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Multiple-sampling Dense Micro-block Edge Difference for Texture Classification

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Abstract

The dense micro-block difference (DMD) is an efficient texture feature extraction descriptor. However, most DMD methods are not comprehensive enough to extract texture features under complex imaging conditions, and the performance is inferior under the condition of fewer training samples. To alleviate the above problems, we present a multiple-sampling dense micro-block edge difference (MDMED) descriptor for texture classification. Specifically, we first employ Gaussian distribution and T-distribution function to produce sampling points in the image patch in order to capture a larger range of feature information. Secondly, we use the intensity and edge difference information between pairs of micro-blocks to build a local MDMED descriptor at different scales, which can capture more detailed texture features at multiple-scales. Finally, we use the improved fisher vector (IFV) to encode the MDMED features, and then put them into the support vector machine (SVM) classifier for texture classification. The experimental results reveal that MDMED outperforms the seven typical methods under the condition of viewpoint changes, illumination and fewer training samples.

Keywords

Dense micro-block difference (DMD), Multi-scale sampling, Texture classification.

1. Introduction

Texture is an important attribute feature in image, and the study of texture features is also a key concern in the field of pattern recognition and image processing [1]. Due to the importance of the texture features, enormous number of applications based on texture features have been highly applied in the computer vision domain, including texture image classification [2], image segmentation [3], face recognition [4], and object detection [5]. Texture image classification is an important branch of texture feature application, and the core part of texture classification/ representation research is texture feature extraction. After more than half a century of texture classification research, various classic theories and algorithms have emerged. They usually including: structural method [6], statistical method [7], model method [8] and frequency domain method [9].

In many texture representation methods, local binary pattern (LBP) [10] is a typical texture feature extraction method that attracted attention. This method is simple to calculate and easy to implement. However, the calculation method of using thresholds for quantization in LBP is led to the loss of intensity information. Mehta et al. [11] presented a novel texture extraction method named dense micro-block difference (DMD). This method does not involve any threshold quantization, which can effectively capture multi-scale, multi-directional information.

However, the DMD method is not stable under the conditions of illumination, image scaling, and fewer training samples. Aiming to alleviate the above problems, in this paper we present an effective texture descriptor: multiple-sampling dense micro-block edge difference (MDMED) for texture representation. Specifically, we first employ Gaussian distribution function and T-distribution function to produce paired sampling points in each image patch. Secondly, we extract pixels intensity and edge difference information from the micro-block pairs generated under various scales and build multi-scale MDMED descriptor. In addition, we use an improved fisher vector (IFV) [12] to encode the features extracted by the MDMED descriptor. Finally, we input the features encoding into a support vector machine (SVM) classifier for texture classification. Related experiments demonstrate that MDMED based method is superior to seven representative methods on available published texture data sets.

The major contributions of our proposed MDMED approach are as below: First, we propose a multiple-sampling method that utlizes Gaussian distribution function and T-distribution function. The paired sampling points generated under the two distribution functions can capture larger scale texture feature information. Second, We propose a multiple-sampling dense micro-block edge difference (MDMED) descriptor by extracting the pixels intensity difference and the edge features information of the four directions, followed by an improved fisher vector (IFV). The proposed MDMED descriptor captures more detailed micro-feature information such as brightness and edges information. Finally, A variety of experiments demonstrate that MDMED based method is superior to the seven represent methods under four available international general texture datasets.

The remaining of the paper is arranged as follows: Section 2 introduces our presented method and the texture classification process based on MDMED. The results of the experiment and the corresponding contrast analysis are shown in Section 3. The final conclusions are given in Section 4.

2. Multiple-sampling dense micro-block edge difference (MDMED)

In this section, we present a multiple-sampling dense micro-block edge difference (MDMED) method to represent an image texture, and further use it for texture classification. In the following, the MDMED based texture representation method will be introduced in detail from four parts: multiple-sampling scheme, micro-block edge feature extraction, multi-scale MDMED feature extraction and image feature coding.

2.1. Multiple-sampling scheme

The MDMED uses image patchs of different sizes for sampling. From these square image patchs of different sizes, using pairs of micro-blocks in different sizes to encode the local structure [11]. As shown in Figure 1, an image patch with a size of 15×15 centered on C_p contains six pairs of micro-blocks connected by straight lines, and the sizes of the micro-blocks are 1×1 and 3×3, respectively. For the convenience of description, Figure 1 only shows six pairs of micro-blocks in one image patch. In the following experiments, we use micro-block pairs of different sizes, such as 4×4 and 5×5. We denote the micro-block pair as (x_i, y_i), $i=1,2,...,N$, where N represents the number of micro-block pairs in an image patch. We employ two sets of sampling points $X=\{x_1, x_2,..., x_N\}$ and $Y=\{y_1, y_2,..., y_N\}$ to determine the center coordinates of all pairs of micro-blocks.

