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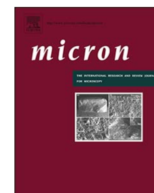

Tutorial

Reconstruction of atomic force microscopy image using compressed sensing

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ABSTRACT

Atomic Force Microscopy (AFM) is one of the most popular and advanced tools for ultra high-resolution imaging and nanomanipulation of nano-scale matter. But AFM imaging typically takes a long time. High-speed and high-precision AFM measurement has attracted wide attention in recent several years. In traditional AFM, simple reduction in the number of measurement points may lose essential sample topography information. To resolve such problems, an AFM image reconstruction method based on Compressed Sensing (CS) theory is applied to reduce image acquisition time without cutting down the image quality. The benefit of using CS approach in AFM is shortening the imaging time, minimizing the interaction with the sample, and finally avoiding sample damage in AFM. Three kinds of testing samples with high and low frequency components were examined by a scanning electron microscope (SEM) and by AFM. An orthogonal Matching Pursuit (OMP) algorithm is employed to reconstruct an AFM image with different sampling rates. Subsequently the reconstruction results of sample topography images are analyzed and evaluated. Using the CS approach in AFM can greatly improve the AFM imaging process. Experimental results show that the obtained reconstructed images have different resolution and quality, depending on the surface morphology of the sample and sampling rates.

1. Introduction

Atomic force microscopy (AFM) (Binnig et al., 1986; Yacoot and Koenders, 2008) has had a tremendous impact on the understanding of science and has been widely used in imaging, metrology and manipulation at the nanometre level since its invention (Han et al., 2011). Atomic force microscope images can be obtained in both air and the liquid environment (Qu et al., 2012). However, AFM imaging is also rather time-consuming because AFM images are traditionally acquired by using conventional Shannon-Nyquist sampling theory, where each line is uniformly sampled by a raster scanning which leads to slow measurement (Ando, 2012). Its slow measurement speed has prevented expansion of its applications to imaging of dynamic processes. Moreover, because of the interaction between the tip and the sample, the long time of measuring process would bring sample damage, sample modification, tip abrasion, tip pollution and image distortion (Han et al., 2014; Han et al., 2012). It is important to minimize or reduce the measurement error and the imaging time for any nanoscale application such as nanofabrication, nano-manipulation and dynamic observation of biological molecules (Dai et al., 2015; Huang and Andersson, 2013; Vicary and Miles, 2009). With the precision of surface topography measurement being of constant concern, it is an enduring objective to balance the measurement quality and the image acquisition time.

Approaches to high-speed AFM (HS-AFM) can be broadly categorized into two branches implemented by using software and hardware to make AFM tip move faster on the sample and improve the imaging quality. The first is the use of alternative physical designs by developing new hardware, for example, small cantilevers, micro resonators, scanning stages, scanners with high resonance frequencies, new actuators and so on (Ando et al., 2008; Fleming and Leang, 2008; Humphris et al., 2005; Mohammadi et al., 2014; Viani et al., 1999). The shortcoming of this approach lies in the complicated hardware design and fabrication, significantly limiting their range of industrial applications. Meantime there has been not enough commercial hardware sources in the market. The second targets the controllers and algorithms such as a combination of feed forward and feedback control algorithms, robust controllers, and iterative control methods (Carberry et al., 2009; Clayton et al., 2009; Lu et al., 2015; Salapaka et al., 2002). Such methods increase costs in AFM measurement, especially bring extra measurement uncertainty and image distortion. Under all these methods, images are built pixel-by-pixel by raster scanning the tip on the sample.

Many other approaches have been proposed to reduce image scanning time and improve AFM measurement accuracy by altering scanning routine and sampling strategies (Chang et al., 2011; Cheng et al., 2008; Mahmood et al., 2011). More influential factors should be taken into account, such as scanning time, scanning pattern, interaction between the sample and tip, abrasion of tip, sample morphology, etc

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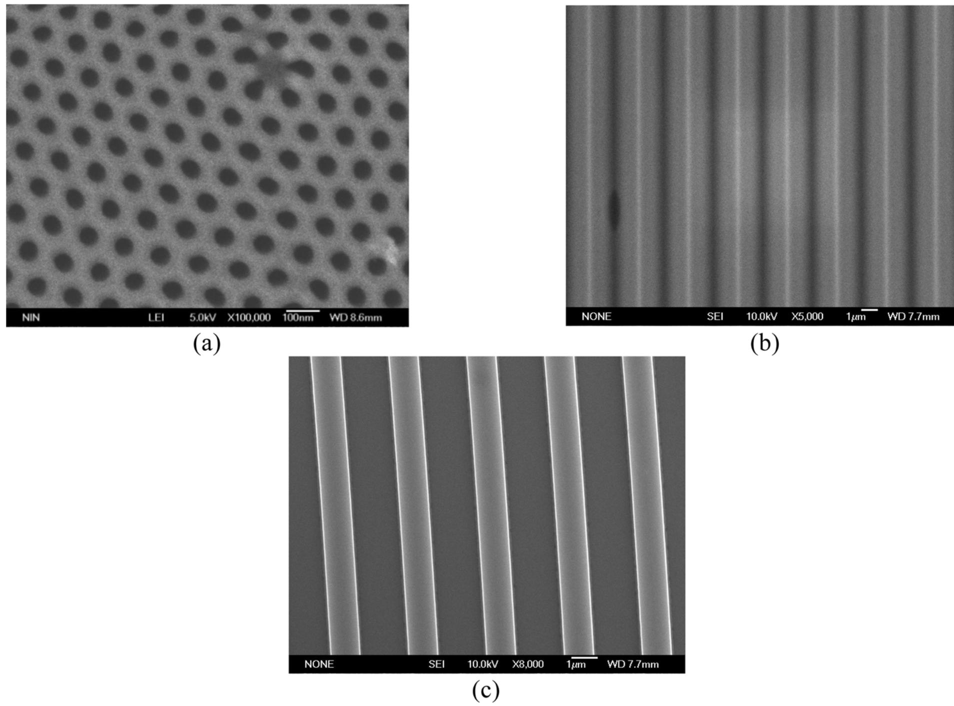

