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Fullwood, David T.; Hansen, Landon; Jackson, Brian; Wright, Stewart I.; Graef, Marc De; Homes, Eric Richards; and Wagoner, Robert, "Influence of Noise Generating Factors on Cross Correlation EBSD Measurement of GNDs" (2017). All Faculty Publications. 1867.
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Influence of Noise Generating Factors on Cross-correlation EBSD Measurement of GNDs

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Abstract

Studies of dislocation density evolution are fundamental to improved understanding in various areas of deformation mechanics. Recent advances in cross-correlation techniques, applied to EBSD data have particularly shed light on geometrically necessary dislocation (GND) behavior. However, the framework is relatively computationally expensive – patterns are typically saved from the EBSD scan and analyzed offline. A better understanding of the impact of EBSD pattern degradation, such as binning, compression, and various forms of noise, is vital to enable optimization of rapid and low cost GND analysis. This paper tackles the problem by setting up a set of simulated patterns that mimic real patterns corresponding to a known GND field. The patterns are subsequently degraded in terms of resolution and noise, and the GND densities calculated from the degraded patterns using cross-correlation EBSD are compared with the known values. Some confirmation of validity of the numerical degradation of patterns by considering real
pattern degradation is also undertaken. The results demonstrate that the EBSD technique is not particularly sensitive to lower levels of binning and image compression, but the precision is sensitive to Poisson type noise. Some insight is also gained concerning effects of mixed patterns at a grain boundary on measured GND content.

**Introduction**

The advent of cross-correlation (‘high resolution’) EBSD (HR-EBSD) has transformed access to high integrity strain gradients (Kacher, et al., 2009; Troost, et al., 1993; Wilkinson, et al., 2006a) and related geometrically necessary dislocation (GND) fields (Gardner, et al., 2010; Ruggles & Fullwood, 2013; Wilkinson, et al., 2010). However, the presence of strain gradients is often associated with increased noise in the EBSD pattern; sensitivity of the measured strain gradient field to this noise has not been fully characterized. Furthermore, cross-correlation methods often work ‘off-line’ – patterns are saved during a microscope scan, and then analyzed afterwards. The cost in terms of EBSD scan time, memory allocation, data transfer time and computational effort is critically related to the required resolution of the saved images. This paper considers the effects of resolution and noise on the integrity of the GND measurement process, both from microscope-generated and post-processing-generated contributions (for a review of related noise issues, see (Wright, et al., 2015)). An analysis of these effects will allow users to make more informed decisions relating to tradeoffs between computational time / effort and data fidelity.

As a vehicle to performing this study, recent developments in the area of high-fidelity dynamically simulated EBSD patterns have enabled the rapid formulation of simulated EBSD scans relating to ‘perfect’ GND fields (Callahan & Graef, 2013) (process described
below). These patterns can then be manipulated to introduce noise, and to determine the
effects of binning parameters, image format / compression, etc. By using ideal EBSD
patterns, the desired relationships between measured and actual GND content can be
accurately assessed.

The presence of GNDs in a crystalline sample leads to elastic strain gradients (generally
assumed to be dominated by lattice orientation gradients) in the local lattice. This is most
easily visualized by imagining a series of edge dislocations that are stacked above one
another, for example in a low angle grain boundary; the net effect is a rotation of the lattice,
required to accommodate the extra planes of atoms. The fundamental theorems of
continuum dislocation theory formally relate the gradients in the lattice strain / rotation to
the GND content. A mathematically convenient way to capture the GND content on the
various slip systems is via the Nye tensor, α, which is defined in two ways that connect the
dislocation structure parameters with the local strain gradients (Kroner, 1958; Nye, 1953;
Ruggles, et al., 2016a):

\[
\varepsilon_{ij} = \sum_m (m) \hat{l}_i (m) \hat{l}_j (m) \quad (1)
\]

\[
\varepsilon_{ij} = \text{curl} = \nabla \times \quad \Rightarrow \quad \varepsilon_{ij} = \epsilon_{ijm} \epsilon_{inm} \quad (2)
\]

In the first equation, the dislocation content on a given slip system, m, is given by \( (m) \);
the Burgers vector is \( \mathbf{b} \), and the unit vector in the line direction is \( \mathbf{v} \). In the second equation,
\( \epsilon \) represents the Levi-Civita or permutation symbol and \( \epsilon_{ijm} \) is the elastic distortion tensor;
the derivatives of \( \epsilon_{ijm} \), indicated by \( \epsilon_{ijm}' \), are therefore the relevant strain gradients that are
required from EBSD measurements in order to establish GND content.
Such strain gradients are observed as small variations in the EBSD pattern as the scan position rasters across the sample surface. By considering relative distortions in EBSD patterns between neighboring scan positions, the associated changes in lattice structure can be detected, and the strain gradients recovered. This is the underlying idea behind cross-correlation EBSD. An EBSD pattern is collected from a given scan point, and a second pattern is taken from a point at a known distance in the desired direction. Regions of interest (ROIs) within the two patterns are compared using convolutions, implemented via fast Fourier transform methods. Subtle distortions in the patterns result in shifts of local features (such as bands and band intersections) that are quantified by the convolution approach. A set of relationships connecting the pattern shifts to the local lattice distortion is solved, resulting in the desired strain gradient in the chosen direction (Ruggles, et al., 2016b):

$$\beta'_i|_p = \frac{\partial \beta}{\partial x_i}|_p = \frac{\beta_{p,p+\Delta x_i}}{L}$$

(3)

where $p$ is the current scan point, $\Delta x_i$ is a step in the $i$th direction, $L$ is the spacing between raster points, and $\beta_{p,p+\Delta x_i}$ is the relative elastic distortion determined by comparing the two patterns from these scan points.

