Texture Classification using Multi-Scale Scheme

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Abstract

Image segmentation by texture processing involves processing an image in sections called blocks. There are some considerable problems that can occur at the boundary of the image (or segmented object), the border between different textures in an image and any small area with high intensity against its background. This paper analyses those problems and proposes a solution using a new block operation called ‘score block operation’ based on multi-scale texture classification.

Keywords: texture, multi-scale scheme, score block operation

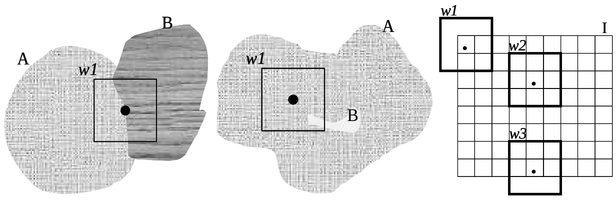
1 Introduction

Image segmentation for both natural images and medical images by texture processing usually involves processing an image in sections called blocks, rather than processing the entire image at once. The blocks have the same size across the image. Every pixel within each large block was assigned the same texture values. This is called distinct block operations. This leads to a significant loss of resolution that is especially unacceptable in medical imaging [6]. To solve this problem, an alternate method was used where the texture values were assigned to a pixel by using a window centered about that pixel [7]. This is called sliding block operations. There are three considerable problems of this operation.

The first problem occurs near the border of different textures. The pixel in the centre of window *w1* in Figure 1(a) is assigned a value calculated from both textures A and B, which could be neither A nor B [6].

The second problem occurs at the neighbor of high strong texture. Strong texture means its texture value is highly distinguishable, so the pixel in the center of window *w1* in Figure 1(b) can be classified as B when the texture of B is more stronger than texture A. This usually happens when Fourier spectra is used for texture analysis and if the texture has a high spectrum.

The third problem occurs at the border of the image. When an image operation is performed over the boundary of an image some of the pixels in a neighborhood may be missing, especially if the center pixel is on the corner of the image (see Figure 1.c). To process these neighborhoods, sliding neighborhood operations pad the borders of the image, usually with 0's [5]. This can lead to an incorrect result for those areas.



(a) (b) (c)

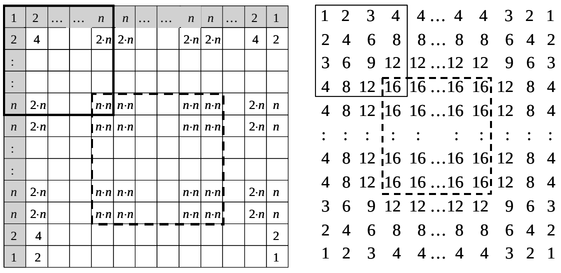
Figure 1. Possible problematic examples

In this paper, we propose a solution using a new block operation called *score block operation* based on multi-scale classification. The score block operation combines both sliding neighborhood operation and distinct block operation with a score for each pixel. In this sense, our system belongs to a multi-scale classification scheme since initial processing is based on block and subsequent processing is based on each pixel.

2 Score Block Operation

Score block operation uses an input image, scored image and classified image. When a scored image is obtained from an input image, the texture value is calculated based on a block of an input image and is assigned to a block in the scored image. Each pixel of the scored image consists of several voting counts and each count collects votes for a certain class. We call these counts ‘score stream’.

Figure 2 shows the overlap frequency of score block operation. Each cell represents $m \times m$ pixels where $1 < m < \beta$ when the block size is $\beta \times \beta$. If an area is overlapped α times, that means the area is referenced α times. Therefore, if the block size is $\beta \times \beta$, and moved by *m* (= β/n), where $1 < m < \beta$ and *m* must be integer**,** the border *(m thick)* of an image is referenced 1 to *n* times, and the inside of the border of an image is referenced by multiplying the topmost row with the leftmost column; that is, 4 to n^2 times. Therefore, the maximum number to be referenced is n2. (see Figure 2(a)). For example, if the block size is 128 pixels × 128 pixels and the block moves 32 pixels (128 / 4) for 75 % overlapping, then n is 4. Therefore, the corner of an image will be referenced for classification once and the inside of an image will be referenced 4 to 16 (42) times (see Figure 2(b)).



