BRIEF Features for Texture Segmentation

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Binary Robust Independent Elementary Feature (BRIEF) has been successfully used as an efficient feature point descriptor. It uses can be found in many computer vision application such object recognition and camera localization. This is due mainly to its discriminating ability and computational simplicity as well as invariant to illumination variations. In this paper we use a slightly modify BRIEF descriptor as a method to measure texture and apply them in texture segmentation application. Experiments are conducted on a standard test suite of test images and shows that BRIEF texture features is better and in some cases compare favorably with other established texture measures.

Keywords: BRIEF, texture analysis, texture descriptors, image processing

1. INTRODUCTION

Texture analysis is an area of intense research. Its two main problems, texture classification and texture segmentation had received considerable attention from research community. This may be due to the important role they played in many disciplines and related applications. Although widely used, currently there is no agreed upon definition of textures. This lack of definition however does not prevent researchers from attempting to define texture in a quantitative way. As a result, over the years, we have seen the emerging of many algorithms to measure texture.

One of them is based on representing texture images statistically as histograms over a discrete vocabulary of local features [1-3]. The method has proven widely effective for many texture analysis tasks especially for image classification. Using the method, images are described locally by vectors of, for example, pixel comparisons in the local neighborhood, then they are assigned to predefined bins according to some partition of the feature space[3]. One of the well-known texture measurement which is based on this paradigm is Local Binary Pattern (LBP)[1].

LBP and its variants have been successfully applied to many diverse area of image processing such as in face recognition, image retrieval and biomedical image analysis. The success of LBP as a texture measure is due to its valuable advantages such as (1) ease of implementation, (2) low computational complexity and (3) invariance to monotonic illumination changes[3]. Although discriminative, LBP and most of its variants have several limitations. Two of them are sensitivity to noise [4-5] and failing to capture the long range textural information [4-6].

In 2010, a representation similar to LBP was described as feature point descriptor and used to match images seen from different viewpoints. This representation is known as Binary Robust Independent Elementary Features (BRIEF)[7]. BRIEF is similar to LBP in the sense that the descriptor is formed based on pixel comparisons in the local neighborhood. Thus BRIEF also shared similar advantages as LBP that is the descriptor is very fast to compute and tolerant to any monotonic increase or decrease of image intensities, which makes the descriptors invariant to illumination. Further, it does not require too many parameters to be set, which make it easily adaptable to various texture analysis application.

The main differences between the two are, first in the selection of test points; LBP relies on a fixed circular geometry for its test points while BRIEF's test points are collected randomly. This can possibly be an advantage for BRIEF features because based on experiments conducted, the performance is better when the test points are collected randomly compared to when they are collected based on specific fixed geometry[4].

Further, this random selection of test points suggested that it is possible to widen the spatial context from which the test points are selected i.e. using a larger sampling radius and with an increase number of test points. As a result BRIEF features can possibly be used to model larger features and to capture texture information over a longer range.

The second important difference between BRIEF and LBP is the use of smoothing operator. When calculating

either BRIEF descriptor or LBP descriptor, only information at single pixels is taken into account, therefore it is very noise sensitive. With BRIEF, to reduce this sensitivity and thus increase the stability and repeatability of the descriptor, the image patch is first smoothed. The BRIEF descriptors are then extracted from the smoothed image patch, thus making them less sensitive to noise.

In this paper, we proposed texture measure which measures the grey scale patterns in local image patches in BRIEF-like representation. Once extracted, the BRIEF-like descriptors are collected to form a histogram and used as image representation. We then performed texture segmentation experiment using BRIEF as texture feature on a standard test suite. The experiment help in answering two important questions: (1) can BRIEF texture be used for texture segmentation?, and (2) how does BRIEF performance compared to other existing texture measurement?

The remainder of this paper is organized as follows. Section 2 start with a brief definition of the original BRIEF descriptor. This is followed by detailed description of our proposed texture measure. The experiment setup, result and discussion are in Section 3, 4 and 5 respectively. Finally Section 6 concludes the paper.