Both the resolution of the EBSD patterns, and noise from various sources, will significantly affect the accuracy of the calculated shifts, and the subsequent fidelity of the calculated strain gradient and GND field. Noise sources include the following:

- Poor sample polish, oxide layers, and hydrocarbon deposition, leading to electron scatter as electrons leave the sample (Jiang, et al., 2015).
• Dislocation content in the sample (both GND and SSD), reducing the periodicity of the lattice and obstructing channeling.

• Grain boundaries within the interaction volume, leading to disruption of structure and mixed patterns.

• Microscope environment issues, such as:
  a. Microscope settings (current, voltage, beam alignment, working distance, etc.), leading to such things as, large interaction volumes, low electron yield, and poor projection of patterns on the phosphor screen.
  b. Detector and camera attributes and settings, such as gain, binning, quality, and position, may contribute noise and distortion.
  c. Electron source (tungsten filament cathode, lanthanum hexaboride cathode, or FEG), influencing the interaction volume, which in turn can increase the number of dislocations contained within the interaction volume and cause a loss in pattern quality.

• Post processing of EBSD patterns, such as:
  a. Background subtraction potentially introduces bias into the results, since it can cause patterns to mistakenly align to features on the detector (such as scratches or pores) by subtracting identical content from each.
  b. Image compression reduces the quality of the images.

In addition to these issues, lack of accurate knowledge of the microscope geometry (in particular, the pattern center (PC) – the relative position of the sample interaction volume and detector) has some influence on the calculated strain gradients. However, this has been
shown to be a minor effect in normal situations due to the fact that all patterns have related errors, leading to a low requirement on PC accuracy (Britton, et al., 2010; Fullwood, et al., 2015). Similarly, optical distortion of the EBSD pattern may influence the pattern fidelity, but will not create large errors for calculated relative distortion between nearby points (Britton, et al., 2010). Large interaction volumes can also increase noise in EBSD patterns in some situations because more dislocations can be contained within the large interaction volume and these dislocations degrade the pattern quality.

In this paper, the various noise and resolution influences will be treated under four headings:

- Binning
- Image Compression
- Poisson Noise
- Mixed Patterns

By examining simulated patterns relating to known dislocation strain fields (discussed below), different noise factors can be incorporated into the analysis and their effects understood. The effect of binning and image compression can be quantified. Random noise can be introduced to gain some insights into noise created by low exposure times, dislocation content, surface damage, low electron yield, or some other internal structural entropy. Furthermore, mixed patterns can be simulated to better understand the effect of an interaction volume spread across multiple grains at a grain boundary (GB).
As these different effects are analyzed, various noise index parameters, available from EBSD analysis software, will also be quantified to determine whether these indices are predictors of strain gradient and GND error in cross-correlation. While different software packages define different measures of noise, we focus on those employed by EDAX (EDAX, Draper, UT, USA), which will be the software package used throughout this paper; other software packages have similar metrics. Measures of noise that are output by the EBSD software include the image quality (IQ), confidence index (CI) and Fit parameter (Wright, et al., 2015).

All of these parameters are a rough estimate of how well the software is able to identify the correct orientation of a pattern. The image quality quantifies the intensity of the Hough peaks of the transformed pattern, and thus gives a measure of contrast between the bands in the pattern and the rest of the pattern (Wright & Nowell, 2006). Confidence index is a measure of how “confident” the software is about the orientation it has assigned to a specific pattern (see OIM software (2015) for more information). A Fit value is a measure of the average angular deviation between the detected orientation and the orientation assigned to the pattern from the program (see OIM software (2015) for more information). They are dependent on many variables found in the program and microscope settings, but can be used as a value to relatively compare patterns.

The impact of resolution and noise has previously been studied to some extent in the context of cross-correlation EBSD. If only the rotation component of the elastic distortion is considered in the definition of GNDs (as is commonly the case – see (Nye, 1953; Ruggles, et al., 2016a)), then the accuracy of the GND calculation is fundamentally related to the
measurement of relative orientation, which has been studied in various ways. For example, early studies estimated orientation resolution of cross-correlation EBSD around 0.006° (Kacher, et al., 2009; Wilkinson, et al., 2006a). This view formed the basis for defining achievable accuracy in GND measurements, such as proposed by Kysar, et al. (Fullwood, et al., 2014; Kysar, et al., 2010); in Fig. 1, the lower limits for measurable GND content are plotted against scan step size for both standard EBSD and HR-EBSD techniques.

Britton et al. investigated noise factors, such as optical distortion, that particularly affect simulated pattern approaches (Britton, et al., 2010). It was also determined by Britton et al. that a bit depth of less than 8 bits can significantly reduce precision and binning can increase noise (Britton, et al., 2013a; Britton, et al., 2013b). An extensive study by Tong, et al. investigates grain boundary effects by mixing EBSD patterns to simulate a GB (Tong, et al., 2015). Wright, et al. considered methodologies of compensating for noise in EBSD patterns using post processing techniques; in particular, noise is introduced into real patterns to control the noise level for the study (Wright, et al., 2015) (see also (Ram, et al., 2015) for a general error analysis in EBSD). Most notably, Jiang et al. have studied the effects of binning and step size on measured GND content, albeit on real patterns, thus setting the stage for this study (Jiang, et al., 2013).
Fig. 1. GND resolution vs. step size (L). The dashed lines indicate a lower bounds estimate of GND resolution for an assumed EBSD orientation resolution of 0.5°, and HR-EBSD resolution of 0.006°, respectively. The solid lines indicate a lower bound on resolution relating to a single dislocation within the volume bounded by a step, and an upper bound relating to variations in the plastic deformation field; the shaded area is the recommended characterization region according to Kysar et al. (Kysar, et al., 2010).

