A Novel Adaptive Descriptor Algorithm for Ternary Pattern Textures

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***Abstract* — Traditional Local Binary Patterns (LBP) and Local Ternary Patterns (LTP) algorithms suffer from: i) the threshold cannot be determined adaptively, ii) low texture description resolution, and iii) only the uniform mode can be encoded. In this paper we propose a local ternary patterns texture descriptor algorithm whose threshold is determined adaptively, and is termed: OECS-LATP: Odd-Even parallel Center-Symmetric Local Adaptive Ternary Pattern. First, the threshold is determined adaptively according to the variation of image gray level. Secondly, the center-symmetric and odd-Even parallel design are adopted in the encoding operation. Not only the contrast of gray-levels between two symmetric pixels with the center pixel is determined but also the contrast of gray-levels between the center pixel and local neighborhood pixels are considered, thus the local texture feature is depicted more effectively. Then the proposed algorithm is compared with LBP, LTP and SILTP algorithms through Brodatz dataset and CUReT dataset. The experimental results show that based on these two datasets, the proposed algorithm surpasses LTP in precision by 6% and 21% respectively, and has great improvement in: i) recognition rate, ii) stronger anti-interference ability and iii) is more robust under the condition of uneven illumination than traditional LTP and SILTP descriptors.**

Key words - texture feature; local ternary patterns; adaptive threshold; image retrieval

I. INTRODUCTION

Image feature representation and acquisition is the basis for the computer vision and image processing technique. Generally, the image features include color, texture, and shape etc, while texture feature is very critical for image analysis and processing. How to acquire image texture feature information has been a hot topic in image feature extraction [1]. Generally, texture is the special pattern composed of periodic or random basic component [2], and it has the characteristic of microscopic irregular and macroscopic regular [3]. Extraction of image texture feature is widely used in computer vision, e.g., image segmentation [4], machine vision [5] and patter recognition [6]. Recently, the texture analysis method can be divided into 4 categories [7]: structure-based method, statistics-based method, space-domain/frequency-domain based method, and joint modeling method. For structure-based method, it focused on how to describe the internal relationship and alignment rules among the basic texture components, thus it was generally applied in image texture analysis and processing due to the simple computation and rotational invariant. LBP (Local Binary Patterns) and LTP [8] (Local Ternary Patterns) were two typical examples of structure-based method.

The texture description method of LBP was firstly proposed by Ojala [9]. For this method, both the structure features and statistical features were considered, and it has the advantage of simple computation and insensitive to objective gray variation, thus it was widely applied in image matching [10], image retrieval [11], and medical image analysis [12]. Based on the work of Ojala, the LBP operator is improved by dimensionality reduction with Uniform LBP in [13], and the advantage is that the computation is reduced, while it can only applied to the case of U>2. In [14], MB_LBP (Multi-Blok Local Binary Pattern) is taken and the gray value of single pixel is substituted by the average gray of the sub-region, thus it improves the anti-interference ability, while reducing the image resolution and recognition rate. For the traditional LBP texture operator, the texture resolution was not very high since it takes the binary pattern and mostly used to describe the texture spatial features.

In order to improve the texture description resolution, the LTP was proposed by Tan [15], and LTP method was further improved by Chen [16]. While the local ternary pattern was directly applied in the encoding, it will result in large gray-level range and degrade the system real-time performance and efficiency. SILTP (Scale Invariant Local Ternary Pattern) is taken in to extract the image features [17]. Although it partly improves the anti-interference ability, the gray value of central pixel is only considered while not the region value when setting the threshold, and thus results in weak robustness.

In this paper, based on the existing disadvantages of the traditional LBP and LTP mode, the LTP operator is improved, and OECS-LATP (Odd-Even parallel Center-Symmetric Local Adaptive Ternary Pattern) operator is designed, which determinates the threshold in an adaptive way to enhance the robustness. Furthermore, to make up the disadvantage that non-Uniform mode was negligent in traditional LTP, the center-symmetric and odd-Even parallel are adopted in encoding operation, which will greatly improve the texture description resolution and also consider the case of non-uniform mode.

