Stripe Noise Removal in Scanning Probe Microscopy of Memristor Materials

Li, Mian; Rieck, Jan; Roerdink, J.B.T.M.; Wilkinson, M.H.F.

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Mian Li[1], Jan Rieck[2], Jos B.T.M. Roerdink[1], Michael H.F. Wilkinson[1]

[1]Bernoulli Institute for Mathematics, Computer Science and Artificial Intelligence, University of Groningen, Groningen, the Netherlands,
[2]Zernike Institute for Advanced Materials, University of Groningen, Groningen, the Netherlands

mian.li@rug.nl, j.l.rieck@rug.nl, j.b.t.m.roerdink@rug.nl, m.h.f.wilkinson@rug.nl

Introduction

Generally, all SPM (Scanning Probe Microscope) scans can be prone to artifacts arising from different experimental effects. The most probable reasons for stripe noise in a SPM scan are dirt or water adhering to the tip, tip degradation due to mechanical wear or unintended surface modification by the tip. In cAFM (conduction Atomic-Force Microscope), artifacts related to electrical effects also need to be taken into account. These include degeneration of the conductive tip coating, tip temperature increase due to Joule heating or tip damage due to too high currents. Unless these artifacts can be avoided by sample preparation and measurement parameters, image filtering techniques are needed to improve the scan quality.

Methods

This noise may vary, and in some images we can see very clear conduction paths, see for example Figure 1(a). The conduction paths are the bright structures in the image, some of which are meandering and twisted, and some are connected in rows. However, in Figure 1(b) we cannot discern the conduction paths clearly because of the banding noise. We therefore designed three different models to remove this noise and compare them.

Unidirectional Total Variation Minimization(UTV)

When destriping via unidirectional total variation (UTV) minimization, the observation image is modeled as the sum of the clean image, which is supposed to have minimum UTV, and a stripe noise. The clean image M^* is recovered via an optimization problem as

$$M^* = \arg\min_{M} \frac{1}{2}\|M - N\|_2^2 + \lambda\|M\|_{UTV} \tag{1}$$

where the notation $\|M\|_{UTV}$ denotes the unidirectional total variation of M

Group Sparse Recovery(GSR)

In destriping via Group Sparse Recovery , the observation image is modeled as the sum of the clean image and a stripe noise which is group sparse or column sparse. The stripe noise G^* is recovered via an optimization problem as follows:

$$G^* = \arg\min_{G} \frac{1}{2}\|G - N\|_F^2 + \lambda\|G\|_{2,1} \tag{2}$$

where the notation $\|G\|_{2,1}$ denotes the $\ell_{2,1}$ norm of G

Low Rank Recovery(LRR)

In image destriping via Low Rank Recovery (LRR), the observation images are modeled as the sum of the clean image and a stripe noise which is of low rank. The stripe noise L^* is recovered via an optimization problem as follows