Method

The overall approach taken in this paper was to produce a set of ‘perfect’ dynamically simulated EBSD patterns that correspond to crystal structure variations over a region of a nickel sample with a known GND content. To simulate various noise and image compression effects, the simulated patterns were then subject to the following processes (see Fig. 2):
1. Level of binning of the EBSD pattern was varied from unbinned to 16x16 binning.

2. Various levels of image compression were applied to the original high-resolution .bmp image.

3. Poisson noise was inserted into the image at a range of levels.

4. Simulated patterns for two different orientations were mixed at varying levels (representing the electron beam interaction volume spanning a grain boundary).

Fig. 2. EBSD patterns with varying types of noise. From left to right: no noise, binning, jpeg compression, Poisson noise, and mixing of patterns.

For each of these factors, the resultant GND content over an area of 1000 data points was calculated from the Nye dislocation density tensor (Ruggles & Fullwood, 2013), and the IQ, CI, and Fit were determined using OIM software from EDAX (2010). The impact of the binning and compression operations on the computational time and memory requirements was also recorded. Details of each factor are outlined in a later section.

**Dislocation Field**

In order to produce a predictable Nye tensor, a homogeneous distribution of edge dislocations was assumed for a hypothetical nickel sample, with the Burgers vector, $\mathbf{b}$, pointing in the x-direction, and the line direction, $\mathbf{v}$, pointing along the z-axis (see Fig. 3) in the region of interest. The plane normal to the z-axis is the sample surface for all simulated
scans in this paper, i.e. the simulated electron beam impinges upon the blue surface shown in Fig 3. In order to provide a specific crystal orientation for the simulated patterns, the (1 - 1 1)[110] slip system was assumed to be operational, with line direction in the [-1 1 2] direction, in the crystal frame. The crystal was brought into the desired alignment with the global frame using a rotation defined by \( \phi_1 = \frac{\pi}{4}, \Phi = -\tan\left(\frac{1}{\sqrt{2}}\right), \phi_2 = 0 \) in Euler angles.

Fig. 3. Schematic of a dislocation within a GND field that results in a continuously rotating lattice, as used for this study. The red \( \perp \) indicates a dislocation within the blue colored bulk material, and \( b \) and \( v \) represent the Burgers vector and line direction of the dislocation, respectively.

Then according to Eq. 1, \( \alpha_{13} = \), and all other components of the Nye tensor are zero. Because this particular rotation was used, the GND values associated with all simulated patterns in this study were calculated solely using the \( \alpha_{13} \) component of the alpha matrix.

Using Eq. 2, and making the common assumption that the strain component of the elastic distortion is negligible, and that, for small rotations, the infinitesimal rotation tensor, \( \omega_3 \) is related to the usual misorientation matrix by:
\[ g \mid I^+ . \]

Then:

\[ a_{ij} = \sum_{n,m} b_{in,m} + \sum_{n,m} g_{in,m} \]

(4)

where \( g_{in,m} \) is calculated by determining the rotation required to realign the lattice at two points that are separated by \( dx \) in the \( m \)-direction, and dividing by \( dx \) (Ruggles, et al., 2016a). This rotation was readily calculated accurately using cross-correlation EBSD.

**Simulated EBSD Patterns**

The simulated EBSD patterns correlating with the lattice and GND field described above were created using EMSoft 3.0, an open-source software package (Graef, 2015). The patterns provide a high-fidelity representation of noise-free EBSD patterns (see Fig. 4 for a representative pattern) that were subsequently injected with the desired noise / filtering. The steps to generate the patterns are described in detail in (Callahan & Graef, 2013). They involve: 1. Monte Carlo simulation of the energy, depth, and directional distributions of back-scattered electrons for the given crystal lattice; 2. Dynamical simulation of the EBSD master pattern, covering all possible back-scatter directions with respect to the crystal lattice; and 3. Simulation of an EBSP (electron backscatter pattern) for a given detector geometry and sample (grain) orientation. The final patterns generated by EMSoft 3.0 do not take into account the point spread function of the optics that projects the photons onto the CCD chip, Poisson noise, or contrast/brightness scaling that can be applied to the pattern using the EBSD vendor software.
Fig. 4 Typical simulated pattern of Si using EMSoft 3.0 (left) and an experimental pattern of Si collected from the SEM (right). The lack of brightness gradient in the experimental pattern is due to background correction applied at the time of collection.

The patterns used in this study were generated with a pixel density equivalent to a high resolution for a typical EBSD detector – 640x640. The images were saved as bitmaps to ensure no loss of quality in the original images. The microscope settings were typical for EMSoft 3.0 simulations and are as follows: CCD detector size – 32 mm², beam current – 150 nA, beam dwell time – 100 µs, and binning mode – 1x1. EBSD patterns for pure Ni were generated for a grid of points across a hypothetical sample of size 10x0.2 microns using 101x3 points, such that the pattern at the origin has the Burgers and line directions aligning with the x and z axes, as described above, and each step of 0.1 um in the x or y direction correlates with a rotation about the z-axis of 0.144 degrees; thus equating to a GND density of approximately 1e14 m⁻². Large rotations have potential to cause inaccuracies in cross-correlation techniques and several studies have examined methods to alleviate this difficulty (Britton & Wilkinson, 2011; Britton & Wilkinson, 2012a; Maurice, et al., 2012) By using an extremely small rotation angle between points, 0.144 degrees, this study assumes negligible error due to large rotations. This hypothetical sample was
replicated ten times with the step size varying by 0.001 microns each time such that a statistically significant amount of data points could be used for data analysis.

