Introduction

（构思）

1、STM是什么2、广泛应用3、但由于什么原因，图像容易存在缺陷4、有哪些人针对这些缺陷做了哪些工作5但是针对大量未知缺陷种类识别和位置的缺陷定位处理仍需人工6.本文针对三种常见的图像缺陷提出一种基于图像分类的自识别自定位的自适应缺陷处理算法。使得图像能自动被识别分类标识含有哪类缺陷并针对各自种类的缺陷特性进行自定位的自适应处理。使得整个图像处理过程无需人工干预且处理高效，准确。

（行文）

Scanning tunneling microscope(STM)，which has ability of direct atomic-precise surface structure determination of objects， was introduced by J. Tersoff in 1984[1]. As a mighty imaging tool, STM has been widely applied in surface science[2, 3], material science[4], chemistry[5], biology[6] and nanotechnology[7],etc. Whereas on account of the STM system needs very high stability to generate high quality image, just slight outside vibration, motor periodic vibration or control system hysteresis may cause defects in morphologies. Hence, image post-processing of STM morphology is a very significant issue for STM application.

Many image process methods have been introduced in STM image restoration and [denoising](javascript:;), such as Wavelet Denoising[8], Sparse Coding[9], Wiener filter[10], TV and criministi algorithms[11] and so on. While all these algorithms were rely on manual classification and manual positioning of defects. Moreover, the complexity and time consumption can be added along with defects amount [increasement](javascript:;) and defects position randomness augment. Therefore, in this study, a novel method for STM image post-processing which combined with defects classification network using CNN and unique image processing method for . Using this method, STM images can be fast restored automatically by defects self-positioning and self-processing (minimizing manual intervention)动名词作状语？. Three typical types of common defects of STM images to be processed are long stripe, short sparse stripe and periodic noise, as presented in Fig.1.

Long stripe and short sparse stripe are both local noise. Long stripe is usually caused by the pinpoint tinny shake when the whole precise mechanical system having outside disturbance. On account of the pinpoint scanning direction is horizontal, almost all long stripe defects present as horizontal linear stripes occupying the whole row or at least quarter. Short stripe is usually generated by system hysteresis before and after the pinpoint scanning to a raised surface topography which abundantly and sparsely appears in an image. The randomness and quantity of these two defects make identification and positioning a very time-consuming and inefficient work（label waste？）.

Periodic noise usually appears globally in an image because of periodic mechanical vibration causing by motor or refrigerant fan rotation. Although several researchers have introduced some methods of restoring strict periodic noise in the time domain[12-14] , methods in the frequency domain are more efficient and generally used for generic periodic noise[15-17]. While on account of the diversity of the periodic noise, positioning the frequency content in the frequency map becomes a difficulty and complexity task.



Materials and methods

(构思)

**材料**：处理的图像材料来源，大小，样本生成时间等等，主要针对的瑕疵对象

**图像处理策略**：

0、总写一下流程---流程图

1. 分类方法，cnn原理，网络构架，训练，三种瑕疵网络的差异改动
2. 长条纹特征分析与处理
3. 随机短条纹特征分析与处理
4. 周期性噪声特征分析预处理

（行文）

2.1 processing materials

The processed STM images were generated by (仪器名称) from 2007 to 2015 which total number is around ten thousand. The image size is 256pixels\*256pixels which has RGB three channels. It is analyzed and found that long stripe, short sparse stripe, periodic noise is the top three main defects of scanning images in spite of the various morphologies these images present.

2.2 image process strategy

As observed in fig1, each defect has its unique feature which has nothing to do with the morphology presented. The valid restoration methods become diverse because of the specificity of each defect which makes distinguishing defect as separate necessary. Furthermore, on account of the independence between defect features and the content presented, classifying defects by computer without manual works are possible. Therefore, the central idea of the developed algorithm consists of two parts:(1) classifying defects and marking all defect types that one image to be processed may have. (2) self-positioning and self-processing of each defect marked by different means according to appointed priority. The flowchart of the develop algorithm is shown in fig.2, and the various detailed steps involved in the algorithm are discussed in subsequent chapters.



