Estimating Accuracy of X-Ray Diffraction Peak Separation

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Abstract

This report investigates the effectiveness of Lab_HEDM.py, a Python script developed by Seunghee Oh for preprocessing X-Ray Diffraction data by removing unwanted secondary peaks. The primary goal of the project is to calculate the success rate of secondary peak removal for the given dataset, and second, to improve the script's ability to replace these peaks with background pixels. The methodology involved generating synthetic data to test the current filtering approach and developing a new algorithm for peak segmentation and removal. This new algorithm was then compared with the preprocessed data to assess the script's performance in removing secondary peaks. Preliminary results have identified instances where Lab_HEDM.py fails to effectively eliminate secondary peaks, though the new algorithm is not yet refined enough to provide an accurate success rate. Further development and testing are required to enhance the precision and reliability of the testing algorithm. Additionally, significant progress was made to develop an effective background replacement method.

Introduction

The first dataset for this project consists of 3600 diffraction images, taken over the course of a complete rotation around the sample. Each image is 4096 x 4096 pixels, and consists of both primary and secondary sets of background peaks, with a considerable amount of background noise. The two sets of peaks are a result of two different wavelengths of light being emitted by the Lab's new MetalJet E1+ 160 kV X-Ray source. Because there are two sets of peaks, a diffraction image analysis on these data would be ineffective, and as a result of this, the second set of peaks must be removed.

The second dataset for this project is the output of a preprocessing algorithm, Lab_HEDM.py. This algorithm removes the set of secondary peaks found in the initial diffraction dataset and replaces each of the peaks with background noise. The success rate of this secondary peak removal must be assessed in order to ensure that the preprocessed dataset may be accurately analyzed.

Methodology

In order to estimate the success rate of secondary peak removal between the two datasets, the task was separated into multiple parts, with the end goal of creating a peak-segmentation algorithm to perform the estimation.

First, the design of synthetic data to imitate the data before preprocessing with both primary and secondary peaks. The purpose of the synthetic data was to primarily promote a better understanding of the diffraction images and the preprocessing algorithm. Through statistical methods and analysis of the datasets, the script test_generator.py (Appendix B) was developed to model diffraction images with a number of primary and secondary peaks of size, count, and features defined by customizable parameter values. While some of the peak parameters were determined by heuristic techniques, both peak intensity

values and image background noise were determined each by a gaussian kernel density estimate, which involves fitting a gaussian sampling distribution to data gathered from the original diffraction image sets.

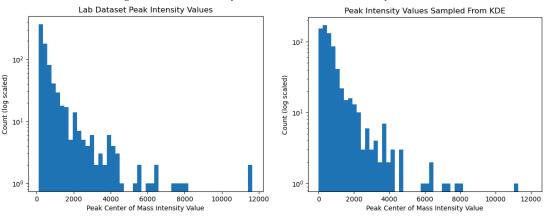


Fig. 1 Lab Dataset vs Synthetic Dataset Peak Intensity Values

As observed in Fig. 1, aspects of the synthetic data such as peak intensity were able to effectively model (although not with complete precision) the diffraction image data. Because of this, the synthetic data was used to test difficult edge cases with different filtering methods.

Second, the methodology involves the selection of a filtering function used in the new testing algorithm (Algorithm.py) for the segmentation of any peaks missed by Lab_HEDM.py. Find_peaks_2d() (found in Appendix C), a function from Python library HEXRD, is used by Lab_HEDM.py in order to identify diffraction peaks by filtering peaks from the background. This function, in combination with OpenCV's morphological transformation cv.MORPH_OPEN (also known as Opening) was used in the latest iteration of Algorithm.py (Appendix A) in order to find missed peaks. This method was motivated by cv.MORPH_OPEN's ability to remove larger, higher intensity pieces of background noise, which then enabled find peaks 2d() to operate at a lower threshold value for identifying peaks.

The algorithm created for testing the preprocessed dataset, Algorithm.py, in its current state:

- 1. For each image in initial dataset, find all peaks and store as polar coordinates
- 2. Compare each image with the three frames before it and three frames after in order to differentiate between primary and secondary peaks
- 3. Replace each secondary peak with background noise sampled from gaussian KDE fit to background surrounding the peak using background generator.py (Appendix E)
- 4. Save new preprocessed image
- 5. Compare secondary peaks found by Algorithm.py to secondary peaks removed from diffraction dataset by Lab HEDM.py, as identified by image dev.py (Appendix D)

Results and Discussion

Test results were taken from groups of 100 diffraction images, as computing resources were limited. The estimated success rate of secondary peak removal as determined by Algorithm.py was 96.38%, although this result is not accurate. Upon manual inspection of individual peak removal cases for Algorithm.py, it was not uncommon to find misidentified secondary peaks. The majority of observed cases flagged by Algorithm.py, however, were instances where the secondary peak appeared to have been identified by Lab_HEDM.py but it had not been removed properly.

Fig. 2 Incorrect Peak Removal Case in Lab Dataset



In this example of incorrect peak removal, Fig. 2 shows the raw image (left), the preprocessed image (right), and the difference between the two images (center). The primary peak, located in the upper corner of each of the images, should be the only peak showing after preprocessing.