**Pattern Degradation Approach**

**Binning** is applied in commercial EBSD software to accelerate the pattern collection and analysis (e.g. indexing) of the captured pattern. Typically, images are binned into 1x1, 2x2, 4x4, 8x8 or 16x16 blocks of pixels, and a new pixel is generated by averaging the intensity of all pixels in the block, and thus replacing the group with a single grayscale intensity (2010). The same approach was applied to the simulated patterns by local averaging of the pixels to produce a new, lower resolution, image at each binning value. In practice, the exposure time is usually reduced as binning is increased because fewer electrons are needed for a decent signal. Exposure time is the amount of time that the phosphor screen is collecting data for a single point in a scan. With longer exposure times, more electrons are able to impinge upon the phosphor screen and a clearer pattern is produced. The lowering of exposure time as binning increases was not simulated in the study and exposure time was held constant.

**Image compression** was applied using the MATLAB ‘imwrite’ function (2014), and applying the default ‘lossy’ compression approach to the jpeg images. The compression level is controlled by the ‘Quality’ flag, which varies from 0 to 100; the highest numbers have the least compression. This ‘Quality’ flag is later used in this paper as a metric to describe compression levels and is written as ‘Compression Quality’. Compression was applied in steps of 10, from 100 to 10. The resultant memory requirements were also recorded as a practical measure of the compression level.
Poisson noise was added to the pattern to reflect noise in electron interactions and camera electronics, in line with previous studies of noise in EBSPs (Cizmar, et al., 2008; Park, et al., 2013; Pinard, et al., 2011; Wright, et al., 2015). Although others have cited Poisson noise as a representative noise type for some factors in the imaging process, its application to specific aspects in EBSD imaging within this paper have been inferred based on statements in the referenced papers. The Poisson noise was introduced using the MATLAB ‘poissrnd’ function, and adjusting the function input variable ‘lambda’. This Poisson noise was then multiplied by the original unadulterated image to get the final degraded pattern. Lambda is a rate parameter which represents the average number of times an event will occur per unit of time. As the value for ‘lambda’ was lowered, the quality of the image decreased. For a clearer understanding of the results, the values of lambda were normalized using a parameter, ‘Poisson Noise Level’, which was calculated by dividing the maximum value of lambda used in this study by the lambda used for a particular instance of noise addition.

To compare trends in noisy simulated patterns with experimental results, ten EBSD scans of a Ta sample were taken with varying exposure times. In order to isolate exposure time as the source of noise, gain was set to zero, 1x1 binning was used, and patterns were saved as 8-bit jpeg images. A contrast normalization filter was used so that patterns collected at a low exposure time could still be indexed by the EBSD collection software. Exposure time was varied in order to explore its effects, as well as mimic oxide layer, hydrocarbon deposition, dislocation content, and any other phenomena that would reduce the electron yield on the phosphor screen. 10x10 micron scans with a step size of 0.1 micron were taken at the same location on the sample for all exposure times using an FEI S-
FEG XL 30 microscope and typical settings. Scans were taken from shortest to longest exposure, which could have introduced noise due to hydrocarbon buildup in the later scans. This noise due to hydrocarbon build up is assumed to be negligible compared to the noise differences associated with the different exposure times. High quality images of the scans were saved and used for cross-correlation.

**Mixed patterns** at grain boundaries were simulated by overlaying patterns of two different orientations, with the contribution from each pattern being scaled linearly relative to the distance from the GB. In reality the contribution from the two patterns has been found to vary after the form of a sigmoid function (Sorensen, et al., 2014). The patterns from the grain of interest were mixed with a pattern from a nearby grain in a linear fashion. To achieve linear mixing of patterns, the GB was assumed to have a 90-degree tilt, the interaction volume was assumed to be cube shaped instead of tear-drop shaped for simplicity, and the pattern intensity of a grain in a mixed pattern was assumed to be proportional to the fraction of interaction volume inside that grain (this last assumption is a reasonable reflection of reality, as per (Tong, et al., 2015). A relatively small step size of 0.1 micron and an unrealistically large probe diameter of 2.2 microns were assumed in order to maintain a realistic step size for GND detection yet also capture a large transition of patterns at the grain boundary.

The three following grain boundaries were observed in this study:

a) A low angle GB, with one side having a GND density of $1e14 \text{ m}^{-2}$ and the other having a density of $1e15 \text{ m}^{-2}$ (misorientation angle of 4.15 degrees, burgers vector of $2.45e-10 \text{ m}$, and dislocation spacing of $3.38e-9 \text{ m}$)
b) A high angle GB, with one side having a GND density of $1 \times 10^{14}$ m$^{-2}$ and the other having a density of 0 m$^{-2}$

c) A high angle GB, with one side having a GND density of 0 m$^{-2}$ and the other having a density of 0 m$^{-2}$

Previous studies have examined dislocation build-up at grain boundaries as an important microstructural characteristic (Bayerschen, et al., 2016; Britton & Wilkinson, 2012b; Guo, et al., 2014; Larrouy, et al., 2015). This study wishes to determine whether pattern mixing at GBs constitutes a form of noise that might be wrongly interpreted as dislocation content. Case c) investigates how pattern mixing at a GB may manifest itself as dislocation density in a cross correlation analysis when no GNDs are present. Cases a) and b) more specifically consider whether the pattern mixing appears as GND build-up in cases where there is a GND field, but no actual buildup at the GB.

In addition to the simulated patterns, a grain boundary in an annealed Ta sample was scanned with EBSD on an FEI S-FEG XL 30 microscope using typical settings in order to compare the simulated data with experimental. Through etching, it was found that grain boundaries on the front and the back of the specimen near perfectly aligned, leading to the assumption of a columnar grains. The scan was 6.325x0.5375 microns and was taken with a step size of .025 microns. The orientation of the left grain (as shown in Fig. 15), given in Bunge Euler angles (degrees), is 88.3, 40.1, 230.8 and the orientation for the right grain is 134.9, 38.7, 192.6. 8-bit jpeg images of the scan were saved and used for cross-correlation.