2.3 defects classification and marking

A STM image may contain more than one type defects which makes defects recognizing a multi-label learning problem. The key challenge of multi-label learning problems is the large size of output space. As the types of label increases, the size of label sets grows exponentially[18]. Thus, a solving method called cross-training which transform the defects classification problem into three independent binary classification problems is to be used[19]. Because of the irrelevance between the different defect labels on each image, the coexistence of other labels can be ignored when training one label[20]. Then, how to set up and train the unique classification network for the three defects become the core problem.

On account of the difficulty in features extraction of traditional supervised machine-based learning methods, such as k-NN, SVM, these methods need some extraction techniques (e.g., SIFT, HOG, GIST)[21]. Hence, the convolutional neural network (CNN) which can extract features automatically and does not need hand designed features is be chosen[22]. The base structure of the proposed CNN network contains 5 convolution layers and 2 fully connected layers as fig.3 presented. The detailed parameters are different according to the diverse features the three defects have as fig.4 presented.



|  |  |  |  |
| --- | --- | --- | --- |
| **Network name** | **Periodic noise** | **Long stripe** | **Short stripe** |
| **input** | *3@256\*256* | *3@256\*256* | *3@256\*256* |
| **Conv1** | *64@256\*256+(RELU)* | *64@256\*256+(RELU)* | *16@256\*256+(RELU)* |
| **Conv2** | *64@256\*256+(RELU)* | *64@256\*256+(RELU)* | *32@256\*256+(RELU)* |
| **maxPool1** | *64@128\*128+(RELU)* | *64@128\*128+(RELU)* | *64@128\*128+(RELU)* |
| **Conv3** | *128@128\*128+(RELU)* | *128@128\*128+(RELU)* | *128@128\*128+(RELU)* |
| **maxPool2** | *128@64\*64+(RELU)* | *128@64\*64+(RELU)* | *128@64\*64+(RELU)* |
| **Conv4** | *128@64\*64+(RELU)* | *128@64\*64+(RELU)* | *128@64\*64+(RELU)* |
| **maxPool3** | *128@32\*32+(RELU)* | *128@32\*32+(RELU)* | *128@32\*32+(RELU)* |
| **Conv5** | *64@32\*32+(RELU)* | *64@32\*32+(RELU)* | *64@32\*32+(RELU)* |
| **maxPoo4** | *64@16\*16+(RELU)* | *64@16\*16+(RELU)* | *64@16\*16+(RELU)* |
| **Full1** | *1@1\*1024+(RELU)* | *1@1\*256+(RELU)* | *1@1\*128+(RELU)* |
| **Full2** | *1@1\*32+(RELU)* | *1@1\*32+(RELU)* | *1@1\*32+(RELU)* |
| **output** | *1@1\*1+(Sigmoid)* | *1@1\*1+(Sigmoid)* | *1@1\*1+(Sigmoid)* |
| **Total parameters** | *17,145,025* | *4,583,617* | *4,443,617* |

2.3.1 periodic noise classification network

CNN is a deep neural network which structure contains input layer, hidden layers, output layer. The hidden layers mainly include convolution layers, pooling layers and full connected layers. The size of pending STM image is 256\*256\*3. So the input layer shape is (256,256,3). The hidden layer of the network consists of 5 convolution layers and each layer flowed with a pooling layer. Although the periodic noise is global noise, the features of it are weak relative to the diverse background morphologies. So the kernel size of each five convolution layers are set to 3\*3 to ensure the effect features of periodic noise can be learned by the network. All stride of each five convolution layers are set to 1 and filters number are 64,64,128,128,64 respectively. All pooling layers are use max-pooling method and 2\*2 kernel size. The nodes number of followed 2 fully connected layers are 1024 and 32. In the hidden layer section, each output will be nonlinearized by the Relu () activation function. The output layer is a 1 node full-connected layer and activation function is sigmoid (). Thus, the output 1 represent pending image has periodic noise and 0 represent it does not have. The specific parameters and output shape of each layer are presented in the second row of fig.4.

2.3.2 long stripe classification network

Long stripe is local noise, the evidence of its features are weaker than periodic noise. If using the same parameters of periodic noise classification network, the overfitting phenomenon, that the accuracy of training set rocket to nearly 100% while the accuracy of validation set rises slowly or even declines, may appear in training. Thus, in order to avoid the network being trained to remember all the samples, the size of the first full connected layer are reduced to 256 as shown in the third row of fig.4.

