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Learning Improved Circular Difference and Statistical Directional Patterns for Texture Classifiaction

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Abstract: Thanks to its simplicity and computational efficiency, Local Binary Pattern (LBP) has been widely utilized in texture classification. Traditional LBP codes the local difference. It also, uses the binary code histogram to model a given image. However, the directional statistical information is not taken into consideration in LBP. In this study, researchers present the Improved Circular Difference and Statistical Directional Patterns (ICDSDP). It is a new textual approach for texture classification accuracy. It is a combination of the circular difference of the directional information with oriented standard deviation. This approach aims at improving the texture classification. Experiments done on Outex and Curetgrey, large texture databases have shown that the application of the proposed texture feature extraction and classification approach can significantly ameliorate the classification accuracy of LBP. Compared to other methods, the proposed scheme could remarkably improve the classification accuracy. It could also, reduce classification.

Key words: Texture analysis, ICDSDP, LBP, outex database, curetgrey database, Chi-square distance

INTRODUCTION

Texture analysis is a subject that is increasingly attracting the interest of modern researchers in computer vision and pattern recognition fields. Generally speaking, it revolves around 4 basic issues: Classifying images based on texture content, image segmentation into homogeneous texture regions, textures synthesizing for graphics applications and shape information establishing from texture cue (Tuceyran and Jain, 1993). In the early stage, researchers focused mainly on extracting statistical features to classify texture images like the co-occurrence matrix method (Haralick *et al*., 1973) and those based on filtering (Randen and Husoy, 1999). When applying these techniques researchers can get better classification results, if the training samples and the testing ones have similar or identical orientation. Researchers have to solve problems related to rotation invariance in order to meet real application requirements. Among the first researchers who dealt with rotation invariant texture classification, researchers can mention (Kashyap and Khotanzad, 1986). They used a circular autoregressive model. After that, many other approaches were explored, such as the hidden Markov Model (Wu and Wei, 1996) and the multi-resolution autoregressive one (Mao and Jain, 1992). Jafari-Khouzani and Soltanian-Zadeh proposed to utilize Radon transform in order to estimate the texture orientation and extract characteristics of wavelet energy for texture classification (Kourosh and Hamid, 2005). Currently Varma and Zisserman (2005), proposed an algorithm based on statistical learning. In such algorithm, a rotation invariant texton library is at first built from a training set. After that an unknown image of texture is classified, according to the distribution of texton. Scale and affine invariant texture classification is considered, as an active research topic. Some pioneer researches have been done by utilizing fractal analysis (Xu *et al*., 2009) and affine adaptation (Lazebnik *et al*., 2005). To classify and extract features, Ojala suggested the Local Binary Pattern (LBP) descriptor (Haralick *et al*., 1973). The latter is a simple and efficient method to model local image patterns. But, it has many disadvantages. It cannot be totally representative of the spatial structure in the image. The LBP descriptor is also, unable to incorporate the directional statistical data and rotation invariant texture classification. Furthermore, LBP-based descriptor cannot overcome such limitations which make it unable to perform high classification rates within the training time of the learning step. Many other methods are concerned with extracting statistical features for texture classification. The contrast (the variance of local image) was combined with LBP for a joint distribution (Ojala *et al*., 2002a) because LBP could not totally represent the image local spatial structure. Nevertheless,

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the contrast has 2 main disadvantages. Firstly, contrast is an isotropic measurement whereas texture images may contain clear orientation. Consequently, the contrast is unable to represent such information. Besides to combine with LBP, contrast needs a quantization procedure. If the training samples number is limited, the quantization step may fail to represent adequately the feature space. In this study, researchers present the Improved Circular Difference and Statistical Directional Patterns (ICDSDP) approach for a more efficient and robust rotation invariant texture classification. The approach aims, at incorporating the directional data with a oriented standard deviation. Furthermore, researchers are concerned with reducing the feature size. In fact, the histogram size in ICDSDP is reduced to 16 patterns instead of 256 with eight neighbor pixels. Experimentations are conducted to show the ICDSDP efficacy and efficiency. This study is made up of the following parts.