In this paper, the previous works on LBP and LTP algorithms are introduced and the drawbacks of LBP algorithm and features of LTP algorithm are analyzed in Section-II. Based on the features of LTP algorithm, the optimal threshold is automatically determined by taking the adaptive ternary method in Section-III. In Section-IV, OECS-LATP description operator is designed to overcome the drawbacks of traditional description operator, and it also improves the effective description ability of image texture. In Section-V, the experiments are performed and results are analyzed, the performance of the proposed algorithm is verified through 3 groups of experiment. Finally, the conclusions are drawn in Section-VI.

II. LBP OPERATOR AND LTP OPERATOR DESCRIPTION

A. LBP Operator

The principle of LBP texture description is to select a local neighborhood for each pixel (center pixel), and compare the gray-level of the center pixel with other pixels in the local neighborhood [18]. If the gray-level values of any local neighborhood pixel is lower than the center pixel, the value of this pixel will be set to 0, otherwise it will be set to 1, and the LBP value of this center pixel is obtained by multiplying the assigned values with corresponding weights and adding the results together. Assume that the gray-level value of center pixel is p_c, and the pixels of local neighborhood is p_i, then the LBP value of pixel (x, y) can be represented as:

$$LBP_{R,N}(x,y)=\sum_{i=0}^{N-1} s(p_i - p_c)\, 2^i \tag{1}$$

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

Where R is the radius of local neighborhood, N is the number of pixels in the local neighborhood. Generally, the size of local neighborhood is selected as 3×3 (pixels), thus there are 8 pixels around the center pixel, and the 8-bit binary encoder is obtained, while the pixel gray-scale is 256 (8-bit). Taking the gray-level of 8-neighoring area for example, the process are showed in Fig.1(a). The binary sequence after threshold comparison is 10000111, and the

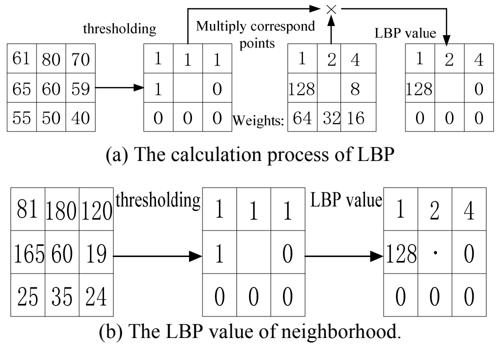


Figure 1. The LBP comparison of two local regions.

LBP value is 135 after decimal conversion. The histogram of the entire image can be achieved from the LBP value of each pixel, and thus the feature vector could be extracted.

From the above computation, it is noticed that LBP operator has the advantage of rotational invariant, balanced contrast and simple computation, however, there are also some disadvantages for LBP, e.g., low texture description resolution, and reliable to center pixel, it only compare the center pixel with its neighborhood pixel, while neglecting the relation among the neighborhood pixels. Thus sometimes although there is large variation for the pixel in the local neighborhood, the encoder is invariant. Take a look at the local neighborhood gray-level in Fig.1(b), it is noticed that gray-level is very different from Fig.1(a), while after LBP operation, the LBP value is 135, equivalent to the LBP of Fig.1(a). Consequently, traditional LBP operator cannot effectively describe the difference before and after nonlinear transformation, it will result in some significant texture feature loss.

B. LTP Operator

In order to overcome the deficiency of low resolution and weak anti-inference of LBP operator, LTP operator is improved based on LBP operator [19], Ternary encoding is taken for LTP operator, and 0, 1, 2 are set in the operator quantization stage, with the threshold t defined by user. The pixel difference in the range of [-t，t] is mapped in to 1, difference larger than t is mapped in to 2, and less than –t is mapped to 0, then s(p_i - p_c) will be transformed into the form of ternary encoding. The specific form is expressed as:

$$s(p_i - p_c) = \begin{cases} 2 & (p_i - p_c) > t \\ 1 & |p_i - p_c| \le t \\ 0 & (p_i - p_c) < -t \end{cases} \tag{3}$$

Where p_i is the gray-level of neighbor's pixel, and p_c is gray-level of center pixel, t is the threshold defined by user, thus the encoding form for the weights is:

$$LTP_{R,N}(x,y) = \sum_{i=0}^{N-1} s(p_i - p_c)\,3^i \tag{4}$$

LTP operator retains the advantages of LBP operator to effectively express the local image texture, pattern, micro-feature and improve the texture description resolution. In addition, it greatly improve the anti-inference ability by varying the threshold t, and act as an equalizer under the condition of uneven illumination. However, the value of t has great effect on the overall performance for LTP operator, thus the choosing of t is very critical. Since t is the threshold defined by user, and a certain threshold can not be applied to all the samples, thus it is necessary to find a way to automatically determinate the threshold t adaptive to the image variation, to further improve the performance of LTP.