These residuals indicate that while the script performs well in most cases, it struggles with certain edge cases, particularly those involving low-intensity secondary peaks or peaks that are close to primary peaks in intensity and position. This misidentification can be attributed to the limitations in the current peak segmentation approach, particularly in distinguishing between peaks that are closely or distantly positioned, or have overlapping intensity distributions.

Conclusions and Future Outlook

The success rate of 96.38% for secondary peak removal, as roughly estimated by Algorithm.py, suggests that the existing preprocessing script is generally effective at identifying and removing unwanted peaks from the X-Ray Diffraction data. However, the accuracy of this success rate remains questionable due to the observed misidentification of secondary peaks by the new testing algorithm.

The implementation of cv.MORPH_OPEN in combination with the find_peaks_2d() function provided a valuable improvement in isolating true peaks from background noise. This approach allowed for a lower threshold in peak detection, increasing the sensitivity of the algorithm. However, this increased sensitivity also led to a higher rate of false positives, indicating the need for further refinement in distinguishing between true and false peaks.

The use of synthetic data for testing proved beneficial, though not without limitations. Future work should focus on refining the synthetic data generation process to better emulate the complexities of real-world diffraction data. Additionally, the peak segmentation and filtering methods in Algorithm.py need to be further developed to improve accuracy and reduce false positives.

Significant progress has been made in developing an effective background replacement method, which could be integrated into Lab_HEDM.py to enhance its performance. Moving forward, the primary focus should be on refining the testing algorithm to provide a more accurate estimation of the success rate and on improving the peak identification process to reduce errors and increase reliability in the preprocessing of X-Ray Diffraction data.

References

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Appendix A: Algorithm.py

```
Author: Lennon Seiders
import h5py
import numpy as np
from scipy import ndimage
import skimage
import imaging
from math import isclose
Algorithm for second peak removal. Run this script and modify settings in Main()
in order to segment and remove peaks from diffraction images and/or compare with lab's algorithm.
np.set_printoptions(formatter={'float': '{: 0.3f}'.format})
radii_first = [1068, 1160, 1220, 1599, 1904]
radii second = [1083, 1171, 1232, 1623, 1932]
r_ranges = [(rad1-10, rad2+10) for rad1, rad2 in zip(radii_first, radii_second)]
filter_thres = 10
filter radius = 3
theta_margin = 0.04
rho_margin = 30
def cart2pol(x, y, center_x=2063, center_y=2059):
       f = h5py.File(file path, 'r')
```

```
for filename in sorted(os.listdir(folder)):
            file_path = os.path.join(folder, filename)
   return np.array(images)
       numpks, pks = imaging.find_peaks_2d(img, 'label',{'filter_radius':filter_radius,
       numpks, pks = imaging.find_peaks_2d_open(img,
cv2.getStructuringElement(cv2.MORPH ELLIPSE,(3,3)))
       numpks, pks = imaging.find_peaks_2d(img, 'label',{'filter_radius':filter_radius,
def find 2pks(scan a, scan b):
        for pk in rad a:
```

```
im2file(img, filename, mkdir=False):
def remove 2pks(toRemove, img):
   bg = np.array(f['synthetic_bg'])
def find_to_remove(raw_scans):
   img dev = True # set to true when testing lab data
```

```
if img_dev:
       lab found = 0
           lab_removed.append(np.array(f1['removed_peaks']))
           lab found += len(lab scan)
diff_found/(lab_found+diff_found), '%)', sep='')
```

Appendix B: test_generator.py

```
Author: Lennon Seiders
import h5py
import random
import numpy as np
from scipy import ndimage
from scipy.stats import gaussian kde
import imaging
import background generator
import math
. . .
Functions for generating and testing synthetic image data. Images are saved in .h5 files
along with a list of primary and secondary peak coordinates.
Set parameter values in main() and run this script in order to generate synthetic images.
. . .
pkvals = np.loadtxt('pkvals.csv', dtype=np.int16, converters=float)
ints_kde = gaussian_kde(pkvals)
def sample(kde):
def generate radial peaks image(peaks per level, newImageFile, p second, p tail, size mult):
    def create peak structure(coord, size, peakIntensity):
```

```
secondary_peaks = []
    for in range (peaks per level):
        create_peak_structure([x,y], size, intensity)
        primary_peaks.append((x, y))
            create peak structure([dx,dy], size, intensity)
            secondary_peaks.append((dx, dy))
newImageFile['imageseries']['secondaryPeaks'] = secondary peaks
for i in range(num images):
    generate_radial_peaks_image(peaks_per_level, newImageFile, p_second, p_tail, size_mult)
```

```
# Test to run different filtering methods on synthetic data. Keeps track of peaks missed and false positives.

def test_synthetic_images(thres, directory='synthetic_images'):
    missed = 0
    false_positive = 0
    correct = 0
    total_pks = 0
    i = 0
    for filename in os.listdir(directory):
        i += 1
        f = os.path.join(directory, filename)
        x, numpks = imaging.find_peaks_2d_test(f, thres)
        total_pks += numpks
        if x > 0: false_positive += x
        elif x < 0: missed -= x
        else: correct += 1
    print(total_pks, 'total peaks tested in', i, 'images')
    print('correct images:', correct)
    print('incorrectly classified:', false_positive)

def main():
    num_images = 10 # number of synthetic diffraction images to be generated
    peaks_per_level = 4 # peaks per radius level
    p_second = 0.5 # probability of secondary peaks being generated for each primary peak
    p_tail = 0.5 # probability of a pair of peaks having additional "tail" noise
    size_mult = 1 # size multiplier. higher value (ex. 1.3) results in a higher chance of generating
large peaks
    generate_images(num_images, peaks_per_level, p_second, p_tail, size_mult)

if __name__ == "__main__":
    main()
```