BASIC LOCAL BINARY PATTERN OPERATOR

The Local Binary Pattern (LBP) is an operator which transforms the input data into an integer labels image. These labels describe the image small-scale appearance. They, most frequently the histogram are then applied for image analysis. The local binary pattern operator was introduced by Ojala *et al.* (1996). It is based on the assumption that texture contains 2 complementary aspects: the pattern and its corresponding strength. The LBP operator original version was applied in an image (3×3) block. At first, this blocks pixels were thresholded by the central pixel value. After that they were weighted by powers of two. At last, they were summed in order to obtain the label for the central pixel. The neighborhood, for each block, consists of 8 pixels. Eventually, a total of 28 labels may be obtained according to the neighborhood pixels value. As a matter of fact, given a pixel in the image with comparing it with its neighbours, an LBP (Ojala *et al.*, 2002b) code is computed:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s\left(g_p - g_c\right)2^p; s(x) = \begin{Bmatrix} 1; x \geq 0 \\ 0; x < 0 \end{Bmatrix} \quad (1)$$

Where:

g_c and g_p	=	{p = 1, 2, ..., P-1} the central pixel gray value and its neighbors
R	=	The neighborhood radius
P	=	The the number of neighbors

After LBP code obtained for each pixel, a histogram is build to describe each texture image. Figure 1 presents an example of LBP code for 1 pixel.

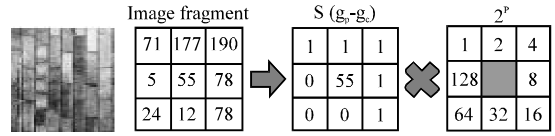

Fig. 1: Examples of the Local Binary Pattern (LBP) codes; LBP = 1×1+1×2+1×4+1×8+1×16+0×32+ 0×64 +0×28 = 1+2+4+8+16 = 31

CIRCULAR DIFFERENCE AND STATISTICAL DIRECTIONAL PATTERN OPERATOR

Many anistropic textures contain rich directional information. Nevertheless, the operators based on the previously presented local binary motifs do not code the use of the directional data integretd in the texture image. In this study, researchers propose an LBP variant sensitive to the directional information of the image. This variant, called CDSDP (Circular Difference and Statistical Directional Patterns) will be more elaboreted in the following paragraph (Trabelsi *et al.*, 2014).

Mathematical formulation of the circular difference patterns operator: The local binary pattern generates a primitive invariant, at a texture gray level. The histogram of the binary motives calculated on a region is used for texture description (Ojala *et al.*, 2002a). After the LBP image synthesis, the LBP histrogram is built as follows:

$$H(k) = \sum_{i=1}^{N}\sum_{j=1}^{M} f\left(LBP_{P,R}(i,j),k\right); k \in [0,K] \quad (2)$$

With (N×M) represents the input image size and the function f is defined as follows:

$$f(x,y) = \begin{Bmatrix} 1; & x = y \\ 0 & \text{otherwise} \end{Bmatrix} \quad (3)$$

However, histogram dimension is so costly to be used as texture descriptor. Besides, this operator does not ensure an invariance vis-vis rotation. It can also, be followed by inaccurate classification. To reduce complexity, researchers use the difference of the gray levels of the neighboring pixels rather than thresholding them by the central pixel gray level. Thus, the dimention of the generated binary motive is reduced to the half while maintaining an adequate coding of the local difference. So, researchers circularly compare only the symetrical pairs with central pixel. If researchers have 8 neighbours, the dimension of the LBP histogram is 2^8 = 256. Now when making the circular differences, the dimension is aqual to 2^4 = 16. Researchers notice that for 8 neighbours,