Different from the traditional DMD sampling point generation strategy, we apply the Gaussian function with a mean of 0 and a variance of $L^2/25$ to produce the set of sampling points in X; use the T-distribution function with $\sqrt{L}$ degree of freedom to produce the sampling points in the Y set, where L is the size of the image patch. As shown in Figure 1, the center coordinates of the red 3×3 micro-blocks are generated by the Gaussian function, and the center coordinates

of the purple 3×3 micro-blocks that exist in pairs are generated by the T-distribution function. Among the micro-blocks with a size of 1×1, the blue squares are generated by the Gaussian function, and the green squares are generated by the T-distribution function.

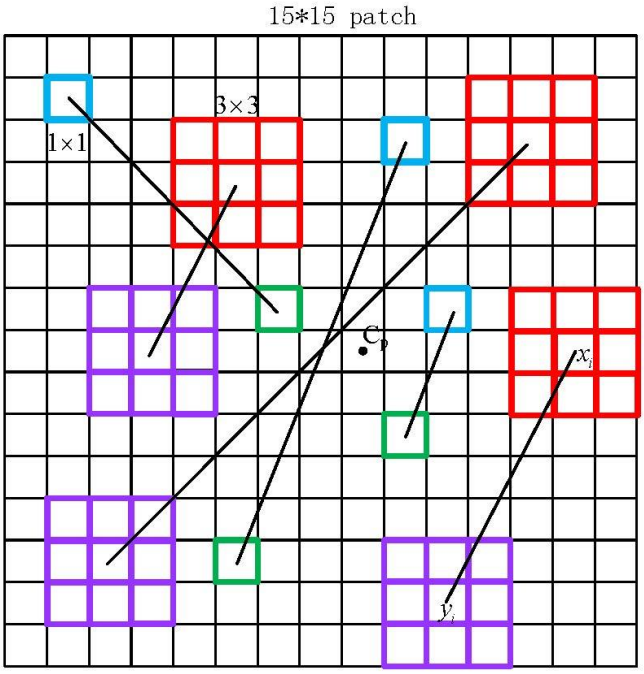

Figure 1: MDMGD sampling diagram

Since the distance between pairs of micro-blocks in an image patch is not constant, the use of T-distribution in an image Patch can capture a larger range of micro-block pairs, which is beneficial to capture information at different scales [13]. In order to enable the paired micro-blocks to capture a larger range of feature information, we use the Gaussian distribution and the T-distribution to generate the sampling point coordinates at the same time. The paired micro blocks generated by different distribution functions can extract wider range feature information than use Gaussian distribution or T-distribution solely.

2.2. Edge feature extraction of dense micro-blocks

After the paired micro-blocks are produced in the image patchs, the integral graph method is used in the original DMD feature to quickly calculate the intensity of the pixels in the sampling area. However, only use the integral graph to calculate difference information between the pair of micro-blocks is not enough. In the field of image processing and computer vision, the edge features of an image can identify points in a digital image that have obvious changes in brightness and darknes [14]. Therefore, we introduce edge feature information into the micro-block pairs to enhance the discriminative information contained in the paired micro-blocks.

More specifically, we first use the prewitt first-order differential edge detection operator for all pixels in each image patch, and obtain the horizontal gradient feature g_x, vertical gradient feature g_y, and two diagonal gradient features of the micro-block g'_x and g'_y. As shown in Figure 2, the corresponding feature vector in the micro-block with the center point x_i and the size s can be expressed as $V_{x_i,s}=(I,g_x,g_y,g'_x,g'_y)$, where I represents the pixel intensity information of the micro-block quickly obtained using the integral image, and the

corresponding micro-block $V_{y_i,s}$ can be calculated in the same way. The difference features between the paired micro-blocks of size s can be calculated as $V_{(x_i,y_i),s} = V_{x_i,s} - V_{y_i,s}$.