*Pattern Analysis and Cross-correlation*
Once a set of patterns was created for a given degradation type, a suitable data file, was created using the same parameters that were input into the EMSoft package and that file, along with the patterns, were processed using the EDAX software in order to collect noise parameters: IQ, CI, and Fit. Typical and consistent settings were used with all of the EDAX software. The patterns were then fed into an open-source cross-correlation EBSD code developed by the authors, OpenXY (BYU, 2015), to analyze the GND content. Cross-correlation measurements in EBSD were originally introduced by Troost et al. and further developed by Wilkinson et al (Troost, et al., 1993; Wilkinson, et al., 2006a; Wilkinson, et al., 2006b). The exact process used in OpenXY is based upon work by Kacher and Landon (Kacher, et al., 2009; Landon, et al., 2008). An important step in HR-EBSD for getting the best analysis is pattern filtering (Wilkinson, et al., 2006a) and its use is evident in various studies (Britton, et al., 2013b; Kacher, et al., 2009). Different filtering techniques and settings were not examined in this study and the default filter settings for OpenXY were used for all data sets analyzed with cross-correlation (default settings were originally determined by optimizing over a series of test cases).

**Results and Discussion**

The original, unadulterated patterns were analyzed by OpenXY, resulting in a mean GND density of 9.3e13 m⁻², with a standard deviation of 3.8e11 m⁻². This was the baseline mean and noise floor for the other tests with degraded images.

**Binning**

Fig.5 displays representative images with varying binning levels. The effect of image binning on the calculated GND density is captured in Fig. 6. All box and whisker plots
shown in this article use the standard rules to determine the size of the box and have a maximum whisker height of \(3/2\) times that of the box (cross hairs indicate all data outside of the box and whisker range). A blue line connecting the medians in the box and whisker plots is to aid the reader in seeing plot trends. Statistical values related to the binning results are reported in Table 1, along with the resultant memory and computational requirements, IQ, Fit, and CI. Percent error in the table indicates the percent error of the mean GND density from the idealized GND density, \(1e14\) m\(^{-2}\).

As can be seen from Fig. 6, 2x2 binning does not have a large effect on the resultant calculated GND density. However, beyond the 2x2 binning, both the mean and standard deviation drift significantly away from those of the original figure. This is not surprising given that binning is effectively the same as reducing the image resolution or increasing the solid angle per pixel in the EBSP. As image resolution is decreased, one would expect the changes in the EBSP to be visible in the cross-correlation results. A study by Jiang showed that experimental binning increased GND content and similar results have been observed by that author in single crystal Si (Jiang, et al., 2013). This is in contrast to the results of this study which show a decrease in mean GND with increased binning. Due to the many factors involved, it is difficult to predict whether GND will go up or down with increased binning, but for this particular set of simulated patterns it was shown that the GND density decreased.

The IQ, CI, and Fit do not appreciably deteriorate although some deterioration is noticeable at higher binning levels. Hence none of these noise indicating variables are strong indicators of accuracy of the cross-correlation results in this case. The level of
binning has a dramatic effect on both memory requirements and time required to process
the data (see the values in Table 1). Because these both drop markedly with 2x2 binning,
and the accuracy of the GND calculation is not drastically reduced at this level of binning,
this may be the optimal level of binning for practical situations.

Fig. 5. Representative images at 1x1 (original resolution of 640x640 pixels), 4x4 and 16x16
binning levels respectively. The inset figures are enlarged versions of the top left corner of each
image to demonstrate the effect of binning at the ROI level.

Fig. 6. Calculated levels of GND after introducing binning into dynamically simulated patterns.
Table 1: Statistical summary of introducing binning into the dynamically simulated images.

<table>
<thead>
<tr>
<th>Binning Level</th>
<th>GND Mean (m(^{-2}))</th>
<th>Percent Error (%)</th>
<th>Max GND (m(^{-2}))</th>
<th>Min GND (m(^{-2}))</th>
<th>Standard Deviation</th>
<th>Memory (%)</th>
<th>Time (%)</th>
<th>IQ (x10(^5))</th>
<th>CI</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Binning</td>
<td>9.34 x10(^{13})</td>
<td>6.60</td>
<td>9.45 x10(^{13})</td>
<td>9.20 x10(^{13})</td>
<td>3.81 x10(^{11})</td>
<td>100</td>
<td>100</td>
<td>1.73</td>
<td>0.97</td>
<td>0.42</td>
</tr>
<tr>
<td>2x2</td>
<td>9.50 x10(^{13})</td>
<td>5.00</td>
<td>9.64 x10(^{13})</td>
<td>9.31 x10(^{13})</td>
<td>6.95 x10(^{11})</td>
<td>25.2</td>
<td>37.9</td>
<td>1.74</td>
<td>0.97</td>
<td>0.42</td>
</tr>
<tr>
<td>4x4</td>
<td>8.49 x10(^{13})</td>
<td>15.10</td>
<td>8.77 x10(^{13})</td>
<td>8.12 x10(^{13})</td>
<td>1.13 x10(^{12})</td>
<td>6.5</td>
<td>22.0</td>
<td>1.76</td>
<td>0.97</td>
<td>0.46</td>
</tr>
<tr>
<td>8x8</td>
<td>7.41 x10(^{13})</td>
<td>25.90</td>
<td>8.05 x10(^{13})</td>
<td>6.62 x10(^{13})</td>
<td>2.44 x10(^{12})</td>
<td>1.8</td>
<td>17.2</td>
<td>1.65</td>
<td>0.96</td>
<td>0.47</td>
</tr>
<tr>
<td>16x16</td>
<td>6.18 x10(^{13})</td>
<td>38.20</td>
<td>8.32 x10(^{13})</td>
<td>4.66 x10(^{13})</td>
<td>5.58 x10(^{12})</td>
<td>0.7</td>
<td>15.7</td>
<td>1.32</td>
<td>0.89</td>
<td>0.52</td>
</tr>
</tbody>
</table>