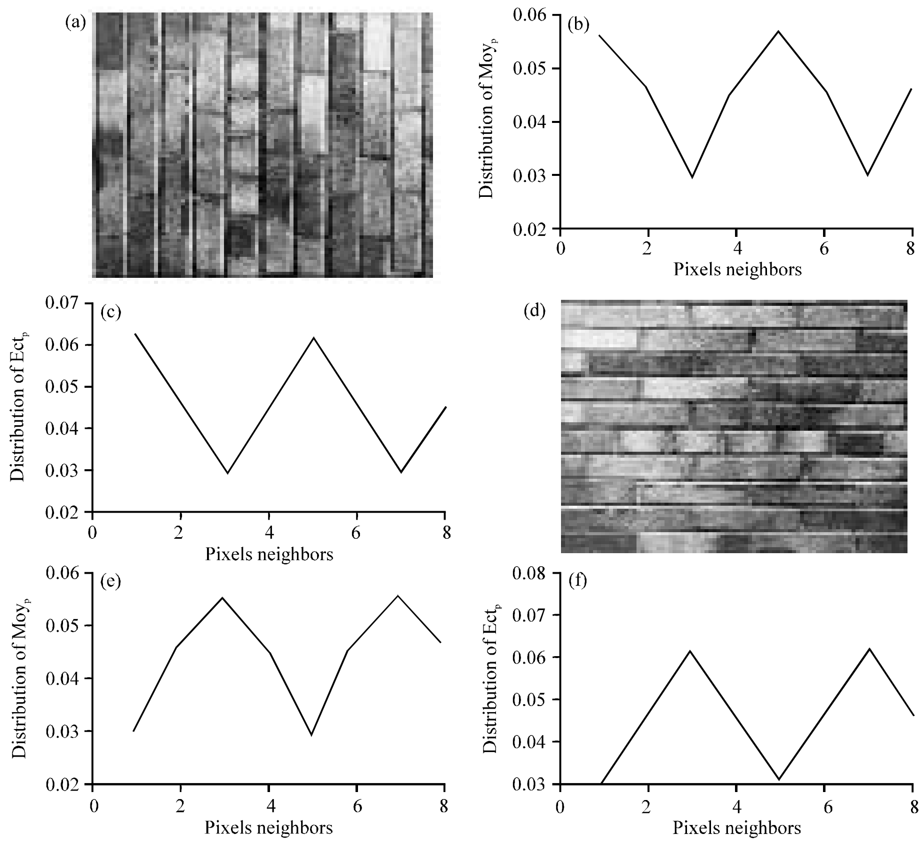

Fig. 2: An example of the image and its responses of the mean and the standard deviation, respectively: a) 0° example; b) Mean of a; c) Standard deviation of a; d) 90° example; e) Mean of d; f) Standard deviation of d

LBPP, R produces 256 different binary motives whereas for the proposed descriptor called the Circular Difference Pattern (CDP), the motives number is reduced to 16. Researchers can ensure the robustness of the calculated diffences operator so as to eliminate any sensitivity towards noise. The $CDP_{P,R,T}$ operator can be presented as follows:

$$CDP_{P,R,T} = \sum_{p=0}^{\frac{P}{2}-1} Thr\left(g_p - g_p + \frac{P}{2}\right) 2^p \tag{4}$$

$$Thr(x) = \begin{cases} 1; & x > T \\ 0; & otherwise \end{cases} \tag{5}$$

The reduction of the T is the adopted threshold. The reduction of the $CDP_{P,R,T}$ operator size leads to the time reduction in the processing of the same coefficient 16. This operator has 2 limitations: First, it does not ensure any invariance towards rotation. Second, it is unable to code all the directions which characterize a given texture. In the following part, researchers will try to overcome these 2 disadvantages.

Mathematical presentation of the operator of the circular differences statistical directional pattern: To code the image different orientations, researchers are going to focus on the characteristic parameters generated for each orientation p, especially the average and the standard deviation. By taking into consideration the local differences above, the average and the standard deviation are defined by:

$$Moy_p = \sum_{i=1}^{N} \sum_{j=1}^{M} \frac{\left|\left(g_p - g_p + \frac{P}{2}\right)\right|}{(M * N)} \tag{6}$$

$$Ect_p = \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{M} \frac{\left(\left|\left(g_p - g_p + \frac{P}{2}\right)\right| - Moy\right)^2}{(M * N)}} \tag{7}$$