III. ADAPTIVE TERNARY PATTERN OPERATOR

In order to solve the problem of determining threshold t difficultly, an adaptive threshold method is proposed in this paper. The principle of dynamically generating the threshold t is based on the degree of dispersion of neighborhood gray contrast value,that is LATP (Local Adaptive Ternary Pattern). Since the threshold t is generated dynamically, it can be applied to different samples, and thus solve the problem of universal adaptability.

The standard deviation σ in Data Statistics reflects the data distribution [20]. The smaller the σ value is, the more concentrated the data distribution is; vice versa, the larger value of σ denotes that the data distribution is discrete with large fluctuation, so the standard deviation σ is set as the threshold t in this paper. In the neighborhood domain of (R, N), the degree of dispersion σ on the gray contrast value between neighborhood pixels and center pixel reflects the variation of the pixel gray values in this region. Consequently, in this paper, the standard deviation σ is taken as threshold t, and the threshold t is dynamically determined according to the variation of contrast value between the center pixel and neighboring pixels, in order to strengthen the image texture feature description and reduce the sample influence. The process of threshold t computation is as follows:

(1) Compute the gray contrast value of center pixel and neighborhood pixel in the range of (R, N):

$$\Delta p_i = p_i - p_c. \tag{5}$$

(2) Compute the mean of the gray contrast values:

$$\overline{\Delta p_i} = (\sum_{i=0}^{N-1} \Delta p_i)/N \tag{6}$$

(3) Compute the variance of the gray contrast values:

$$D = (\sum_{i=0}^{N-1} (\Delta p_i - \overline{\Delta p})^2)/N \tag{7}$$

(4) Compute the threshold t:

$$t = \delta = \sqrt{D} \tag{8}$$

From the above process, it is noticed that the threshold t reflects the degree of dispersion of samples. The threshold t is automatically obtained with the aid of statistical method, and it varies with the changing of image gray-level, thus can applied to different samples. Fig.2 shows an example of LATP algorithm for a local neighborhood, the threshold t is adaptively gained firstly, and then LTP ternary encoding is performed.

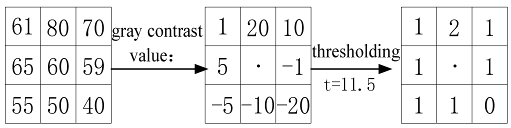


Figure 2. The threshold computation of LATP operator.

For the LATP method, the optimal threshold t is determined by the variance of neighborhood pixels, and it can adapt to the illumination difference of different area in an image. The fixed threshold is replaced by dynamic threshold, thus it is adaptive. LATP maintains the advantages of the traditional LTP, and also optimize the threshold t, thus it solve the problem of threshold variation intra-sample and inter-sample, improve the texture description resolution and robustness.

IV. DESIGN OF OECS-LATP DESCRIPTION OPERATOR

Since ternary encoding is taken for LATP operator, the texture description resolution is higher than LBP, however, the description dimension is also larger (3^N), it will greatly increase the computation complexity, and affect the real-time performance. Take the neighborhood of (1, 8) for example, the gray-level range for LATP is $LATP_{1,8}=3^8=6561$, while the LBP is $LBP_{1,8}=2^8=256$, so the computational complexity of ternary encoding is obviously higher than LBP. For this case, there are 2 ways to reduce the computational complexity, one is the mode of rotational invariance taken by Zhu [21], 24 modes with uniform values of 0, 2, 3, or 4 is taken for computation. Although the dimension and computational complexity are reduced, it neglected the case that when the Uniform value is not 0, 2, 3, or 4. The other way taken is to divide ternary into positive and negative modules, and the 0, 1, 2 ternary mode is replaced by -1, 0, 1:

$$s(p_i-p_c)=\begin{cases}1 & (p_i-p_c)>t\\ 0 & |p_i-p_c|\le t\\ -1 & (p_i-p_c)<-t\end{cases} \tag{9}$$