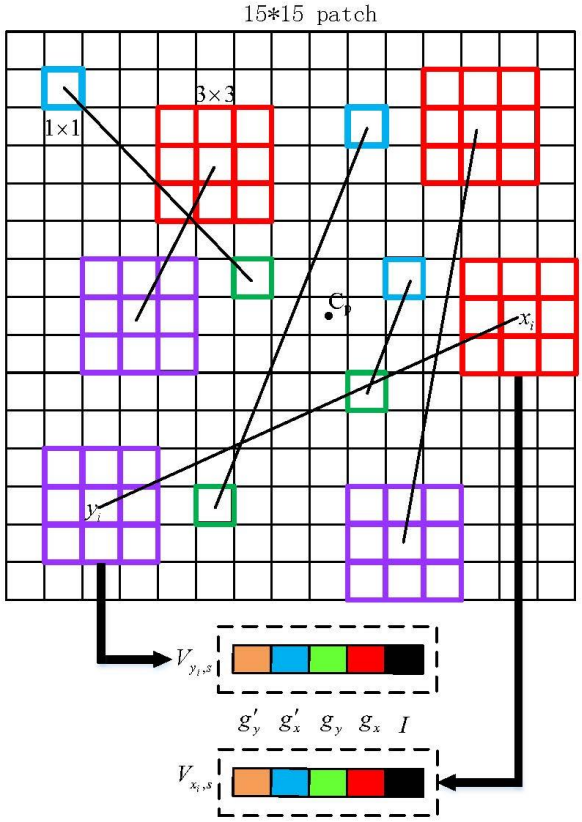

Figure 2: Schematic diagram of micro-block edge feature extraction

It is worth noting that, Figure 2 only shows six pairs of micro-blocks in the local area of the 15 × 15 image patch. In our specific experiment, we will use image patchs and micro-blocks of different sizes, such as: 14 × 14; 1 × 1 and 2 × 2 micro-block pairs. Combining paired pixels intensity difference features with edge features can provide more detail features information about the local structure.

2.3. Multi-scale MDMED Feature Extraction

Using different distribution functions to generate micro-block pairs can describe the upper features of the local texture structure in different directions. In order to enable the image patch to capture more discriminative information, we sample the micro-block pairs at multiple scales. First, we define a set $U = \{u_1, u_2, ..., u_m\}$ of micro-block pair scales, where m represents the number of scale information contained. Each image patch of different size contains N micro-block pairs, the number of micro-block pairs contained in each scale is $N_t = N/m$. Then we can rewrite the sampling point coordinate sets X and Y in the micro-block pair as $X = [X_{u_1}, X_{u_2}, ..., X_{u_m}]$ and $Y = [Y_{u_1}, Y_{u_2}, ..., Y_{u_m}]$ to identify micro-block pairs of different scales. We use V_{U_m} to represent the scale information contained in the paired sets of micro-blocks at different scales, and V_{U_m} can be defined as

$$V_{U_m} = \left\{ (X_{(m)}^{N_{t+1}}, Y_{(m)}^{N_{t+1}}), ..., (X_{(m)}^{N_t}, X_{(m)}^{N_t}) \right\}. \quad (1)$$

In an image patch, based on the set of paired micro-blocks V_{U_m}, we calculate the features information of the paired blocks at different scales u_m and connect the feature vectors to generate MDMED feature descriptor at multiple scales, which can be expressed as

$$V_{(X_{u_m},Y_{u_m}),u_m} = \left[V^{N_{t+1}}_{(X_{(m)},Y_{(m)},s_m}, \ldots, V^{N_t}_{(X_{(m)},Y_{(m)},s_m} \right]. \quad (2)$$

By cascading MDMED descriptor at all scales, we obtain MDMED descriptor $V^{MDMED}_{(X,Y),U}$ at multiple scales. The $V^{MDMED}_{(X,Y),U}$ can be dedfined as follows

$$V^{MDMED}_{(X,Y),U} = \left[V_{(X_{u_1},Y_{u_1}),u_1}, \ldots, V_{(X_{u_m},Y_{u_m}),u_m} \right]. \quad (3)$$

The MDME descriptor formed by combining the feature vectors of micro-block pairs at multiple scales can effectively describe the intensity features and edge difference information in different directions.

2.4. Image Feature Coding

In order to encode local MDMED descriptor as global descriptor, here we use the improved fisher vector (IFV) [12] to encode. Fisher coding uses Gaussian mixture models (GMM) to fit the local features of the pictures, and utilize the stratified sampling method to randomly set the training set. The original fisher vector is used to obtain partial derivatives of the weight, mean, and variance. However, the improved fisher vector found that the weight does not affect the performance of the encoding, so only the partial derivative of the mean and variance is obtained. The fisher vectors are stitched together by taking the partial derivative of the K multivariate Gaussian distribution parameters of the GMM. Therefore, the encoded MDMED global feature vector length is 2KC, where C is the local feature dimension, and K is the multivariate Gaussian distribution number of the GMM. The encoded fisher vector first uses square root regularization, and then uses L2 regularization [12].