2. BRIEF AS TEXTURE MEASURE

In order to use the BRIEF descriptor as a texture measure, a slight modification to the original BRIEF definition is introduced. In this section we will start with a short description of the original BRIEF, followed by a detail description of the proposed modification. In particular we will discussed issues involving how the test between pixel pairs is defined, the spatial arrangement of the test location that make up the pixel pairs and the length of the descriptor (i.e. the number of pixel pairs).

2.1 OVERVIEW OF BRIEF DESCRIPTOR

BRIEF descriptor is originally used for feature matching. The original brief descriptor is formed by taking a smoothed image patch and computing the result of a predefined binary test of *n* pixel pairs. The pixel pairs are chosen from within the patch and their intensities are compared, if one pixel is less than the other then the binary test result is set to '1' otherwise it is set to '0'. This test, τ for a patch *p* of size *S x S* is defined in Eq. 1.

$$\tau(p; x, y) = \begin{cases} 1 & \text{if } p(x) < p(y) \\ 0 & otherwise \end{cases} \quad (1)$$

Where *p(x)* and *p(y)* are the pixel intensities in a smooth patch *p* at locations *x* and *y*. Choosing a set of *n* location pairs will uniquely defines a set of binary tests.

The final output of the BRIEF operation on an image patch is then defined as a binary string of length *n*, which correspond to:

$$f_n = \sum_{1 \le i \le n} 2^{i-1} \tau(p; x_i, y_i) \quad (2)$$

In the original paper the values of *n* used are 128, 256 and 512.

2.2 MODIFICATION

2.2.1 TEST DEFINITION

The original BRIEF descriptor requires the image patch to be smoothed before obtaining the pixel pairs comparison. However the use of smoothing raises a concern that is it may cause loss of image detail. Because of that for our proposed work we opt not to use the smoothing process. To handle noise we introduce a threshold when comparing the pixels, i.e. the result of the binary test is set to '1' if the difference between a pixel pair is greater than a threshold and '0' otherwise. The formal definition of the new comparison test τ is as Eq.3, and the resulting BRIEF descriptor is defined in the same manner as Eq. 2.

$$\tau(p; x, y) = \begin{cases} 1 & \text{if } p(x) - p(y) > Threshold \\ 0 & otherwise \end{cases} \quad (3)$$

Where *p(x)* and *p(y)* are the pixel intensities in a patch *p* at locations *x* and *y*. The threshold will help to increase the stability of the descriptor especially when calculating BRIEF descriptors in a uniform region which can be dominated by noise.

2.2.2 SPATIAL ARRANGEMENT OF PIXEL PAIRS

Work by Colander et al.[7] experiments with several spatial arrangement of the test locations or pixel pairs. They tested both symmetrical and regular spatial arrangement and also on random spatial arrangements. Based on the experiments, they conclude that the random strategy performed better than the symmetrical and regular strategy. Because of that in this work, we also use random selection of pixel pairs from within the patch. The pairs are predefined during initialization, and then the same pairs are used for training and analysis of all texture classes.

2.2.3 LENGTH OF PIXEL PAIRS

In the original work, 256 pixels pairs were used to form a BRIEF descriptor. Since our plan is to use the descriptor in a histogram framework, the use of 256-bit descriptor will result in a very large histogram. Therefore, in our implementation a much shorter BRIEF descriptor is used. And as will be shown later, for texture segmentation, a smaller number of pixels pairs is already sufficient and able to demonstrate good performance.