$$L^* = \arg\min_{L} \frac{1}{2}\|L - N\|_F^2 + \lambda\|L\|_* \tag{3}$$

where the notation $\|L\|_*$ is the nuclear norm of L

Simulated Noise

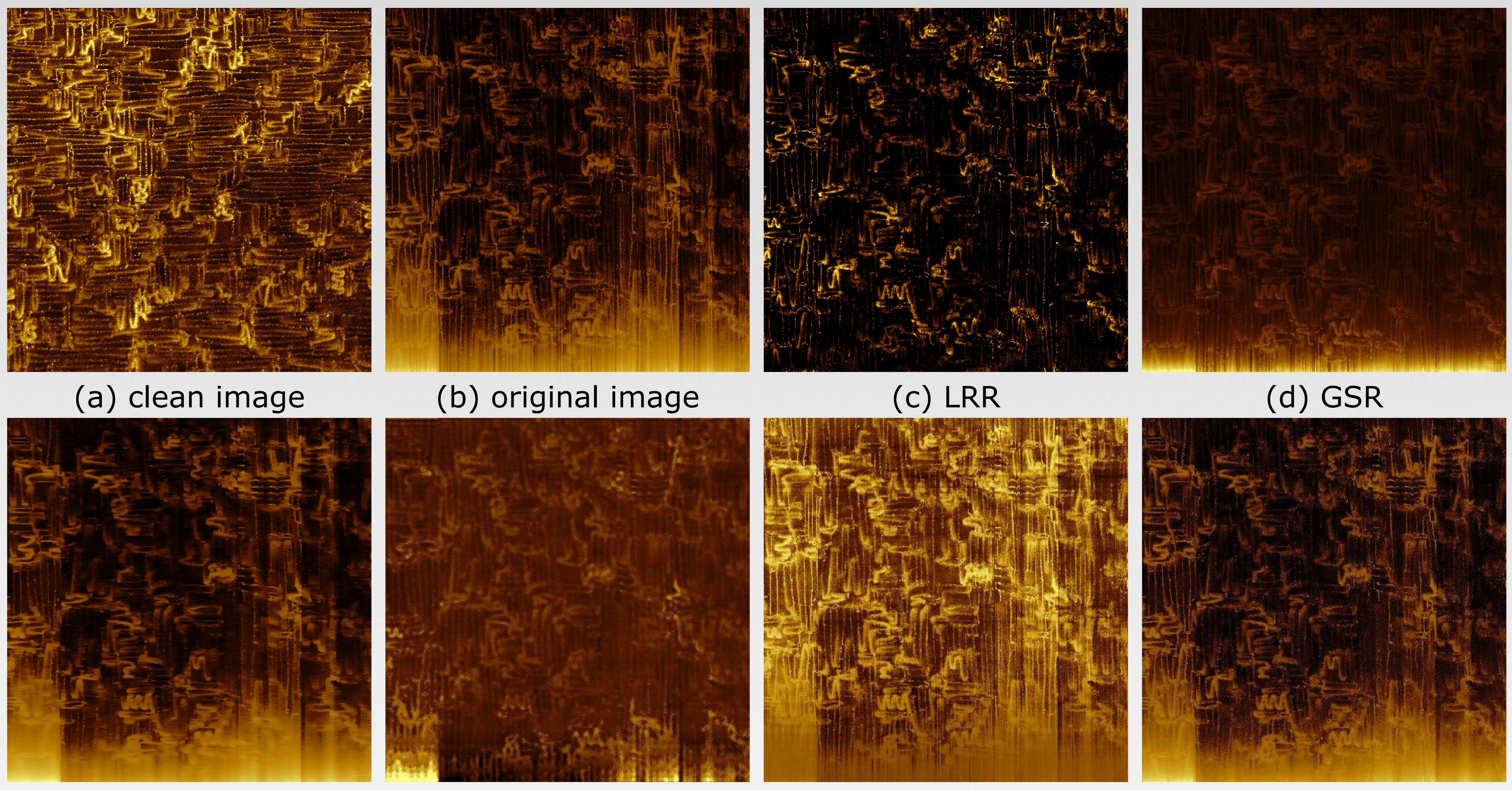
By comparing Figure 1(a) and Figure 1(b), we can see that the stripe noise makes it difficult to see the conduction paths. The current on the tip is conducting from the bottom to the top of the sample, so the stripe noise is the strongest at the bottom, and then slowly disappears as the current dissipates in the conduction paths of the sample.

According to the characteristics of this noise, we reduce the column sparse noise vertically by multiplying it with an inverse proportional factor and then blur the reduced image by Gaussian smoothing. Then the noise model can be defined as

$$\mathcal{G} * [A(x, y) \cdot \frac{1}{x + c}], \tag{4}$$

where A is Group Sparse noise, $\mathcal{G}$ represents a Gaussian kernel and $*$ represents 2d convolution operation. We added this noise model to the ground truth, and the result is shown in Figure 2(a).