2.5. Classifier

In order to classify texture images, we use SVM to classify IFV-encoded image descriptors. The SVM classifier can output the best hyperplane in a multi-dimensional space to separate different categories [11]. Therefore, we use linear kernels to input MDMED descriptor into the SVM classifier. Figure 3 shows the flow chart of the texture classification method based on multi-sampling dense micro-block edge difference (MDMED)

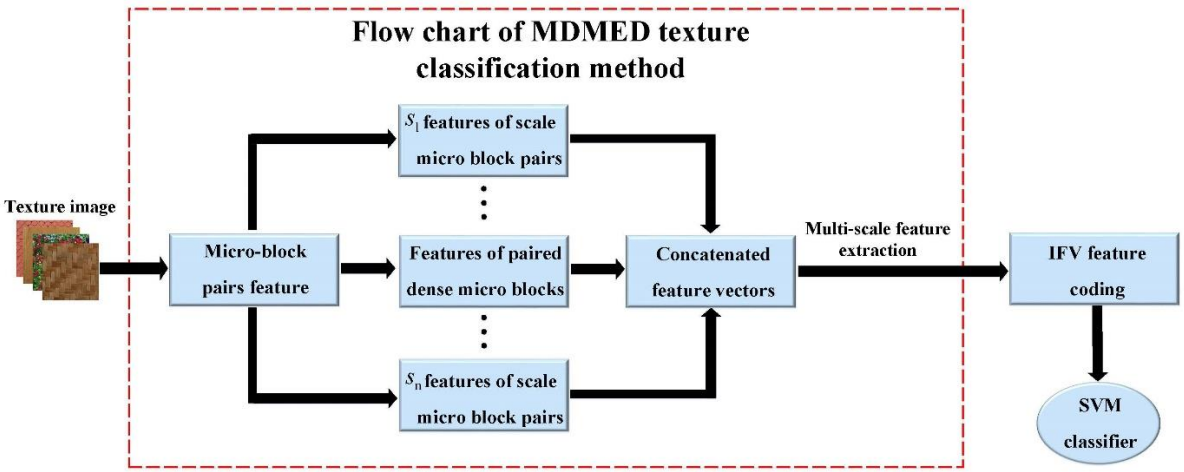

Figure 3: The flow chart of the presented MDMED-based texture classification method

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3. Experimental results

In this section, we will perform experiments on two representative international general texture data sets (Brodatz, CURet), and compare with seven classic texture classification methods. The texture data set under the complex conditions (such as CURet) further reduces the training set samples, which is used to demonstrate the classification performance of our proposed method.

3.1. Experimental settings

In the following experiment, we describe the parameters of different image blocks and micro-block sizes as (L, s), where L is the size of image patch, s is the size of the micro-block pair. The size of the image patch L is set 9×9 to 15×15, and the size of the paired micro-block is set 1×1 to 5×5

In the SVM classification part, the half of the samples of each type samples are randomly selected as the test set, and the remaining half as the training set; in the experiment of reducing the training sample, the specific training set size is introduced instructions in the experimental results section. The samples in the training set and the test set are divided into ten times, and the average classification accuracy rate (ACAR) of the ten experimental results is used as the final experimental result. The regularization parameters and the maximum number of iterations in the SVM classifier are set in the same way as DMD.

3.2. Texture data sets

Brodatz is the most famous international general texture database. As shown in Figure 4, we use texture images of 40 categories in the texture set. Each type of image is divided into 16 non-overlapping experimental samples with a size of 160*160, which contains a total of 640 (40*16) image.