**Image Compression**

A visualization of the degradation of image quality with image compression is shown in Fig. 7 (see “Pattern Degradation Approach” in this paper for more details on the definition of compression and “Compression Quality”). The impact on GND calculation from compressing the simulated images is captured in Fig. 8 and Table 2. The figure illustrates that significant levels of compression can be achieved without having a large impact on the resultant GND calculations. IQ, CI, and Fit are all negligibly affected by the compression process. Similarly, the time taken to process the images by OpenXY does not change significantly. On the other hand, the memory requirements drop consistently with each level of compression, as captured by the data in the table. Hence, an optimal level of compression is likely to be a ‘quality’ value somewhere between 50 and 90 (between 1/20 and 3/20 of original image memory requirements).
Fig. 7. Representative images at original resolution and 50% and 10% quality respectively. The inset figures are enlarged versions of the top left corner of each image to demonstrate the effect of compression at the ROI level.

Fig. 8. Calculated levels of GND after introducing compression into dynamically simulated patterns.

<table>
<thead>
<tr>
<th>Compression Quality</th>
<th>GND Mean (m$^{-2}$)</th>
<th>Percent Error (%)</th>
<th>Max GND (m$^{-2}$)</th>
<th>Min GND (m$^{-2}$)</th>
<th>Standard Deviation</th>
<th>Memory (%)</th>
<th>Time (%)</th>
<th>IQ (x10$^5$)</th>
<th>CI</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Uncompressed</td>
<td>9.34 x10$^{13}$</td>
<td>6.60</td>
<td>9.45 x10$^{13}$</td>
<td>9.20 x10$^{13}$</td>
<td>3.81 x10$^{11}$</td>
<td>100</td>
<td>100</td>
<td>1.73</td>
<td>0.97</td>
<td>0.42</td>
</tr>
<tr>
<td>100</td>
<td>9.34 x10$^{13}$</td>
<td>6.60</td>
<td>9.46 x10$^{13}$</td>
<td>9.20 x10$^{13}$</td>
<td>4.00 x10$^{11}$</td>
<td>100</td>
<td>100</td>
<td>1.73</td>
<td>0.97</td>
<td>0.43</td>
</tr>
<tr>
<td>90</td>
<td>9.34 x10$^{13}$</td>
<td>6.60</td>
<td>9.49 x10$^{13}$</td>
<td>9.15 x10$^{13}$</td>
<td>4.90 x10$^{11}$</td>
<td>100</td>
<td>104</td>
<td>1.73</td>
<td>0.97</td>
<td>0.43</td>
</tr>
<tr>
<td>80</td>
<td>9.34 x10$^{13}$</td>
<td>6.60</td>
<td>9.58 x10$^{13}$</td>
<td>9.05 x10$^{13}$</td>
<td>7.83 x10$^{11}$</td>
<td>100</td>
<td>104</td>
<td>1.73</td>
<td>0.97</td>
<td>0.42</td>
</tr>
</tbody>
</table>
Table 2: Statistical summary of introducing compression into the dynamically simulated images.

Poisson Noise

The consequence of introducing Poisson noise at various levels into the original images is graphically displayed in Fig. 9. The resultant dramatic effect on the calculated GND density is captured in Fig. 10 and Table 3. The calculated mean GND level is not greatly affected by the noise (at reasonable levels), but the standard deviation rapidly increases as noise is introduced. Interestingly, the IQ, CI, and Fit do not decrease until the highest three levels of noise are applied.

Representative EBSD patterns taken experimentally at various exposure times can be found in Fig. 11. The effect on the calculated GND density is seen in Fig. 12 and Table 4 and follows a similar trend as the simulated patterns. The percent error values for the experimental patterns are based off the mean GND from the highest exposure time. The larger variance in GND values compared to that of the simulated patterns is most likely due to a greater difficulty in precisely identifying the orientation during the cross-correlation process. The IQ, CI, and Fit all decrease much more drastically than for the simulated patterns. The simulated patterns were not being degraded to the same level as experimental patterns, which can be seen by inspecting the pattern with the highest degradation in Fig. 9 compared to the pattern with the lowest exposure time in Fig. 11.
Because the noise from both the simulated patterns and experimental patterns gave such a high standard deviation for the calculated GND, noise of this type could play a significant role in determining the approach one uses in collecting EBSPs.

![Representative images of original image, and images with Poisson noise levels of 16 and 128 respectively. The inset figures are enlarged versions of the top left corner of each image to demonstrate the effect of Poisson noise at the ROI level.](image)

**Fig. 9.** Representative images of original image, and images with Poisson noise levels of 16 and 128 respectively. The inset figures are enlarged versions of the top left corner of each image to demonstrate the effect of Poisson noise at the ROI level.

![Calculated levels of GND after introducing Poisson noise into dynamically simulated patterns.](image)

**Fig. 10.** Calculated levels of GND after introducing Poisson noise into dynamically simulated patterns.
Fig. 1. Patterns of Ta captured from the microscope at exposure times of 10 ms, 5 ms, 3 ms, and 1 ms respectively.

Fig. 12. Calculated levels of GND from experimental scans taken at various exposure times.

Table 3: Statistical summary of introducing Poisson noise into the dynamically simulated images.