Fig. 1. SEM images of testing samples. (a) PAA film. (b) TGG1 grating. (c) TGZ3 grating.

(Chen et al., 2013). The application of compressed sensing (CS) was proposed to improve the imaging rate and accuracy in the context of surface metrology and AFM measurement (Andersson and Pao, 2012; Arildsen et al., 2016; Luo and Andersson, 2015a; Luo and Andersson, 2015b; Ma, 2010; Oxvig et al., 2017; Xi et al., 2013). CS is a new type of sampling theory (Baraniuk, 2007; Donoho, 2006). Compared with the traditional approach of the well-known Shannon Sampling theorem, CS is built on a solid mathematics foundation that certain signal can be reconstructed from what was previously believed to be highly incomplete information if the signal can be compressed (Baraniuk et al., 2010; Candes and Wakin, 2008; Oxvig et al., 2014). An obvious benefit of using CS approach in AFM is that the tip-sample interaction is greatly reduced.

A series of simulation experiments are established based on the above ideas. The porous and anodic alumina (PAA) film with more detailed features and the gratings (TGG1and TGZ3) with more smooth regions are used as testing objects. Firstly, the target area of sample surface is scanned by SEM and AFM. Then obtained spare images with different sampling rates from 0.1 to 0.8 are reconstructed by a greedy algorithm called Orthogonal Matching Pursuit (OMP) algorithm. In our work, the sampling rate and reconstruction results of AFM images are discussed and analyzed. The OMP image reconstruction method with suitable sampling rates makes a contribution to shortening the acquirement time of images and compressing the image data for high-accuracy AFM measurement.

2. Compressed sensing in AFM

2.1. Compressed sensing algorithm

Suppose that a real signal x is a length-n signal. If x can be well approximated using only k coefficients under some linear transform $x = \Psi\alpha$, it is called k-sparse or compressible. For the mathematical notation that follows, let $\Phi = \{\phi_1, \phi_2, ..., \phi_n\} \in R^{m\times n}$ be the measurement matrix whose m-dimensional vectors are all statistically independent. Combining these vectors to the n-dimensional signal, $< \phi, x >$, a m-dimensional data vector was achieved.

$$y = \Phi x = \Phi\Psi\alpha = A\alpha \tag{1}$$

Where $y \in R^{m\times 1}$ are the observed measurements, Φ is an $m \times n$ measurement matrix with $m \ll n$. Since the process is non-adaptive, the measurement matrix is selected beforehand. Ψ is an $n \times n$ basis transform matrix and α is the sparse representation of the real signal. $A = \Phi\Psi$ is an $m \times n$ sensing matrix which should satisfy the Restricted Isometry Property (RIP).

In the general CS case, Φ can be chosen as a random matrix from a suitable distribution such as random Gaussian and Bernoulli matrices. However, they are impossible to be applied in the AFM application because they are dense matrices. Each measurement of CS typically relies on a linear combination of many elements of the signal. Using a single probe, the AFM can only measure a single point at a time. This means that the linear combination cannot be obtained. An identity matrix with some of its row removed is a good choice in AFM application as the measurement matrix Φ. In each row of Φ, there is only a single one and zeros elsewhere. One possible realizations is:

$$\Phi_{m\times n} = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 & 0 \\ 0 & 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 0 \end{bmatrix} \tag{2}$$

Such a measurement matrix ensures that only a single pixel of the image is required for each measurement. Sampling rate sr can have impact both on the reconstruction time and the quality of the reconstruction.

$$sr = \frac{m}{n} \tag{3}$$

2.2. Orthogonal matching pursuit algorithm

Several exhaustive overviews of CS have been described (Arildsen et al., 2016; Baraniuk et al., 2010; Oxvig et al., 2014). Here the OMP algorithm (Sermwuthisarn et al., 2012; Tropp and Gilbert, 2007; Wang et al., 2012) is briefly presented, which is sufficient to provoke our approach. Due to the major benefit of speed and ease of implementation, it is a nice alternative for signal reconstruction as a problem dual to sparse approximation. The key of the OMP algorithm is to find the index λ_t to solve this optimization issue.

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