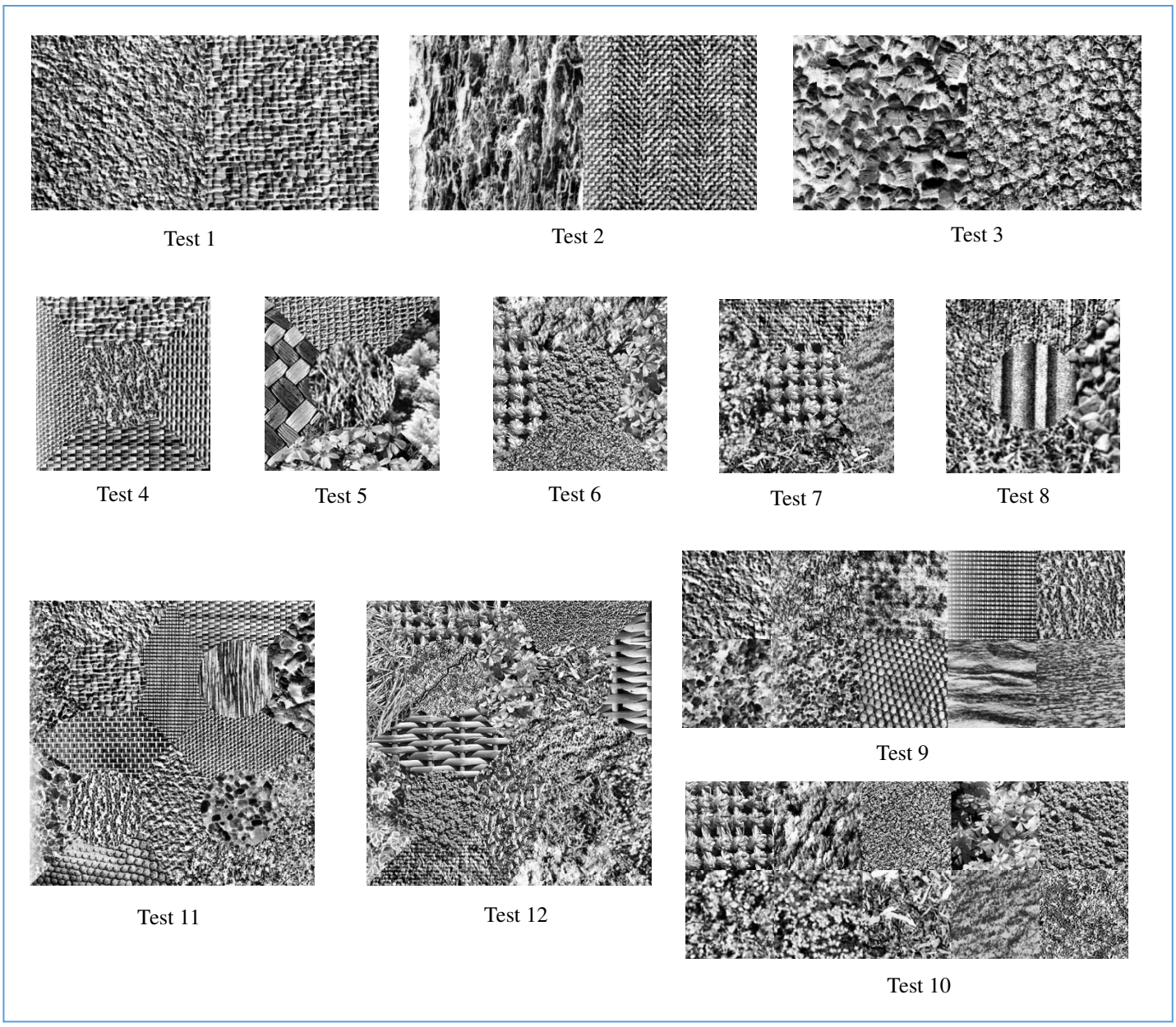

Fig.1.Texture mosaics used in the segmentation experiment

3. EXPERIMENTS

The test suite[8-10] used in the experiment is shown in Figure 1. There are twelve test images in the test suite, consisting of images with two, five, ten and sixteen texture classes. The test images in the test suite are of varying complexity, for example, in the test suite, there are images with two textures and simple border as well as images with 16 textures and complex borders. The texture images used to form the test suites are all visually stationary, i.e. their visual property does not change too much over the image and were obtained from Brodatz album[11], the MeasTex Image Texture Database[12] and the MIT Vision Texture database [13].

Initial experiment with BRIEF shows that BRIEF performance is better when a larger pixel pairs is used. On the other hand, given the size of the test and training images using a too large pixel pairs may result in a histogram which is too sparse. Furthermore it was also observed that the optimal BRIEF parameter for each texture types is different. Because of the said reasons, in the experiment, we systematically evaluate the BRIEF representation over a range of parameter settings, i.e. for the patch sizes, we used 3x3, 5x5 and 7x7, for pixels pairs we used 7, 8, 9 and 10 and we vary the threshold from 0 to 12.