(a) (b)

Figure 2. The overlap frequency of score block operation

The method has two steps as follows (see Figure 2):

1. raster scan convolution on input image with step size at $m = \beta/n$ to vote each block ($\beta \times \beta$)
   1.1 process on block at a time,
   1.2 classify the whole block,
   1.3 collect votes for a certain class for score stream in each pixel
2. raster scan convolution on scored image with step size at $m = \beta/n$ to find the most frequent score in score stream for each pixel

After the first step, all pixels of the output image, called 'scored image', retain a score stream obtained based on a block texture and after the second step we obtain the classified image based on each pixel. Therefore, the input image is run through the multi-scale classification process.

3 Texture Analysis

To test our score block operation, we use 2 dimensions discrete fast Fourier transform and quasi-Gabor filter [1] to extract an images feature vector with 42 dimensions. *k* nearest neighbor algorithm [2] is applied to classify the image feature vector. During our different experiments, we empirically selected β = 128, n = 4 (so m is 32) and $k=5$.

4 Experimental Results

We tested score block operation with the 10 composite Brodatz image (640×640). Our system compared the results with a sliding block operation and score block operation using the same texture analysis method. We did not pad with '0' for the additional rows and columns, so the border of the image is not classified when a sliding block operation is used. Figure 3(a). Figure 2(a), which consists of D102, D21, D47, D51 and D111, shows the unclassified boundary of the image and the unclear border between the different textures when a sliding block operation was used. This is because of our score block operation classifies whole block and assigns the class value to whole block. Therefore it is 100% success rate to classify the boundary of the image. The areas are classified with the correct class even though we did not pad the additional rows and columns with '0'.

For all 10 composite Brodatz image test set, the border between the different textures has been improved greatly when score block operation was used. The border is classified as much as the overlap frequency, so it classifies the border areas to the correct class.

We also tested our algorithm with the image D47 (256 ×265) which has a small (32×32) distinct texture (D51) with higher intensity than the background texture at the middle of the image (see Figure 3(b)). The average intensity of the background texture is 95 and the middle texture is 426. When our system transforms a block (128×128) in the input image with 2D-DFFT, the high intensity texture (D51) affects its block strongly when the block includes any small part of D51. This leads to unexpected results when a sliding block operation was used. Even a small presence of D51 in a block will tend to result in the whole block being classified as D51.

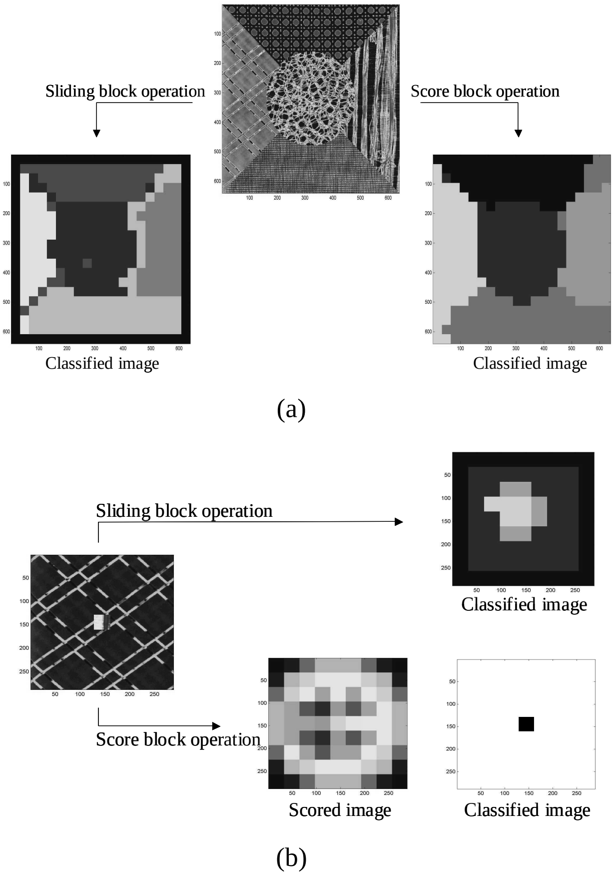
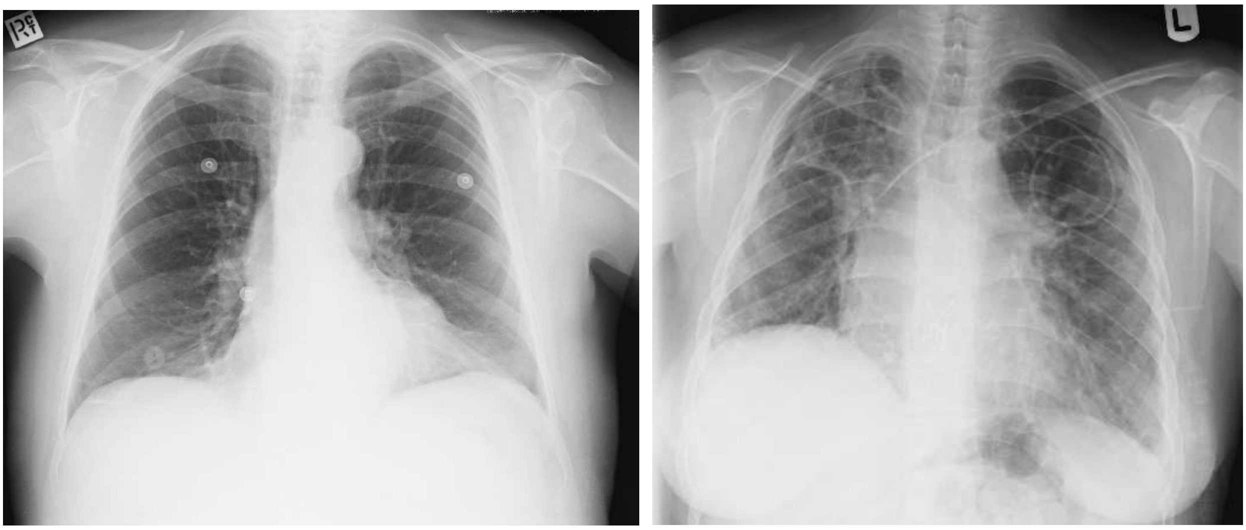