<table>
<thead>
<tr>
<th>Poisson Noise Level</th>
<th>GND Mean (m(^{-2}))</th>
<th>Percent Error (%)</th>
<th>Max GND (m(^{-2}))</th>
<th>Min GND (m(^{-2}))</th>
<th>Standard Deviation</th>
<th>IQ (x10(^5))</th>
<th>CI</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>No Noise</td>
<td>9.34 x10(^{13})</td>
<td>6.60</td>
<td>9.45 x10(^{13})</td>
<td>9.20 x10(^{13})</td>
<td>3.81 x10(^{11})</td>
<td>1.73</td>
<td>0.97</td>
<td>0.42</td>
</tr>
<tr>
<td>1</td>
<td>9.34 x10(^{13})</td>
<td>6.60</td>
<td>1.06 x10(^{14})</td>
<td>7.86 x10(^{13})</td>
<td>4.30 x10(^{12})</td>
<td>1.72</td>
<td>0.97</td>
<td>0.43</td>
</tr>
<tr>
<td>2</td>
<td>9.33 x10(^{13})</td>
<td>6.70</td>
<td>1.39 x10(^{14})</td>
<td>7.42 x10(^{13})</td>
<td>6.18 x10(^{12})</td>
<td>1.72</td>
<td>0.97</td>
<td>0.42</td>
</tr>
<tr>
<td>4</td>
<td>9.32 x10(^{13})</td>
<td>6.80</td>
<td>1.22 x10(^{14})</td>
<td>6.72 x10(^{13})</td>
<td>9.31 x10(^{12})</td>
<td>1.71</td>
<td>0.97</td>
<td>0.43</td>
</tr>
<tr>
<td>8</td>
<td>9.25 x10(^{13})</td>
<td>7.50</td>
<td>1.34 x10(^{14})</td>
<td>4.58 x10(^{13})</td>
<td>1.34 x10(^{13})</td>
<td>1.70</td>
<td>0.97</td>
<td>0.43</td>
</tr>
<tr>
<td>16</td>
<td>9.08 x10(^{13})</td>
<td>9.20</td>
<td>1.50 x10(^{14})</td>
<td>2.30 x10(^{13})</td>
<td>1.86 x10(^{13})</td>
<td>1.69</td>
<td>0.97</td>
<td>0.44</td>
</tr>
<tr>
<td>32</td>
<td>8.70 x10(^{13})</td>
<td>13.00</td>
<td>1.79 x10(^{14})</td>
<td>-8.45 x10(^{12})</td>
<td>3.05 x10(^{13})</td>
<td>1.64</td>
<td>0.97</td>
<td>0.45</td>
</tr>
<tr>
<td>64</td>
<td>8.75 x10(^{13})</td>
<td>12.50</td>
<td>2.44 x10(^{14})</td>
<td>-8.07 x10(^{13})</td>
<td>4.94 x10(^{13})</td>
<td>1.52</td>
<td>0.96</td>
<td>0.47</td>
</tr>
</tbody>
</table>
Table 4: Statistical summary of experimental patterns with varying exposure times.

<table>
<thead>
<tr>
<th>Exposure Time (ms)</th>
<th>GND Mean (m$^{-2}$)</th>
<th>Percent Error (%)</th>
<th>Max GND (m$^{-2}$)</th>
<th>Min GND (m$^{-2}$)</th>
<th>Standard Deviation</th>
<th>IQ (x10$^6$)</th>
<th>CI</th>
<th>Fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>1.15 x10$^{13}$</td>
<td>0.00</td>
<td>9.88 x10$^{14}$</td>
<td>-1.10 x10$^{15}$</td>
<td>2.66 x10$^{14}$</td>
<td>6.98</td>
<td>0.91</td>
<td>0.59</td>
</tr>
<tr>
<td>9</td>
<td>1.14 x10$^{13}$</td>
<td>0.87</td>
<td>1.08 x10$^{15}$</td>
<td>-9.83 x10$^{14}$</td>
<td>2.87 x10$^{14}$</td>
<td>6.76</td>
<td>0.92</td>
<td>0.58</td>
</tr>
<tr>
<td>8</td>
<td>1.39 x10$^{13}$</td>
<td>-20.87</td>
<td>1.17 x10$^{15}$</td>
<td>-1.25 x10$^{15}$</td>
<td>3.13 x10$^{14}$</td>
<td>6.57</td>
<td>0.91</td>
<td>0.61</td>
</tr>
<tr>
<td>7</td>
<td>1.88 x10$^{13}$</td>
<td>-63.48</td>
<td>1.38 x10$^{15}$</td>
<td>-1.51 x10$^{15}$</td>
<td>3.43 x10$^{14}$</td>
<td>6.24</td>
<td>0.89</td>
<td>0.65</td>
</tr>
<tr>
<td>6</td>
<td>1.67 x10$^{13}$</td>
<td>-45.22</td>
<td>1.52 x10$^{15}$</td>
<td>-1.36 x10$^{15}$</td>
<td>3.71 x10$^{14}$</td>
<td>5.96</td>
<td>0.88</td>
<td>0.66</td>
</tr>
<tr>
<td>5</td>
<td>3.06 x10$^{13}$</td>
<td>-166.09</td>
<td>1.72 x10$^{15}$</td>
<td>-1.65 x10$^{15}$</td>
<td>4.14 x10$^{14}$</td>
<td>5.74</td>
<td>0.85</td>
<td>0.92</td>
</tr>
<tr>
<td>4</td>
<td>4.11 x10$^{13}$</td>
<td>-257.39</td>
<td>1.72 x10$^{15}$</td>
<td>-2.04 x10$^{15}$</td>
<td>4.91 x10$^{14}$</td>
<td>5.27</td>
<td>0.81</td>
<td>0.79</td>
</tr>
<tr>
<td>3</td>
<td>7.79 x10$^{13}$</td>
<td>-577.39</td>
<td>2.69 x10$^{15}$</td>
<td>-2.63 x10$^{15}$</td>
<td>6.32 x10$^{14}$</td>
<td>4.74</td>
<td>0.68</td>
<td>0.93</td>
</tr>
<tr>
<td>2</td>
<td>1.30 x10$^{14}$</td>
<td>-1030.43</td>
<td>3.69 x10$^{15}$</td>
<td>-3.81 x10$^{15}$</td>
<td>8.61 x10$^{14}$</td>
<td>4.06</td>
<td>0.38</td>
<td>1.31</td>
</tr>
<tr>
<td>1</td>
<td>6.57 x10$^{14}$</td>
<td>-5613.04</td>
<td>7.56 x10$^{15}$</td>
<td>-5.93 x10$^{15}$</td>
<td>1.62 x10$^{15}$</td>
<td>3.32</td>
<td>0.03</td>
<td>2.07</td>
</tr>
</tbody>
</table>