And then the ternary encoding is decomposed into positive and negative modules. For the positive module, -1 in the original code is changed to 0, and the other values keep invariant, while for the negative module, 1 in the original code is changed to 0, -1 changed into 1, and the other values keep invariant. Finally a group of binary number is obtained by taking the OR operation on these two modules. For example, an image after threshold is 1100(-1)(-1)00, the specific procedure of this method is illustrated in Fig. 3. Actually its objective is to decompose the original ternary code into two binary LBP codes. The dimension and computation complexity is reduced, but -1 is changed into 1, thus -1 is equivalent to 1, and the encoding process is:

$$s(p_i-p_c)=\begin{cases}1 & (p_i-p_c)>t\\ 0 & |p_i-p_c|\le t\\ 1 & (p_i-p_c)<-t\end{cases}$$

So the resolution and performance of ternary encoding will be greatly affected.

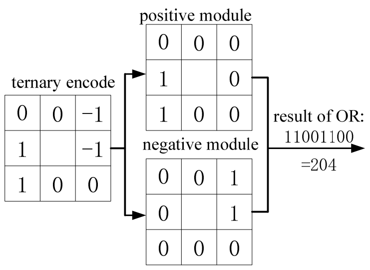


Figure 3. The calculation of positive and negative modules

In this paper, the Odd-Even parallel Center-Symmetric Local Adaptive Ternary Pattern (OECS-LATP) is proposed. It could decrease the feature dimension and computational complexity, while the texture information is effectively described. The procedure for OECS-LATP description operator is as follows:

$$H_1=\sum_{i=0}^{N/2-1} s(p_i-p_{i+N/2})\,3^i \tag{10}$$

$$H_2=\sum_{i=0}^{N/2-1} s(p_{2i}-p_c)\,3^i+\sum_{i=0}^{N/2-1} s(p_{2i+1}-p_c)\,3^i \tag{11}$$

$$LTP_{R,N}=H_1+H_2 \tag{12}$$

Where $s(x)$ is the weighting parameter with:

$$s(x)=\begin{cases}2 & x>t\\ 1 & |x|\le t\\ 0 & x<-t\end{cases} \tag{13}$$

Where t is the adaptive threshold, and obtained as Equation(5)~(8). Fig. 4 shows the process of encoding, the description operator is consists of H_1 and H_2, H_1 is to describe the relationship between the two center symmetry pixels of the center pixel. It indicates the multi-level difference of the symmetry pixels in a neighborhood, and it can also replace the gradient operator to describe local gray-level distribution. The extracted features by H_1 indicates the gray-level variation of local image area, and also have better ability of anti-interference to noise. H_2 is to describe the relationship between the neighborhood pixels and the center pixel. It indicates the variation between the neighborhood pixels. In order to reduce the computational dimension, the odd and even pixels are computed in parallel in the H_2, thus the image texture variation is described and computation complexity is reduced, the max dimension is 34+34+34=243.

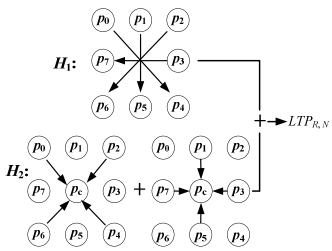


Figure 4. The algorithms of OECS-LATP.

V. EXPERIMENT RESULTS AND DISCUSSION

A. Brodatz Experimental Dataset and CUReT Experimental Dataset

In this paper, in order to validate the performance of OECS-LATP operator, Brodatz image texture set with even illumination(http://download.csdn.net/download/mm_fly/4403997) and CUReT image texture set with uneven illumination(http://www1.cs.columbia.edu/CAVE/software/curet) are selected for testing, and the testing performance is compared with LBP and LTP. Brodatz image texture set is generally regarded as typical image texture set, which include 111 kinds of natural texture image, 24 kinds of even texture image, and 87 kinds of uneven texture image. The size of each image is 640×640(pixels), several even texture pictures are shown in Fig. 5(a), and some uneven texture pictures are shown in Fig. 5(b). Since there is only one image for each kind of Brodatz image texture set, so each image is segmented into 16 sub-images of 160 × 160(pixels) for detection testing in this paper. The Fig. 6 shows image D42 after segmentation, 10 sub-images of which are used for training set, and the other 6 are used for testing set. In order to fully measure the algorithm performance, Brodatz image texture set is divided into 2 parts for testing: Part A1 include 24 kinds of even texture sets (384 sub-images), and Part A2 include 87 kinds of uneven texture sets (1392 sub-images). The testing will repeat for 50 times and take the average as the final results.