The directional features Moy_p and Ect_p, can describe useful the oriented information in the texture image (Fig. 2). In order to take account of the textures in the image, it is important to adopt the differences of the neighbouring pixels gray level. The idea is thus to introduce a weighting vector that modulates the different contributions of the neighbouring pixels in the difference. $W = (W_1, ..., W_p, ...W_n)$, the implemented weights vectors. W_p is chosen to minimize the following sum:

$$W_p = \arg\min_\beta \left\{ \sum_{i=1}^{N} \sum_{j=1}^{M} \left| g_p(i,j) - \beta * g_{p+\frac{P}{2}}(i,j) \right|^2 \right\} \quad (8)$$

The obtained weight vector defines the statistical direction for the whole image. CDSDP operator can be adaptively presented as follows:

$$CDSDP_{P,R,T} = \sum_{p=0}^{\frac{P}{2}-1} Thr\left(g_p - W_p * g_{p+\frac{P}{2}} \right) 2^p \quad (9)$$

At this juncture, each weight W_p is projected along one orientation for the total texture image.

IMPROVED CIRCULAR DIFFERENCES STATISTICAL DIRECTIONAL PATTERN

In the proposed CDSDP method, the adapted weight parameter is used to minimise the directional difference. Thus, the CDSDP operator can useful improve the classification accuracy. However, the CDSDP descriptor not takes into account the statistical values of the Moy_p and Ect_p parameters. Since, researchers applied a weight parameter W_p to minimize the directional difference along each orientation, researchers can added these statistical feature by concatenating with CDSDP code. Furthermore, the standard deviation can reflect the height difference of homogeneous or heterogeneous texture image. Accordingly, researchers aims to concatenated the standard deviation information with CDSDP code and its called ICDSDP on that account. According to the statistical direction W_p, the expressions of the average and those of the standard are analogously defined as follows:

$$Ect_p^* = \sqrt{\frac{\sum_{i=1}^{N} \sum_{j=1}^{M} \left(\left| \left(g_p(i,j) - g_{p+\frac{P}{2}}(i,j) * W_p \right) \right| - Mean \right)^2}{(M * N)}} \quad (10)$$

The ICDSDP descriptor is presented by arranging the vector of CDSDP with the Ect_p^* vector.

EXPERIMENTAL RESULTS

To evaluate the texture discriminant power by the ICDSDP operator, researchers make a series of experiences on 2 data bases having public textures:

- Outex database (Ojala *et al*., 2002b), containing 24 textures classes obtained under 3 different lightings and at 9 shooting angles
- Curetgrey database (Columbia-Utrecht) containing 61 classes having a real world texture. Each representation has different lighting combinations and viewing angles (Dana *et al*., 1999)

In this study, researchers have chosen 92 images of each class with a shooting angle <60. These databases are so important, as they have large variabilities both in external conditions (shooting angle and brightness) and in the orientation of texture (rotation, isotropy, etc.).

For each texture image, a signature vector ICDSDP is generated for its classification. This step is made up of a similarity measure followed by a simple classifier: The closest neighbours.

Similarity measurement: Researchers can define many parameters to evaluate similarity between 2 given histograms, as histograms intersection, the relation of true logarithmic semblance and the statistical measure of χ^2. In this study, researchers adopt the χ^2 distance defined as followed:

$$\chi^2(S,M) = \sum_{n=1}^{N} \frac{(S_n - M_n)^2}{S_n + M_n} \quad (11)$$

Where, N is the vectors of features dimension (ICDSDP vectors) S and M. Snet M-n are, respectively nime components of of S and M.

Performance measurement on an outex data set: In this part, researchers consider two series of outex database testing: TC10 (Outex TC00010) and TC12 (Outex TC00012). These 2 series of image tests contains the same 24 texture classes.

Each of which is obtained under 3 different lightings (horizon, inca et T184) (Fig. 3) and 9 different rotation angles (0, 5, 10, 15, 30, 45, 60, 75 and 90°) (Fig. 4).