Mixed Patterns

A series of simulated patterns mixing is demonstrated in Fig. 13. The calculated GND content from the three different GBs that were simulated is summarized in Fig. 14. Both the GBs that contained GNDs showed a smooth transition from one GND value to another. An increase in GND content is seen at the GB when there is no GND content on either side of the GB. Most likely this increase is not visible in the other two GB due to its comparatively small amplitude.

Resulting GND content, IQ, CI, and Fit from the experimental mixed patterns are shown in Fig. 15. The four plots in Fig. 15 are horizontally aligned with the inverse pole figure (IPF) and are the same scale such that a data point in the plots correspond to a point in the IPF directly above. The region affected by this grain boundary was approximately 2 microns across (for a general in-depth look at interaction volume with application to EBSD...
see (Chen, et al., 2011)). Because the step size for an HR-EBSD scan is generally not much smaller than 1 micron, the GB effected area will only affect a few scan points across the GB and have a minimal effect. There is a GND increase of about 1.5 times the approximated value at the GB and there is a marked degradation in all noise parameters. Because the IQ, CI, and Fit for both the simulated high angle GBs (top and middle in Fig. 14) so closely resembled those of the experimental scan, they were not shown and can be assumed to follow the same trends. The low angle GB had similar IQ behavior as all the others but the CI and Fit remained relatively constant across the GB. With the patterns between the grains being so similar across the simulated low angle GB, the EDAX software was still able to identify the orientations and maintain high quality levels with the CI and Fit parameters.

Based on the results from the simulated data, one could anticipate a transition from one GND level to another, when moving from one grain to another, with a slight increase in GND content at the GB due to the noise of mixed patterns. Experimentally the GND increase at the GB is much greater than the simulated GB; this is likely due to other pattern degradation factors coming in to play at the GB besides pattern mixing. This discrepancy between simulation and experimental may show that the simulation methods used in this paper are not adequate at representing a GB for HR-EBSD analysis.
Fig. 13. A series of dynamically simulated patterns mixing from one orientation to another in a linear fashion. The middle pattern is representative of a scan point directly on a grain boundary, with a 50% pattern contribution from both grains.

Fig. 14. Calculated GND values from three different simulated GBs. The top two are high angle GBs and the bottom is a low angle GB.
Fig. 15. GND values from OpenXY and image quality parameters from EDAX software of data from an experimental scan across a GB.

Conclusions

The study of dislocation content in crystalline materials is fundamental to the ability to fully understand and model them. Cross-correlation EBSD has provided a valuable tool for extracting the GND content for such studies. However, offline analysis of high-quality EBSD patterns can be expensive in terms of memory and time and, more importantly, time spent collecting patterns on the microscope is valuable.
The results in this paper indicate that the quality of the measured GND content may be allowable at lower levels of binning and compression, such as 2x2 binning and a compression quality of 80. IQ, CI, and Fit had a minor correlation with binning level but little to no correlation with compression level. A binning level of 2x2 achieves a 4-fold reduction in memory requirements, and almost a 3-fold reduction in run-time without dramatically reducing accuracy. Although compression level does not significantly affect run-time, a compression ‘quality’ level of 80 can achieve a 9-fold reduction in memory requirements without significant reduction in accuracy.

The insertion of Poisson-type noise into the image (for example, due to exposure time, oxide layers, hydrocarbon deposition, or poor electron yield) does have a significant effect on the mean GND density content, but the standard deviation of the detected GND content rapidly increases with increased noise levels. These results proved to be similar to experimental results with a varying exposure time. IQ, CI, and Fit in both simulated and experimental patterns did correlate with noise but more closely resembled relative values than a predictor for any set of patterns. Due to the potential for very high GND standard deviation rates, this type of noise can greatly inhibit the accuracy of calculated results and should be avoided.

In characterizing how pattern mixing at a GB affects cross-correlation measurements of GND, it is apparent that simulated mixed patterns were not a good representation of experimental results. Simulated mixed patterns at a GB produced a fairly smooth transition in GND content from one grain to the other, while experimental results showed a slight increase in GND content at the GB. This discrepancy can be attributed to the fact that there
are many other sources of noise associated with an experimental GB other than the mixing of patterns. To study noise at a GB using simulated patterns, a more in depth approach would need to be taken. Although the cross-correlation results between simulation and experimental did not reasonably compare, some connections between simulation and experimental concerning IQ, CI, and Fit were able to be made.

High quality dynamically simulated patterns from EMsoft 3.0 have allowed the characterization of various effects of noise on the measured strain gradient. Simulated patterns have proven to be useful in identifying the particular problems faced in this paper, but they could also be applied to many other types EBSD scenarios to exploit the strengths and pitfalls of cross-correlation techniques.

**Acknowledgements**

This research was supported by U.S. Department of Energy (DOE), Office of Science, Basic Energy Sciences (BES), under Awards DE-SC0012587 and DE-SC00012483. MDG acknowledges an Air Force Office of Scientific Research (AFOSR) MURI program (contract # FA9550-12-1-0458). Many thanks to Jordan Christensen for help with pattern generation and to the journal reviewers for their many helpful comments.
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