Compared to Brodatz image texture set, CUReT (Columbia-Utrecht Reflectance and Texture set) is more complex. It includes 61 kinds of texture images. Each kind of images include 92 images of same object in different lighting conditions or different shooting angles, so there is large difference between images even in the same kind of images, thus it is generally considered as texture database with great challenges. Part of CUReT images are shown in Fig. 7, some pictures of same object in different lighting conditions are listed in the first row, and some of different kinds of images are listed in the second row. The size of each image is 640×480(pixels). Because CUReT images are very large, 30 kinds of images are selected from 61 kinds of images for testing, and then 20 images are selected out for each kind of images.

(a) some examples of even texture images (A1)

(b) some examples of uneven texture images (A2)

Figure 5. Some examples of Brodatz images.

Figure 6. The 16 sub-images cut from D42.

Figure 7. Some examples of CUReT images.

For each image, it is split into 12 sub-images with size of 160×160 (same size as sub-image in Brodatz image texture set), and then 8 sub-images are selected as training set, and 4 images are selected as testing set. The total number of sub-images for testing is 7200. The testing procedure will repeat 50 times, and take the average as the final results.

B. Threshold t Setting and Detection Classification criterion

In this paper, OECS-LATP operator is utilized to extract the image texture features, and the first step is to adaptively determinate the threshold t. In theory, it needs to recalculate the threshold t for each pixel. In the actual process, there is no necessary to calculate the threshold t for each pixel when considering the system computation complexity and actual image variation. We split an image to be detected into several blocks, the threshold t for the center pixel of each block will be obtained as Equation (5)~(8), and the threshold t would be set as the threshold for whole block. Based on the computation complexity and image gray-level variation, the size of each block is set as 10×10 (pixels) in this paper. The nearest-neighbor classifier is used for retrieval, and the similarity for two images is measured by the Euclidean distance in texture histogram:

$$X^2(H_1,H_2)=\sum_{i=0}^{242}\frac{(h_{1i}-h_{2i})^2}{(h_{1i}+h_{2i})} \tag{14}$$

Where H_1、H_2 are the texture histograms for two images respectively, h_{1i}、h_{2i} are the image gray- levels respectively. The detection performance is measured by precision rate and recall rate.

C. Experiment Result Discussion

In order to better validate proposed algorithm, the performance of LBP, traditional LTP, SILTP and OECS-LATP algorithm was compared. The process of experiments is as follows:

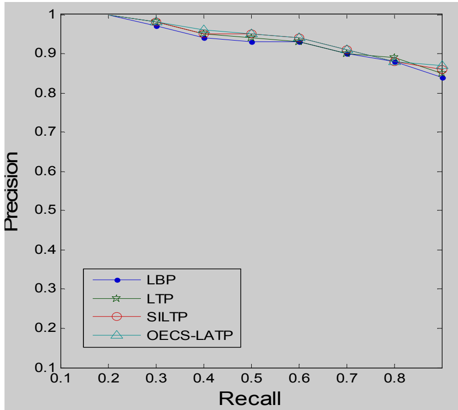
(1) The parameter settings for the experiments are: for the experiments in this paper, 8-neighborhood computation is selected, that is the radius of neighborhood R = 1, and the neighborhood pixel number N = 8. The threshold t for LTP algorithm is set as 20, while The threshold t for SILTP algorithm is set as $0.1\times p_c$. The size for each block in OECS-LATP operator is 10×10 pixels. Testing hardware setting are CPU-Pentium, basic frequency– 3.0 Ghz, Memory–2.0 GB, and the programs are written in Vc-language.