There are 20 samples of texture images, having the dimension 128×128 for each category under each parameter (lighting and angles). Before features extraction of LBP, each texture sample was normalised to an average intensity of 128 and standard deviation of 20. For TC10, learning is made from inca samples and 0 angle. Then, it has been tested with the eight rotation angles. A total of 480 (24×20) learning models and 3840 (24×8×20) validation samples. For TC12, learning is made with the samples, as TC10 and then tested with the caught samples of t184 or horizon.

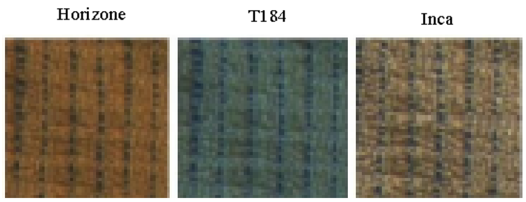

Fig. 3: Example of 3 different illuminance

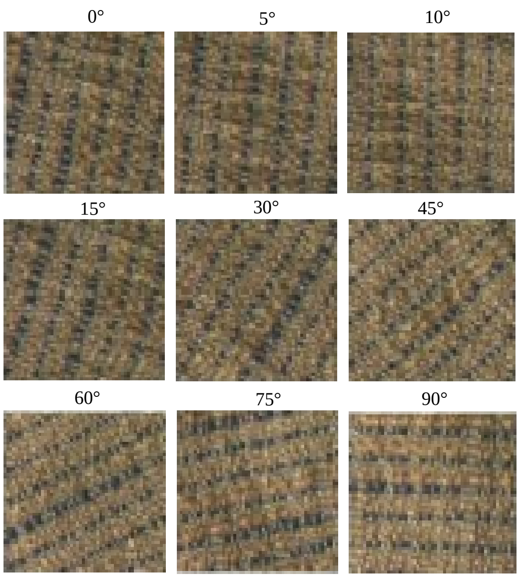

Fig. 4: Example of the 9 different orientations with illuminance Inca

Researchers can distinguish between a total of 480 (24×20) learning models and 4320 (24×20×9) validation samples. Table 1 represents classification results with ICDSDP scheme. For comparison purposes, researchers added CDSDP, LBP and VAR operators. In Table 1, researchers can notice that the ICDSDP scheme present always better classification rate compared to CDSDP scheme. Besides, VAR and LBP operators result in performances which are often neighbours and always lower than those obtained by ICDSDP. In the other hand, researchers tested the choice of number of neighborhood with the same radius. Researchers can notice that $ICDSDP_{16,1}$ increases the performance by 10% compared with $ICDSDP_{8,1}$. The 1 can also notice that operateur ICDSDP presents better performance with TC10 where researchers present different orientations.

Performance measurement on curetgrey data set: To validate the proposed descriptor, researchers consider in this section a database having a public texture Curetgrey, as it allows to study invariance using texture rotation (it contains textured images and their rotated versions).

Table 1: Classification rate (%) using different schemes

Schemes	TC10	TC12 (t184)	TC12 (horizon)
$LBP^{ri}_{8,1}$	84.8	65.30	63.7
$LBP^{ri}_{6,1}$	86.8	68.30	64.7
$VAR_{8,1}$	50.8	55.30	53.7
$VAR1_{6,1}$	52.8	59.10	54.2
$CDSDP_{8,1}$	84.8	81.70	80.1
$CDSDP_{16,1}$	94.8	84.70	82.1

Table 2: Classification rate (%) using different neighborhoods

P, R	8, 1	16, 1
$LBP^{rui2}_{P,R}$	58.0	66.5
$LBP^{rui2}_{P,R}/VAR_{P,R}$	68.1	70.1
$CDSDP^{rui2}_{P,R}$	70.8	81.7
$ICDSDP^{rui2}_{P,R}$	80.6	91.8

Curetgrey database contains 61 textures. For each one, researchers associate 205 caught images under different viewing angles and lighting conditions. Researchers distinguish between 118 images whose viewing angles are <60. The learning for each class is made by selecting the 23 first images. Consequently, researchers used 1403 models for the learning step and 4209 samples of test. Classification rates for different operators are listed in Table 2.