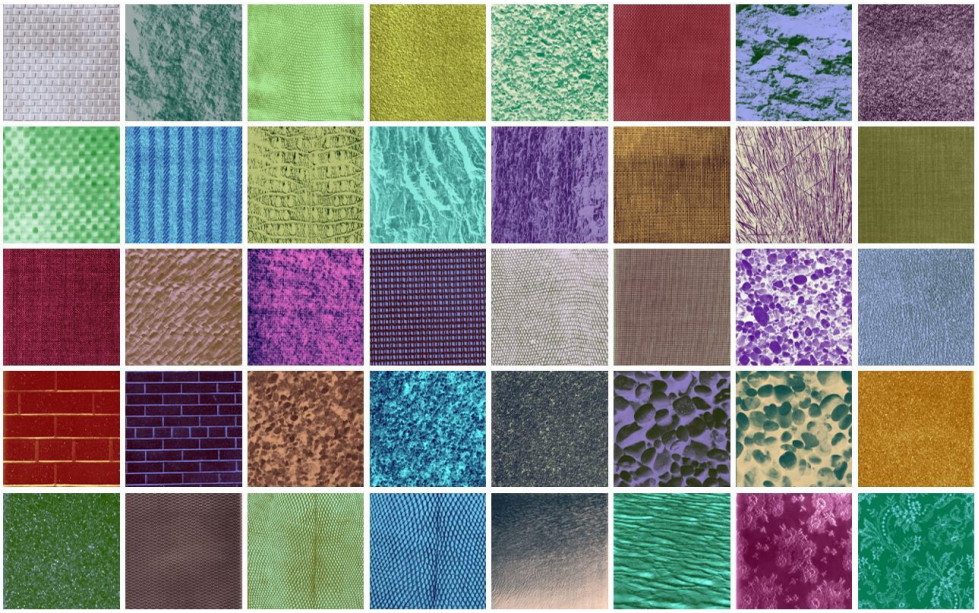

Figure 4: The 40 texture classes in Brodazt

The imaging condition of CUReT texture data-set integrated image is complex. It composes of images obtained under a range of viewing angles and light sources, which leads to major changes in the appearance of textures. Figure 5 shows 40 categories of textures in the CUReT texture set, the whole texture data-set contains 61 texture categories, each category contains 92 images with a size of 200*200. In the following experiment, we use texture images of all

categories in the texture set, and a total of 5612 (61*92) experimental samples with a size of 200*200 are included.

Figure 5: The 40 texture classes in CUReT

3.3. Classification performance and comparison

We compared with seven representative texture classification methods, such as LBP [10], completed modeling of local binary pattern (CLBP) [15], complete local binary counting pattern (CLBC) [16], extended contrast local binary pattern (ECLBP) [17], multi-scale counting and difference representation (MCDR) [18], DMD [11] and jumping and refined local pattern JRLP [19].

Table 1: The ACARs (%) of Brodatz data set using different parameters (L, s)

Block size (s × s)	Patch size (L × L)			
	9×9	11×11	13×13	15×15
1×1	99.81	99.87	99.78	99.62
2×2	99.48	99.78	99.75	99.78
3×3	99.81	99.84	99.78	99.65
4×4	99.84	99.84	99.81	99.78
5×5	99.78	99.81	99.81	99.84

Table 2: The ACARs (%) of Brodatz data set using different training samples

Method	T_8	T_2
LBP [10]	89.56	82.57
CLBP [15]	98.44	93.70
CLBC [16]	97.97	92.43
MCDR [18]	91.44	82.05
ECLBP [17]	98.59	95.89
JRLP [19]	97.84	94.16
DMD [11]	99.78	97.19
MDMED	99.84	97.21

Table 1 reports the experimental results in Brodatz texture database. MDMED can achieve the highest classification accuracy of 99.87% under the (L,s) of (11,1), and the experimental accuracy under different parameters is relatively stable. Table 2 shows the experimental results under different training samples, where T_8 indicates that half of the samples are used as the training set, and the remaining half are used as the test set. T_2 represents that the training samples are reduced to 2 in each class, and the remaining samples are used as the test set. Aiming to maintain a impartial comparison with the DMD method, here we set the parameter (L,s) as (15,5). Obviously, the MDMED method can achieve the highest classification accuracy under different training sets.

Table 3: The ACARs (%) of CUReT data set using different training samples

Method	T_{46}	T_3
LBP [10]	71.69	45.26
CLBP [15]	93.08	58.59
CLBC [16]	95.95	56.88
MCDR [17]	87.27	52.44
ECLBP [18]	82.48	39.92
JRLP [19]	98.54	76.64
DMD [11]	98.47	70.70
MDMED	98.93	77.53

As shown in Table 2, we use the parameter T_{46} to represent half of the sample training and the other half of the sample testing, the parameter T_3 means that reduce the training samples in each class to 3, and the remaining samples are used for testing. The imaging conditions of the CUReT texture set are more complex than Brodatz. MDMED can achieve the highest classification accuracy under different number of training samples. After reducing the training samples to 3, MDMED uses an advanced sampling scheme and extracts abundant edge feature information, the classification accuracy under complex experimental conditions is 6.83% higher than that of DMD.

4. Conclusion

In this paper, we present an effective local texture descriptor, named multiple-sampling dense micro-block edge difference (MDMED). We first use different distribution functions to generate sampling points in the image patch. Secondly, we use the intensity difference and edge feature information between pairs of micro-blocks to construct local dense feature descriptors under different sampling points. Finally, we use the improved fisher vector to encode the features, and then input them into the classifier for texture classification. Finally, the experimental results demonstrate that the MDMED based method is significantly improving the classification performance under the condition of viewpoint changes, illumination and fewer training samples.

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