataset, we did use 10 classes from the dataset. Only 10 images for each class, 100 images for the learning phase. The images are under 0°, 30°, 45° and 60° angles of rotation and "inca" illuminate. Each used image size is 128*128 pixels. For testing the rotation effect, we used the following angles 5°, 10°, 15°, 75° and 90°. Concerning the test of illumination, the used images are under the "Horizon" and "TL84" spectra of the illuminates.

The second dataset, the Brodatz textures dataset experimentations challenged the grey level changes and the mirror effects. Where the thirteen texture images was exploited as a training simple, the same images with a different grey level are used as a testing simple, after that the training simple was artificially flipped horizontally and vertically in order to test the mirror effect robustness, ending with a challenge combine the flipped images with the grey level changing ones. The results are available in table 3.

5. CLASSIFICATION AND COMPARISON

In this section, the evaluation of our proposed regrouping behaviour for texture classification, in addition to a comparison to other LBPs variants.

Figure 8. Simples from Outex Texture Dataset

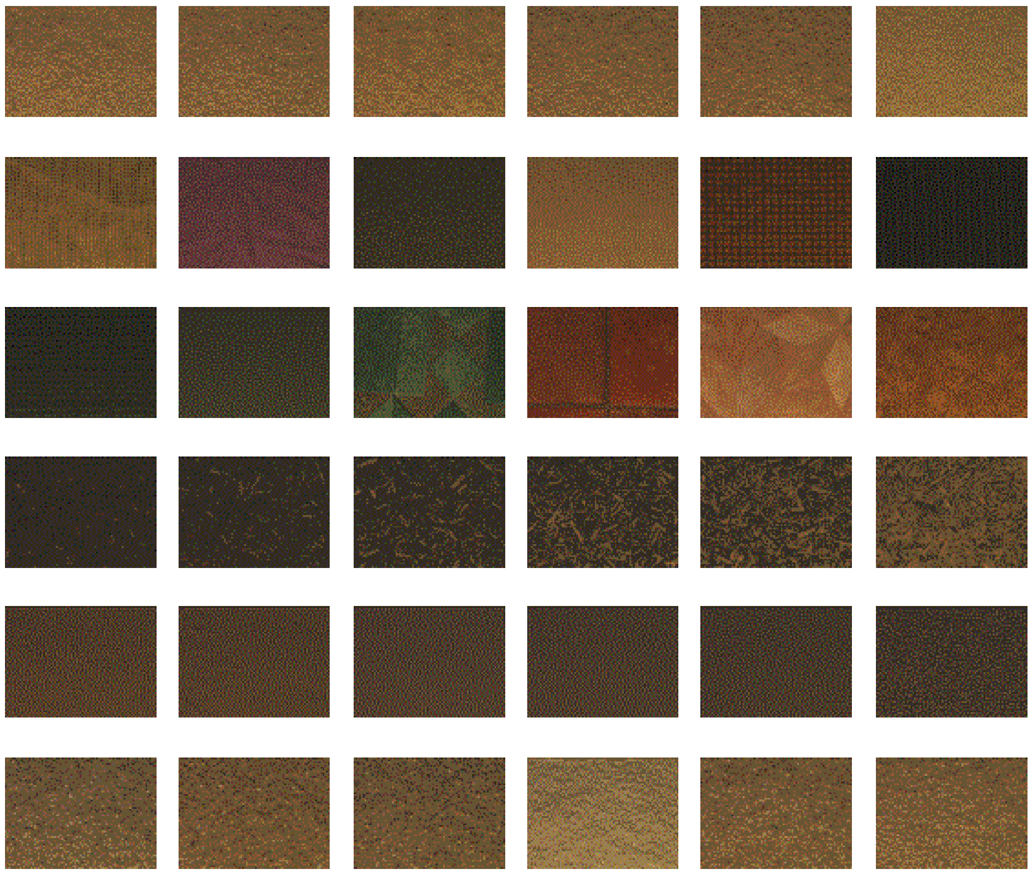


Figure 9. Images of Brodatz textures dataset

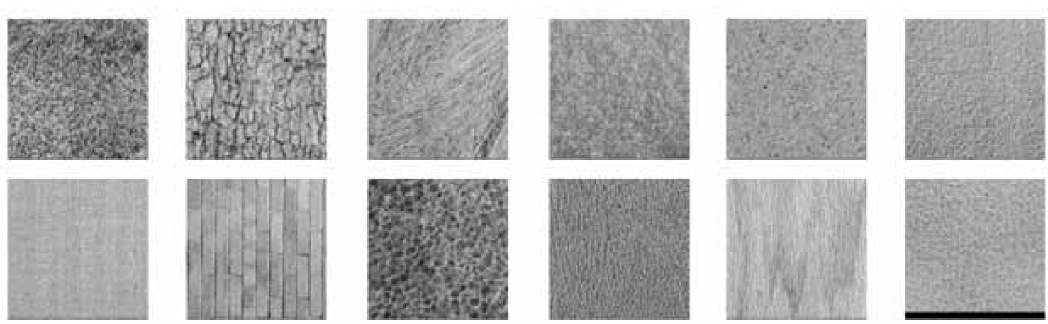


Table 2 shows the results of Outex Texture Dataset, where we can notice that the higher score is 99.99% return to the 5° rotation angle, where you cannot tell the difference between the original and the rotated image. After that descries in results is noticed which is completely normal, we can justify this descries with the fact that the images are changed, with disappears of some parts and the appearance of some new ones. Concerning the illuminate tests, the recognition rate is 92.13%