(2) According to the method in section 4.1, the selected images from Brodatz and CUReT sets are split into sub-images with size of 160×160, and then these sub-images will be divided into training set and testing set respectively. Finally all the sub-images will be transformed into corresponding texture images based on the algorithm of LBP, LTP, SILTP and OECS-LATP.

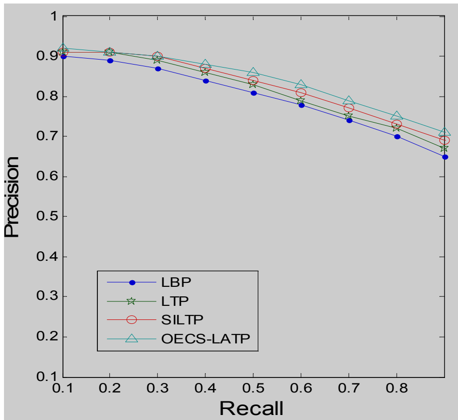
(3) The texture histogram of the sub-images in the training set from Brodatz and CUReT sets is extracted as feature vector.

(4) The texture histogram of the sub-images in the training set is extracted as feature vector, and then the image retrieval is performed according to Equation (14), thus we can search out the original image categories for the images in the testing set, and calculate out the results for LBP, LTP, SILTP and OECS-LATP algorithms.

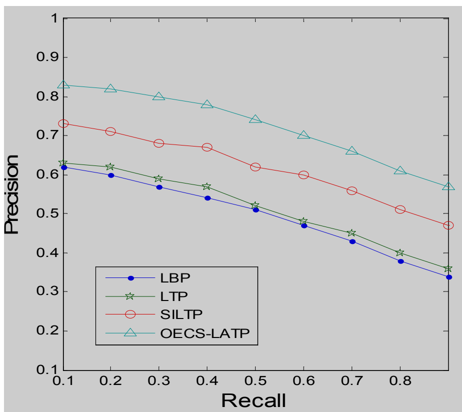
(5) After repeated experiments, the average values are taken as final results, the testing performance for part-A1 and A2 in Brodatz texture set and CUReT set is demonstrated in Fig. 8.



(a) the results of A1 texture images.



(b) the results of A2 texture images.



(c) the results of CUReT texture images.

Figure 8. Performance comparison among four algorithms.

In order to further analyze the influence of size of block on the performance with OECS-LATP operator, 1 × 1 (pixels), 10×10 (pixels) and 20×20 (pixels) are selected as the size of block for testing. The testing results on CUReT image texture set are listed in Table-1.

From Fig. 8, it is noticed that for the retrieval recognition of A1 image set, the average precision is very high (above 85%) with minor difference for all four algorithms, because the image texture in A1 is even, and the difference of all the sub-image after segmentation is small, thus small difference between testing samples and training samples. Consequently the retrieval precision is relatively high. While for the A2 image set, the retrieval precision of 4 algorithms are a little lower compared to that of A1, because the irregularity of the uneven texture in A2 results in great difference in the 16 sub-images after segmentation. From Fig. 6, it is noticed that after segmentation there are significant difference among the sub-images, thus will cause the great difference in testing samples and training samples, and affect the performance. Fortunately, OECS-LATP algorithm takes the adaptive ternary encoding in this paper, it not only considers the relationship between two symmetry pixels of the center pixel, and also the relationship between neighborhood pixels and center pixel when describing the texture features, thus the detection precision has improved approximately 6% compared with LBP and 4% with the SILTP. Consequently, the performance is improved under the conditions of some information loss for OECS-LATP algorithm.

TABLE-1 PERFORMANCE COMPARISON FOR DIFFERENT ALGORITHMS

	Average Precision (%)	Retrieval Time (ms)
LBP	47	150
LTP	49	155
SILTP	58	156
OECS-LATP(1×1)	73	200
OECS-LATP(10×10)	70	160
OECS-LATP(20×20)	61	158