The segmentation was made on a pixel by pixel basis, whereby each pixel was classified into one of the training classes. Given an image pixel, a BRIEF histogram is calculated using its neighborhood, then similarity measures against all training class are computed and the pixel is assigned to the most similar one. In this work Chi-squared distance is used as the distance measure. To quantitatively evaluate the segmentation performance, for

each test image we calculate the percentage of correctly labelled pixels or the segmentation accuracy.

4 EXPERIMENTAL RESULT

The result for each test image is summarized in Table 1. It report the highest average segmentation accuracy obtained by each test image and their respective parameters. Based on the result we can see that BRIEF features were able to segment the various textures quite well. For simple two texture classes, the accuracy achieved in all cases is above 95%, while for more complex texture composites the accuracy drops, as expected, but still within acceptable rate. The two lowest accuracy were 76.7% and 76.9%, obtained with 10 and 16 texture classes respectively. Both test images were made up from texture classes obtained from the MIT Vision Texture database.

Figure 2 shows the effect of threshold on the segmentation accuracy. During this experiments other parameter are kept at their optimal values. As can be seen from the figure, the optimal threshold is texture dependent.

Table. 1. Highest segmentation accuracy for each image and their respective parameters.

TEST IMAGES	ACCURACY (%)	PATCH SIZE	PIXEL PAIRS
Test 1	99.4	7x7	7
Test 2	99.5	7x7	9
Test 3	97.9	3x3	7
Test 4	95.0	7x7	9
Test 5	92.4	3x3	8
Test 6	87.8	3x3	9
Test 7	87.9	3x3	10
Test 8	91.8	7x7	10
Test 9	84.0	7x7	8
Test 10	76.7	3x3	8
Test 11	82.9	7x7	10
Test 12	76.9	5x5	9

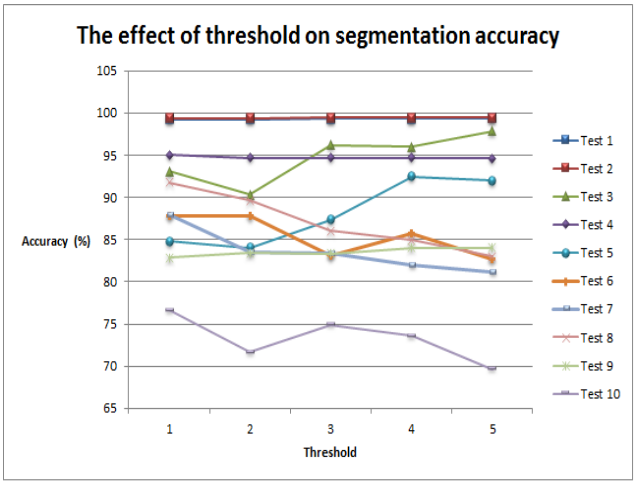

Fig.2. Effects of changes in threshold upon segmentation success. Each curve represents the different test images.

4.1 COMPARISON WITH OTHER METHODS

As the test images that we used were previously tested in Maenpa et. al [8] and Randen et al. [9], we used the results reported in the two papers to benchmark the proposed approach. Since the performance measure used in both works is based on calculating the percentage of misclassified pixels or error rate, we will used the error rate as the metric for the comparison. Table 2 lists the results.

The work in Randem et. al. evaluate several filtering approaches to segment the test images mentioned earlier. Among the filtering techniques evaluated is Discrete Cosine Transform, Dyadic and optimized Gabor filter bank, Daubechies wavelets and optimized FIR filter. In addition they also evaluated GLCM and multiresolution autoregressive. The results in the Table 2 are the highest result obtained by their work for the respective test images.

The work in Maenpa et. al. on the other hand used local features based on LBP and Multi-predicate LBP (MP-LBP). MP-LBP is a type of LBP descriptors which are calculated over multiple neighborhood sizes. In their work, the best performance MP-LBP is calculated with neighborhood size of *3x3* and *7x7*. Therefore these results were used for comparison.