Table 2. Results (%) of LBPG on Outex Texture Dataset

	Rotation					Illuminate	
	5°	10°	15°	75°	90°	TL84	Horizon
LBPG	99.99	99.78	98.57	96.66	97.67	92.13	95.57

Table 3. Results (%) of LBPG on Brodatz Texture Dataset

V5 555	Mirror effects(1)		Grey level changes(2)	(1) +(2)
	Flipped vertically	Flipped horizontally		
LBPG	99.99%	99.99%	99.99%	99.99%

on TL84 and 95.57% on Horizon; the changes in illuminate spectre make a minor modification in images details.

The results of Brodatz textures dataset are very promoting, the tests are done with two factors, the grey level changes and the mirror effects (not available on the dataset, created artificially), testing each one alone or even when we combine between them; the recognition rate is 99.99%. The grey level changes is assured by the way the LBP method work, where the comparison of pixels grey values doesn't interested in deference value but focusing on the sign (greater or smaller) . What concern the mirror effects our grouping behaviour affords the immunity to the image by collection the patterns with all the possible flipped position to gather.

The LBP operator is by definition invariant against any monotonic transformation of the grey scale, because it threshold the pixel neighbours by the sign of difference not the exact value, that is why the results does not change by changing the images grey level, when is applied on the entire image.

For the mirror affect our strategy of regrouping guaranty that the flipped patterns will always be under the same group. In figure 10, orange bars are representing a histogram of the mean value of Brodatz original images, yellow bars are representing a histogram of the mean value of Brodatz flipped images and the green ones are representing a histogram of the mean value of Brodatz grey

Figure 10. The regrouping histograms of mean values of Brodatz dataset images

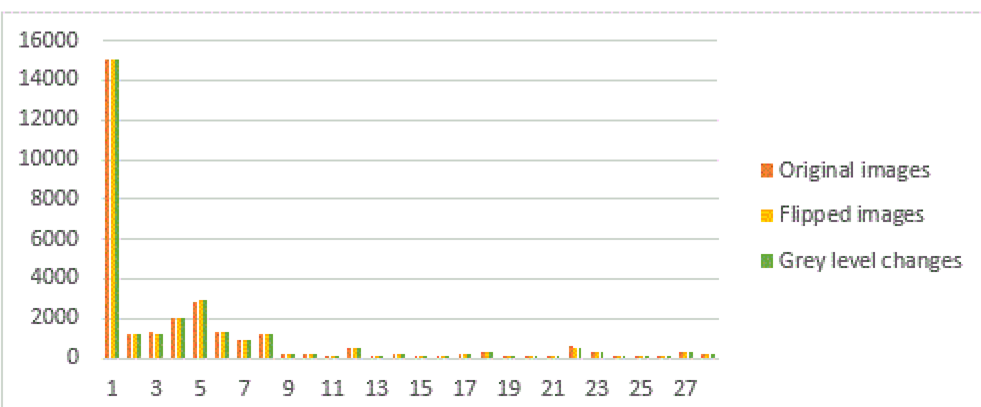


Table 4. Classification scores (%) for LBP, NTLBP, CLBC and our Method LBPG on the two datasets, Outex and Brodataz

	Dimension vector	Outex	Brodatz
LBP	256	92.14	90.70
NTLBP	16	84.24	89.31
NLBP	14	96.48	91.23
CLBC	9	97.16	95.85
LBPG	28	**98.33**	**99.99**

level changed images. The average difference between the training samples and the test samples images is equal to 1.01%.

In table 4, our proposed method proves that it can give satisfactory experimental results. To test the rotation, illumination, mirror effect, and grey level changes invariances of our proposed method LBPG; experiments are achieved on the Brodataz and Outex databases.

LBPG demonstrates the good capability in texture classification domain, challenging four methods the original LBP, NTLBP, NLBP and CLBC, in the first column, the size of the feature vector extracted by each method, the second and third ones are the results of the applied method on Outex and Brodatz Datasets respectively.

6. CONCLUSION

This paper presents a study of a new regrouping behaviour of LBP method for texture classification, The heuristic groupings of patterns focus on uniformity stander, some studies eliminate non-uniform patterns justifying this action with the fact that they are few, others make benefits from them. We did follow the second path keeping all patterns except the zero pattern, grouping all the patterns into 28 groups, the groups turn to a vector descriptor, the matching step using it to define the texture image classification. Focusing on two goals, the first is to keep the computational complexity of LBP and achieve a better timing by reducing the vector descriptor size, the second is increasing the robustness against rotation, illuminates, grey level, and the mirror effects, the results are motivating. We look forward to raise our objectives combining this new regrouping with machine learning techniques as Convolutional Neural Networks (CNN) classifier or Support Vector Machine (SVM), testing it over large datasets.

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