For CUReT image texture set, each kind of images are several images of same object in different lighting conditions or different shooting angles, thus the accuracy of 4 algorithms are all lower than previous experiments. The largest decreasing degree is from LBP, the highest precision is 62%, and average accuracy is 47%. While for the OECS-LATP algorithm in this paper, the highest accuracy is 83%, and average precision is 70%, 23% higher than LBP, 21% higher than LTP, and 12% higher than SILTP, thus the detection performance of OECS-LATP algorithm is obviously better than the other 3 algorithms. Since LBP and LTP take the fixed threshold of gray-level, and they are sensitive to uneven lighting illumination, so it will result in lower detection precision. Although the threshold for SILTP varies as the change of images, it varies based on the central pixel without considering of the neighboring pixels, thus the detection performance is not very good. However, for OECS-LATP algorithm in this paper, the optimal threshold t is adaptively determined based on all pixels in the region and ternary encoding is taken to improve the resolution. In addition, it not only considers the relationship between two symmetry pixels of the center pixel, and also the relationship between neighborhood pixels and center pixel when designing the description operator. Consequently, it has higher resolution and robustness under the conditions of uneven lighting illumination and partial information loss. In order to further validate our proposed algorithm, a texture image taken by author is transformed into local texture images, and the parameters setting are same as the above experiments. The results are shown in Fig. 9. The original image in the figure is under uneven lighting illumination, we noticed that there are also uneven bright points after LBP and LTP algorithm, and this phenomenon is little improved with SILTP algorithm, while it is greatly improved with the OECS-LATP algorithm in this paper.

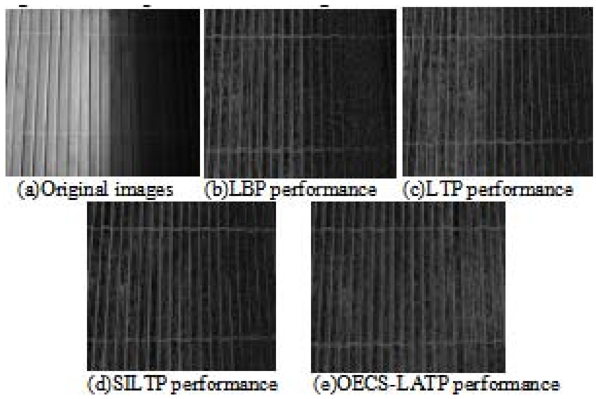


Figure 9. Original image and texture images for different algorithms.

From Table-1, the size of block has great effect on the performance of OECS-LATP algorithm. The smaller the block is, the more reasonable the threshold t is, and the testing accuracy will be higher, while it will last for longer time, thus it is better to make a trade off between accuracy and timeliness.

From the above experiments, it is concluded that the main advantages for the OECS-LATP algorithm in this paper are applications in the cases of uneven lighting illumination and partial information loss.

VI. CONCLUSIONS

In this paper, OECS-LATP is proposed to overcome the disadvantages of the traditional LPB and LTP algorithm:

threshold is not automatically determined, texture description resolution is not very high, and only Uniform mode is encoded. OECS-LATP takes ternary encoding to improve the texture description resolution. In addition, the optimal threshold t is adaptively determined based on the variance of local gray-level variation, thus even images can be obtained under large variation illumination condition. Finally, the description operator not only considers the relationship between two symmetry pixels of the center pixel, and also the relationship between neighborhood pixels and center pixel, thus the texture information can be fully captured, and the system computation complexity is lowered. Consequently, compared to the traditional LBP, LTP and SILTP algorithm, the OECS-LATP algorithm proposed in this paper greatly improve the texture resolution and robustness under the conditions of partial information loss or uneven lighting illumination.

One drawback of the proposed operator is that the image is divided into several blocks in rigid way, and then the threshold t for each block is adaptively determined. Hence in the future work, we will focus on how to divide the image into several blocks in flexible way based on the variation of image texture, and then adaptively determine the threshold t for each block, thus the performance of the proposed algorithm will be further improved.

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REFERENCES

[1] K. C. Song, Y. H. Yan, W. H. Chen and X. Zang, "Research and Perspective on Local Binary Pattern," Acta Automatica Sinica, vlo.39, no.6, pp.730-744, 2013.

[2] S. Ma, K. Liu and G. Xu, "Illuminaton analysis of texture image based on colour statistics invariange," Computer Applications and Software, vlo. 31, no.2, pp.233-237, 2014.