Appendix C: imaging.py

```
Author: Lennon Seiders
import h5py
from scipy import ndimage
import cv2
This file contains hexrd's (https://github.com/HEXRD/hexrd) find peaks_2d() function for filtering
diffraction images,
as well as an alternate method and a test to be used with synthetic data.
These functions are to be used in other scripts for filtering and testing.
sigma_to_fwhm = 2.*np.sqrt(2.*np.log(2.))
fwhm_to_sigma = 1. / sigma_to_fwhm # = 0.42....
def find peaks 2d(img, method, method kwargs):
           img > method kwargs['threshold'],
 lef find_peaks_2d_open(img, kernel=cv2.getStructuringElement(cv2.MORPH_ELLIPSE,(3,3)), thres=40):
```

```
img = cv2.morphologyEx(img, cv2.MORPH_OPEN, kernel)
def find_peaks_2d_test(filename, thres=38):
   img = np.array(f['imageseries']['images'])
   img_primary_peaks = np.array(f['imageseries']['primaryPeaks'])
   img_secondary_peaks = np.array(f['imageseries']['secondaryPeaks'])
   true_pks =np.append(img_primary_peaks, img_secondary_peaks, axis=0)
   found pks = find peaks_2d(img, 'label', {'filter_radius':3, 'threshold':thres})[1]
       identical = np.allclose(true_pks, found_pks, atol=1)
       return len(found_pks) - len(true_pks), len(true_pks)
```

Appendix D: image_dev.py

```
Author: Lennon Seiders
import os
import numpy as np
import cv2
import imaging
Creates deviation images by subtracting preprocessed images from raw scans.
Resulting images are peaks and noise removed by preprocessing algorithm:
Set directory paths and number of images to generate prior to running this script.
num files = 20 # choose how many deviation images to create from lab dataset
raw directory = 'nobg 2024-03-13-21-19-01-scan Ti7Al z25p5 deg360 step0p1 rot45'
prep directory =
Ti7Al_deg360_step0p1_after_preprocessing\Ti7Al_z25p5_deg360_step0p1_rot45_0to3600_ver3p1_mult1p6_3600_
mimg9'
result_directory = 'img_dev/'
size = (4096, 4096)
center = (2063, 2059)
radii first = [1068, 1160, 1220, 1599, 1904]
radii second = [1083, 1171, 1232, 1623, 1932]
mask = np.zeros(size, dtype=bool)
mask2 = np.zeros(size, dtype=bool)
x = np.arange(size[0])
y = np.arange(size[1])
xx, yy = np.meshgrid(x, y)
distances = np.sqrt((xx - center[0])**2 + (yy - center[1])**2)
for r1, r2 in zip(radii_first, radii_second):
def set radii elements(array, center, radii, value):
```

```
files1 = sorted(os.listdir(raw_directory))
files2 = sorted(os.listdir(prep_directory))
count = 0
for raw_f, prep_f in zip(files1[:num_files], files2[:num_files]):
   r_img = np.array(f1['imageseries']['images'][0,:,:])
   p_img = np.array(f2['imageseries']['images'][0,:,:])
   img_dev = r_img - p_img
   result['image_dev'] = img_dev
for dev_f in os.listdir(result_directory):
cv2.getStructuringElement(cv2.MORPH_ELLIPSE,(3,3)))
   numpks, pks = imaging.find_peaks_2d(masked_image, 'label',{'filter_radius':3, 'threshold':5})
```

Appendix E: background_generator.py

```
Author: Lennon Seiders
import h5py
import numpy as np
import scipy.stats as stats
Script for obtaining accurate background noise by sampling windowed kernel desnsity estimates of lab
Run this scripy to create a file titled 'background.h5', synthetic background noise mimicking that
of the lab dataset's images.
111
directory = 'nobg_2024-03-13-21-19-01-scan Ti7Al_z25p5_deg360_step0p1_rot45'
if os.path.isfile('gaussian_kde_full.h5'):
def set points along radii(img):
def get_background(path):
   img = np.array(file['imageseries']['images'], dtype=np.int16)
def background_to_gaussians(img, windowing_exp=5):
```

```
num_windows = pow(2, windowing_exp)
           end row = start row + window size
           kde_list.append(kde)
           new_samples = np.array(kde.resample((window_size)*(window_size)).flatten().tolist(),
dtype=np.int16)
           new samples [new samples > 100] = 0
```