2.3.3 short sparse stripe classification network

Short sparse stripe is also local noise, and the sparsity and randomness are higher than long stripe. Furthermore, on account of the tinny size of each stripe, the feature of short sparse stripe is the weakest among three defects. In order to make the weeny feature can be retained during convolution, the stride of first two convolution layers are increased and the filters number change to 16 and 32 as demonstrated in fig.4.

2.4 defects restoration methods

What defects a pending image contained has been marked by the classification network in section 2.3. Thus, the following work is restoring the image in what way and in what priorities. Because of the restoring methods of three defects have different slight side effects which may affect other defects restoration on pending images, the order of each process is important to ensure the remediation effect. The priority level of three defects is defined as eq.1:

(1)

The reason of the rank will be mentioned in the following sections along with details of each restoration algorithm.

2.4.1 long stripe restoration

Long stripe defect is a kind of image damage which main causes are pinpoint tinny shaking. Some studies have proposed some effective algorithms of image damages restoration for different types of damages.

Total Variation(TV) algorithm was proposed by L.Rudin & S.Osher in 1992,and was amended and used for image inpainting by Chan in 2002. The principle of TV is that restore the pending region in pixels through the information of the boundary pixels from the outside of marked region. The mathematical formula of TV model is eq.2:

(2)

Among the expression, E is represented the marked pending region and D is represented the other region and u is represented the pixel value in the pending region. If u0 is defined as the original pixel and u is defined as the restored pixel, the expression of u is eq.3:

(3)

Because of TV using the outside boundary information, this restoring method are effective only when the damage size is relatively small. Otherwise the restoration result will become blur in center section of marked pending region as fig.5 shown.

Criminisi algorithm is a global searching algorithm used widely in texture repairing. The principle of criminisi is that chose one pixel (denoted by p) which has the highest confidence weight (eq.4) among the boundary of pending area, and chose the area of specified size (9\*9 in this article) around p as a template. Then find the best-matched (SSD standard, eq.5) area in unbroken region to replace the template area, and meanwhile update the confidence weight of p. By parity of reasoning, repeat the preceding procedure and the pending area will be restored after the end of the iteration.

But because of the globality of the searching and matching, when the pending area is smaller than the template, the restoring result may have some pseudo texture, as fig 5.



To solve the shortcoming of the two algorithm and make the best of the two method, [11]proposed a method which combing the two in restoring STM image damages.

While this method need manual positioning and judging of the defects. Hence, a self-positioning, self-judging and self-restoring algorithm is proposed.

Through the analysis of the long stripe defects, a phenomenon is found that the texture difference between damaged rows and adjacent lines are much larger than that between undamaged rows. Thus, we proposed a novel index parameter called ‘row gradient’ (denoted by RG) which present the sharpness of transition between two rows. The formula of RG is eq6:

(6)

Where x is the row of the image; n is the width of the image; p is the image matrix. As the fig.6 shown, the RG value of the damaged rows are prominently higher than others, and RG value the rows above and under the damaged line are about half of damaged rows’.

Then, the kernel work is finding the suitable threshold value of RG to divide the damaged rows and undamaged rows. In one pending image, the majority of the rows are undamaged, thus the average of the RG is nearly represent the datum RG value of undamaged rows. Also, the standard deviation of the RG can represent the extent of the RG augment of the damaged rows. Thus, the threshold value is defined as eq.7:

（7）

After remove the rows adjoin the damaged row, the pending rows can be marked as fig.6.

Then, choose the restoring method automatically through whether the damaged rows are intensive, the judge formula is eq.8:

(8)

To sum up, after the algorithm mentioned above, the pending image marked having long stripe defects can be restored automatically without any manual intervention.

2.4.2 Short sparse stripe restoration

Short stripe defects can be viewed as global sparse outliers, although they are separately looked as local damages. Beside the sparse defects, the undamaged area of the pending image is identified as low-rank matrix. On this assumption, the restoring process is become a work that recover the low-rank section of the pending image. Although the problem is N-P hard, a super-duper solution to those low-rank and sparse decomposition problem was introduced by Emmanuel Cand´es et al in 2010 called Robust Principal Component Analysis (RPCA).

Rpca原理，提出，用于，和短条纹噪声的适用，效果。算法示意图，效果图

2.4.3周期性噪声

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2.4 defects