[3] Penatti O. A. B, Valle E and Torres R. S, "Comparratives Study of Global and Texture Descriptors for Web Image Retrieval," Journal Visual Communication and Representation, vol.23, no. 2, pp.359-380, 2012.

[4] H. X. Wang, J.H. Fan, Y. Li, "Research of shoeprint image matching based on SIFT algorithm," Journal of Computational Methods in Sciences and Engineering, vol. 16, no. 2, pp. 349-359, 2016.

[5] W. Zhou, H.Q.Wang.,C.M. Yang etc, "Decision tree based medical image clustering algorithm in computer-aided diagnoses," Journal of Computational Methods in Sciences and Engineering, vol. 15, no. 4, pp. 645-651, 2015.

[6] Loris N, Atessandra L and Sheryl B, "Survey on LBP based texture descriptors for image calssifition," Expert System with Applications, vol.39, no.3, pp. 3634-3641, 2012.

[7] J. Y. Zhang, H. P. Zhao and S. Chen, "Face recognition based on weighted local binary pattern with adaptive threshold," Journal of Electronics & Information Technology, vol.36, no.6, pp.1327-1333, 2014.

[8] Lior W, Tal H and Yaniv T, "Effective uncon-strained face recognition by combining multiple descriptors and learned background statistics," IEEE Pattern Analysis and Machine Intelligence, vol.33, no.10, pp.1978-1990, 2011.

[9 S. R. Zhou, J. P. Yin, "LBP Texture Feature Based on Haar Characteristics," Journal of Software, vol.24, no.8, pp.1909-1926.2013.

[10] C. L. Qiu, Q. Tao, R. L. Fan and P. Z. Wang, "Zircon image matching method based on description of SIFT feature by LBP," Journal of Jinlin University (Engineering and Technology Edition), vol.44, no.6, pp.1793-1798, 2014.

[11] H. J. Qu, J. Li, Y. R. Wu ect, "Statistical texture image retrieval combining filter selection and phase information," Application Research of Computers ,vol.31, no.12, pp.3894-3897, 2014.

[12] Y. N.Chu, Y. Y. Wang and J. W. Zhu, ect, "Improved LBP descriptor in pancreas endoscopic ultrasound image feature extraction," Chinese Journal of Scientific Instrument, vol.35,no.12, pp.182-185, 2014.

[13] S. Lin, W. Wu and W. Q. Yuan, "Palm vein identity recognition based on local texture description operator," Chinese Journal of Scientific Instrument,vol. 35, no.10, pp.2306-2313, 2014.

[14] G.P. Dai, H. B.Lin, "Palm Print Detection Based on Nonsubsampled Contourlet Transform and MB_LBP Histogram Algorithm," Chinese Journal of Sensors and Actuators, vol.27, no.10, pp.1387-1393,2014.

[15] X..Y. Tan, Trigge B, "Enhanced local texture feature sets for face recognition under difficult lighting conditions," Proceedings of the 3rd International Conference on Analysis and Modeling of Faces and Gestures.Brazil, pp.168-182, 2007.

[16 L. F. Chen, Y. M. Liu and Y. Liu, "An image matching algorithm combining SIFT and its correspond- ing scale LTP feature," Computer Engineering & Science, vol.37, no.3, pp.582-588, 2015.

[17 G. L.Yang, D. Zhou, J. H. Zhang, "Moving Object Detection Algorithm Using SILTP Texture Information," Computer Science, vol.41, no.4, pp.302-318,2014.

[18] J. Li and Allins N. M, "A comprehensive review of current local features for computer vision," Neurocomputing, vol. 71, no.10-12, pp.1771-1787, 2008,

[19] J. Tian, G. L. Wang and Z. T. Qiao, "Moveing objects detecting LTP combining with illuminaton compensation," Computer Measurement & Conter, vol.23, no.10, pp.3434-3437, 2015.

[20] D.Q. Wu, Z. Z. LÜ, W.R.Hao, "Analysis of The Influence of Distribution Parameters on Variance Distribution," Engineering Mechanics, vol.31, no.5, pp. 238-243, 2015.

[21] Q. D. Zhu, X. Liu and C.T. Cai, "Image local invariant feature description with high robustness and uniqueness," Systems Engineering and Electronics,vol. 35, no.9, pp.1983-1988, 2013.