Figure 3. The result from Brodatz test set

5 Application

Our ongoing project is an interpretation of a chest radiograph. Texture analysis is the most important process of an interpretation of a medical image and we adopt the 'Score Block Operation' to analyze the lung texture of a chest radiograph.

The application system built the image databases (IDB) which consist of three classes: normal, dots and grapes. The system extracted the lung field from the input image using the knowledge base lung field extraction method [3, 4]. A very high number, which is bigger than the maximum intensity of the radiograph, is set for the background that is the non lung region, so that our method was not applied on the non lung region.



(a) dis01 (normal) (b) dis23 (abnormal)

Figure 4. Chest radiographs

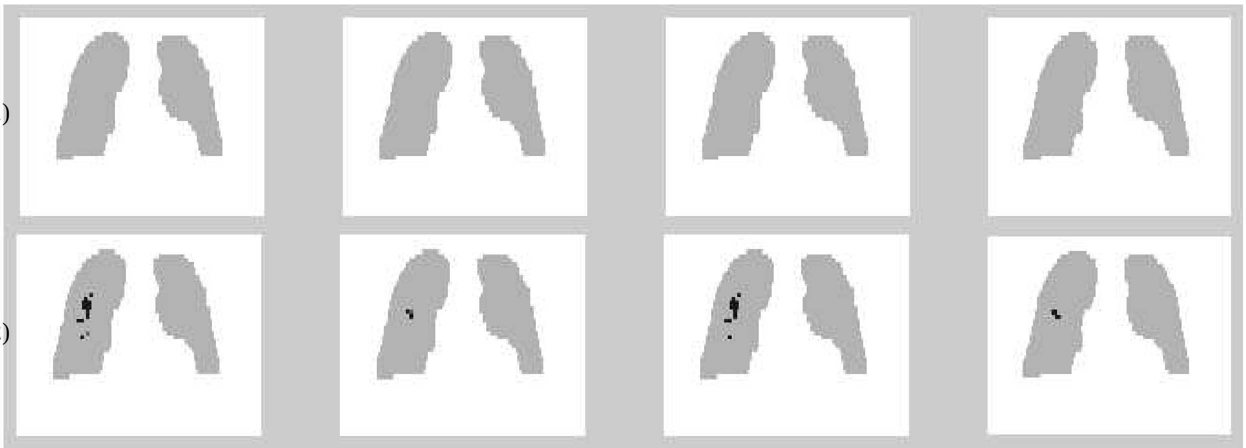


Figure 5. The classified image of dis01 (normal)