Compared with filtering approaches, in most cases BRIEF's performance is better. The test image where BRIEF performance is lower than the filtering based approach is Test 2, with a difference of 0.1%. Although lower, considering that the error rates achieved for BRIEF in this test images is less than 1%, we conclude that the result still demonstrates good performance from BRIEF features. Compared with LBP and M-LBP, the result can be said as comparable. If the average error rates for all test images is compared, BRIEF features is better than LBP by 1.6 and MP-LBP by 0.02%.

Table. 2. Comparison of segmentation result with other approaches. MP-LBP refers to Multi-predicate LBP calculated using neighborhood of size 3x3 and 7x7.

TEST IMAGES	ERROR RATE (%)			
	BRIEF	LBP_{3x3}	MP-LBP	FILTERING
Test 1	0.6	0.3	0.4	0.7
Test 2	0.3	1.0	0.8	0.2
Test 3	2.1	9.9	5.3	2.5
Test 4	5.1	6.2	6.7	7.2
Test 5	7.6	18.1	14.3	18.9
Test 6	12.2	12.1	10.2	20.6
Test 7	12.1	10.0	9.1	16.8
Test 8	8.2	10.9	8.0	17.2
Test 9	16.0	22.8	18.1	32.3
Test 10	23.35	19.2	21.4	27.8
Test 11	17.1	16.8	15.3	34.7
Test 12	23.1	20.8	20.7	41.7
Mean error	**11.4**	**12.3**	**10.9**	**18.4**

5. DISCUSSION

Filtering approaches have been shown to demonstrate good accuracy in many applications of texture segmentation. However the computational complexity of filtering approaches is often very high. LBP is another texture feature which has been shown to perform well in texture segmentation and in some cases better than filtering approaches. Furthermore it is of low computational complexity, making it preferable for many applications.

However, basic LBP has several drawbacks. One of them is the fact that it is computed over a 3x3 neighborhood, thus they are unable to capture the long range texture information. For that reason, MP-LBP was created. MP-LBP is a combination of LBP histograms obtained by calculating LBP histogram over multiple neighborhood sizes. Thus this representation is able to cater for a longer range of texture information. The advantage of MP-LBP over LBP is clearly demonstrated in Table 2.

BRIEF can also be used as textural feature for texture segmentation, as demonstrated by the experiment's result. Based on average error rates obtained from the test images, our approach is better than the filtering approaches and LBP approaches and comparable to MP-LBP performance.

Other than better performance, BRIEF offers some advantages over the other approaches. First contrary to filtering approaches describe by Randen et.al, our method employs a single features for all test images and it is much simpler than their sophisticated filtering. It is important to note that some of the best result achieved by Randen et. al are obtained using optimized filters. Second, one interesting feature of BRIEF is it can be used with any neighborhood size, thus the spatial support area can be adjusted based on requirements. Thus BRIEF offers an alternative to differentiate images containing textures with different scales.

Compared to MP-LBP, the BRIEF descriptors need only be calculated once, whereas with MP-LBP, the descriptor is calculated over multiple neighborhood and their joint histograms are used as features. This will increase not only the computational burden but aliasing effects may also occur[6].

6. CONCLUSIONS

In this paper a method for constructing local texture descriptors based on BRIEF representation was presented. The proposed algorithm results in a binary code for each pixel, which can be subsequently used to construct a histogram representation. We then performed a supervised texture segmentation experiment using BRIEF as features. The results obtained from the experiments helps in answering the two question posed in the introductory question. The answer to the first introductory question, 'Can BRIEF texture be used for texture segmentation?' is yes as demonstrated by the experiments result. The second question was 'How does BRIEF performance compared to other existing texture measurement?' Based on the experiments result, using average error rate as reference, our proposed approach performed better than filtering approaches and basic LBP and comparable to MP-LBP describe in the two paper mentioned earlier.

The results so far showed promises in using BRIEF as a texture measure. Thus in future, we would like to experiment BRIEF with images with more variable image conditions. In particular, we would like to determine how BRIEF cope with noisy image. Further investigation on the value of the threshold is also needed. In this investigation, the threshold is determined empirically. In future we will look into making it adaptive.

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