Figure 1: Visual Comparison on Natural Noise

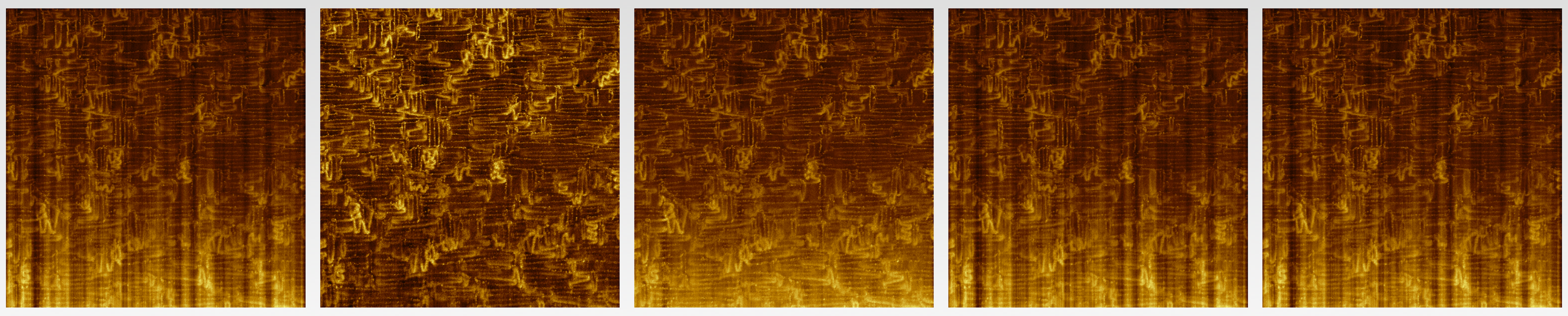


(a) clean image (b) original image (c) LRR (d) GSR

(e) UTV (f) destripe2 (g)median (h) SNRWDNN

The images after denoising by different methods: LRR, GSR and UTV are the methods mentioned in section 2. Destripe2 is one of the destriping methods specific for AFM images. Median is one of the destriping functions in Gwyddion. SNRWDNN is a Stripe Noise Removal Wavelet Deep Neural Network which is designed and trained to remove stripe noise. Part (e) indicates that UTV-vertical removes some irrelevant textures in the vertical direction. We can see in (d) that GSR removes more stripe noise than UTV but it also removes part of the conduction paths. Comparing (c) with (d), the texture of the conduction paths becomes very clear with LRR. Destripe2 did partly remove some stripe noise, but from (f) we can see that there are still a lot of stripe noises that have not been removed. SNR removes part of the noise but also removes most of the conduction paths. Only LRR removes the banding noise successfully without losing too much conduction path. In (g) we know that although the texture of domain walls looks enhanced after the median method, the stripe noise is also enhanced. SNRWDNW did remove some stripe noise but still left some in the image(h).

Figure 2: Visual Comparison on Simulated Noise



(a)simulated noise (b)LRR (c)GSR (d)UTV (e)SNRWDNN

The results after removing the simulated noise: It can be visually observed that the results are similar to those in Figure 1. Only LRR does preserve clear conduction paths.

Table 1: Quantitative Image quality Comparison

Comparison of image quality by PSNR and SSIM.

the results on one image											
noisy image		LRR		UTV1		UTV2		GSR		SNRWDNN	
PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
15.8368	0.6897	**23.1452**	**0.9366**	15.7946	0.6792	15.8047	0.6744	15.7141	0.7341	15.8940	0.8140
the average results on 800 pairs of samples											
noisy image		LRR		UTV1		UTV2		GSR		SNRWDNN	
PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
15.8368	0.6897	**21.5542**	**0.9114**	16.2618	0.6626	16.2486	16.5382	0.7524	0.7341	16.3733	0.6921

Conclusion

Due to the extremely small size of the energized tip of the microscope and the high density of scans on the sample, a lot of banding noise is encountered when acquiring images by c-AFM. In this paper, we compared fifteen methods to remove the banding noise caused by these lateral measurements of ferroelastic oxide materials.

Firstly, We compared the denoising results of the three proposed methods with other 11 different state-of-the-art methods, which including all of the destriping methods in Gwyddion, one deep learning method (wavelet neural network), two destriping methods used to be proved to have a good performance on AFM images. The comparison on natural noisy image shows that the LRR model has the best destriping visual result and it runs fast among most methods. Secondly, we designed and proposed a noise model which was added to the ground truth in order to provide quantitative image quality results by PSNR and SSIM. Both the visual and quantitative results consistently suggest that LRR is the preferable method. Finally, we created the new ground truth dataset by reflection and cropping transformations and added random stripe noise to create a new noisy images dataset since more image data is needed to verify this. The average value of 800 PSNR and SSIM results show the same conclusion that LRR has the best performance.

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