From the experimental study, researchers notice that ICDSDP operator offers the greater classification accuracy. Indeed, researchers can note an improvement by 10% of this operator classification if compared with the traditional LBP descriptor. Besides, the increase in the number of the neighbours and neighborhood radius makes the discrimination with ICDSDP operator so rich and significant.

CONCLUSION

LBP operator is widely used in texture classification. But, it might be inefficient due to some limitations. In this study, researchers propose a new local texture descriptor by concatenating the proposed with the oriented standard deviation. The ICDSDP scheme aims to present the directional data in order to achieve greater accuracy and robustness of the classification in the rotation invariant texture. Experimental results are based on the comprehensive Outex and Curetgrey texture databases. From the experimental results, researchers can notice that our method has better performance than other approaches of texture classification illustrated in the state of art.

REFERENCES

Dana, K.J., B. van Ginneken, S.K. Nayar and J.J. Koenderink, 1999. Reflectance and texture of real-world surfaces. ACM Trans. Graphics (TOG), 18: 1-34.

Haralick, R.M., K. Shanmugam and I. Dinstein, 1973. Textural features for image classification. IEEE Trans. Syst. Man Cybernet., SMC-3: 610-621.

Kashyap, R.L. and A. Khotanzad, 1986. A model-based method for rotation invariant texture classification. IEEE Trans. Pattern Anal. Mach. Intell., 4: 472-481.

Kourosh, J.K. and S.Z. Hamid, 2005. Radon transform orientation estimation for rotation invariant texture analysis. IEEE Trans. Pattern Anal. Mach. Intell., 27: 1004-1008.

Lazebnik, S., C. Schmid and J. Ponce, 2005. A sparse texture representation using local affine regions. IEEE Trans. Pattern Anal. Mach. Intell., 27: 1265-1278.

Mao, J. and A.K. Jain, 1992. Texture classification and segmentation using multiresolution simultaneous autoregressive models. Pattern Recognition, 25: 173-188.

Ojala, T., M. Pietikainen and D. Harwood, 1996. A comparative study of texture measures with classification based on featured distributions. Pattern Recognit., 29: 51-59.

Ojala, T., T. Maenpaa, M. Pietikainen, J. Viertola, J. Kyllonen and S. Huovinen, 2002a. Outex-A new framework for empirical evaluation of texture analysis algorithms. Proceedings of the 16th International Conference on Pattern Recognition, August 11-15, 2002, Quebec, Canada, pp: 701-706.

Ojala, T., M. Pietikainen and T. Maenpaa, 2002b. Multiresolution Gray-scale and rotation invariant texture classification with local binary patterns. IEEE Trans. Pattern Anal. Mach. Intell., 24: 971-987.

Randen, T. and J.H. Husoy, 1999. Filtering for texture classification: A comparative study. IEEE Trans. Pattern Anal. Mach. Intell., 21: 291-310.

Trabelsi, R.B., A.D. Masmoudi and D.S. Masmoudi, 2014. A new texture classification using circular difference and statistical directional patterns. Proceedings of the IEEE International Conference on Cloud Computer Information Systems, January 2014, Hammamet, Tunisia.

Tuceyran, M. and A.K. Jain, 1993. Texture Analysis. In: Handbook of Pattern Recognition and Computer Vision, Chen, C.H., L.F. Pau and P.S.P. Wang (Eds.). World Scientific, Singapore, pp: 235-276.

Varma, M. and A. Zisserman, 2005. A statistical approach to texture classification from single images. Int. J. Comput. Vision, 62: 61-81.

Wu, W.R. and S.C. Wei, 1996. Rotation and gray-scale transform-invariant texture classification using spiral resampling, subband decomposition and hidden Markov model. IEEE Trans. Image Process., 5: 1423-1434.

Xu, Y., H. Ji and C. Fermuller, 2009. Viewpoint invariant texture description using fractal analysis. Int. J. Comput. Vision, 83: 85-100.