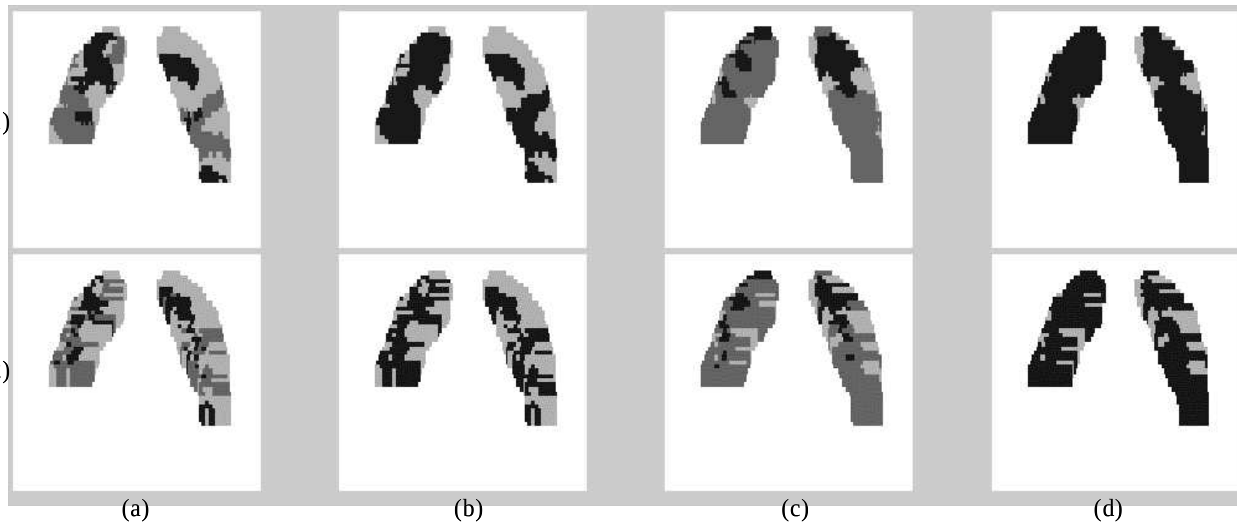


Figure 6. The classified image of dis23 (abnormal)

The application system built the image databases (IDB) which consist of three classes: normal, dots and grapes. The system extracted the lung field from the input image using the knowledge base lung field extraction method [3, 4]. A very high number, which is bigger than the maximum intensity of the radiograph, is set for the background that is the non lung region, so that our method was not applied on the non lung region.

The system then applies the multi-scale classification process. In the first process, the system scans the lung field to take a 128×128 block, classifies the block and scores the block based on the IDB. The block moves by 32 pixels and repeats the process until the whole lung is scanned. Finally, in the second classification process, the scored image is classified to indicate the abnormalities such as 'dots' or 'grapes' texture.

Figure 4(a) is a normal chest radiograph (dis01) and Figure 4(b) is an abnormal chest radiograph (dis23) with interstitial lung disease. Figure 5 shows the classified image of the dis01 chest radiograph which is normal. Figure 6 shows the classified image of the dis23 chest radiograph which has a serious interstitial lung disease, so the lung fields include 'dots' and 'grapes' texture. The columns (a) to (d) present the results from different texture analysis methods and the row (1) presents the result of our method using score block operation and the row (2) presents the result from a general block operation. Most dark areas mean 'grapes' texture and most light areas mean 'normal' texture.

6 Conclusion

Since the contents based image retrieval scheme has been proposed, many algorithms have also been developed for image texture analysis as well as image texture classification. However, for natural images or medical images, the image border, the border between different textures in an image, and the effect of the small area with high intensity have not been considered even though they are very practical problems to be solved.

In this paper, we proved our algorithm could solve those problems. There is no need to pad the additional rows and columns. As the results show, our 'multi-scale classification' and 'score block operation' delivers more accurate results than a general block operation. Furthermore, this method could be applied to any kind of image, so the algorithm is very generic.

The other considerable problem is the block size. The choice for the size of the block has significant implications for the textural analysis. A large block is desirable since it represents more texture pattern, thereby providing a more accurate texture analysis. However, too large of a block tends to decrease the resolution by smearing the borders. A small block handles the borders, but it may not contain enough information to recognize texture pattern. We found our score block operation also solved the block size problems. We can choose any block size, which may includes enough texture pattern to represent, and we can have a high resolution by the small number of pixels to move the block to the next position. The method in this paper can lead to accurate texture calculations with high resolution.

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