## Real Micro Crystals - Data Engineering & Exploration

Michael Janus, June 2018

last update: October 2018

Use the functions on a real (small) data set.

For explanation and how to usage functions, see the notebook **imgutils_test_and_explain.ipynb**

## 1. Import the used modules, including the one with test functions:

In [246]:
```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)

import matplotlib.pyplot as plt
import pandas as pd

import imgutils
```

In [247]:
```
# Re-run this cell if you altered imgutils or imgutils_test
import importlib
importlib.reload(imgutils)
```

Out[247]:
```
<module 'imgutils' from 'C:\\JADS\\SW\\Grad Proj\\sources\\imgutils.py'>
```

## 1. Get image files

In [87]:
```
df_imgfiles = imgutils.scanimgdir('../data/Crystals_Apr_12/Tileset7', '.tif')
print(df_imgfiles)
```

```
                                        filename
0  ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-...
1  ..\data\Crystals_Apr_12\Tileset7\Tile_001-002-...
2  ..\data\Crystals_Apr_12\Tileset7\Tile_001-003-...
3  ..\data\Crystals_Apr_12\Tileset7\Tile_002-001-...
4  ..\data\Crystals_Apr_12\Tileset7\Tile_002-002-...
5  ..\data\Crystals_Apr_12\Tileset7\Tile_002-003-...
```

## 2. Get Image Slice Statistics

This set contains 6 images. Let's slice those up in 4 by 4; this will give total of 6 x 4 x 4 = 96 slices. And also apply the statistics on each slice.

In [4]:
```
statfuncs = [imgutils.img_min, imgutils.img_max, imgutils.img_range, imgutils.img_mean, imgutils.img_std, imgutils.img_median]
df = imgutils.slicestats(list(df_imgfiles['filename']), 4, 4, statfuncs)
print("records: ", df.shape[0])
df.head()
```

```
records:  96
```

Out[4]:

| | filename | s_y | s_x | n_y | n_x | alias | img_min | img_max | img_range | img_mean | img_std | img_median |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 0 | 4 | 4 | img0_0-0 | 5419.0 | 12927.0 | 7508.0 | 8955.557637 | 489.754848 | 8960.0 |
| **1** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 1 | 4 | 4 | img0_0-1 | 5248.0 | 12854.0 | 7606.0 | 8883.137305 | 501.739963 | 8893.0 |
| **2** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 2 | 4 | 4 | img0_0-2 | 6084.0 | 10737.0 | 4653.0 | 8786.996070 | 327.512136 | 8786.0 |
| **3** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 3 | 4 | 4 | img0_0-3 | 7105.0 | 12208.0 | 5103.0 | 8679.430512 | 273.673569 | 8679.0 |
| **4** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 1 | 0 | 4 | 4 | img0_1-0 | 4534.0 | 10926.0 | 6392.0 | 8982.867158 | 380.410977 | 8980.0 |

**Normalize** the statistics using 'standarization'

In [5]:
```
stat_names = imgutils.stat_names(statfuncs)
print(stat_names)
```

```
['img_min', 'img_max', 'img_range', 'img_mean', 'img_std', 'img_median']
```

In [6]:
```
df.isnull().values.any()
```

Out[6]:
```
False
```

In [7]:
```
imgutils.normalize(df, stat_names)
df.head()
```

Out[7]:

| | filename | s_y | s_x | n_y | n_x | alias | img_min | img_max | img_range | img_mean | img_std | img_median | \|img_min\| | \|img_max\| | \|img_range\| | \|img_mean\| |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 0 | 4 | 4 | img0_0-0 | 5419.0 | 12927.0 | 7508.0 | 8955.557637 | 489.754848 | 8960.0 | 0.272467 | 0.099593 | -0.110160 | 0.615795 |
| **1** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 1 | 4 | 4 | img0_0-1 | 5248.0 | 12854.0 | 7606.0 | 8883.137305 | 501.739963 | 8893.0 | 0.208221 | 0.071800 | -0.086875 | 0.289248 |
| **2** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 2 | 4 | 4 | img0_0-2 | 6084.0 | 10737.0 | 4653.0 | 8786.996070 | 327.512136 | 8786.0 | 0.522312 | -0.734208 | -0.788528 | -0.144258 |
| **3** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 3 | 4 | 4 | img0_0-3 | 7105.0 | 12208.0 | 5103.0 | 8679.430512 | 273.673569 | 8679.0 | 0.905910 | -0.174153 | -0.681605 | -0.629277 |
| **4** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 1 | 0 | 4 | 4 | img0_1-0 | 4534.0 | 10926.0 | 6392.0 | 8982.867158 | 380.410977 | 8980.0 | -0.060035 | -0.662250 | -0.375329 | 0.738935 |

In [8]:
```
stat_normnames = imgutils.normalized_names(stat_names)
print(stat_normnames)
```

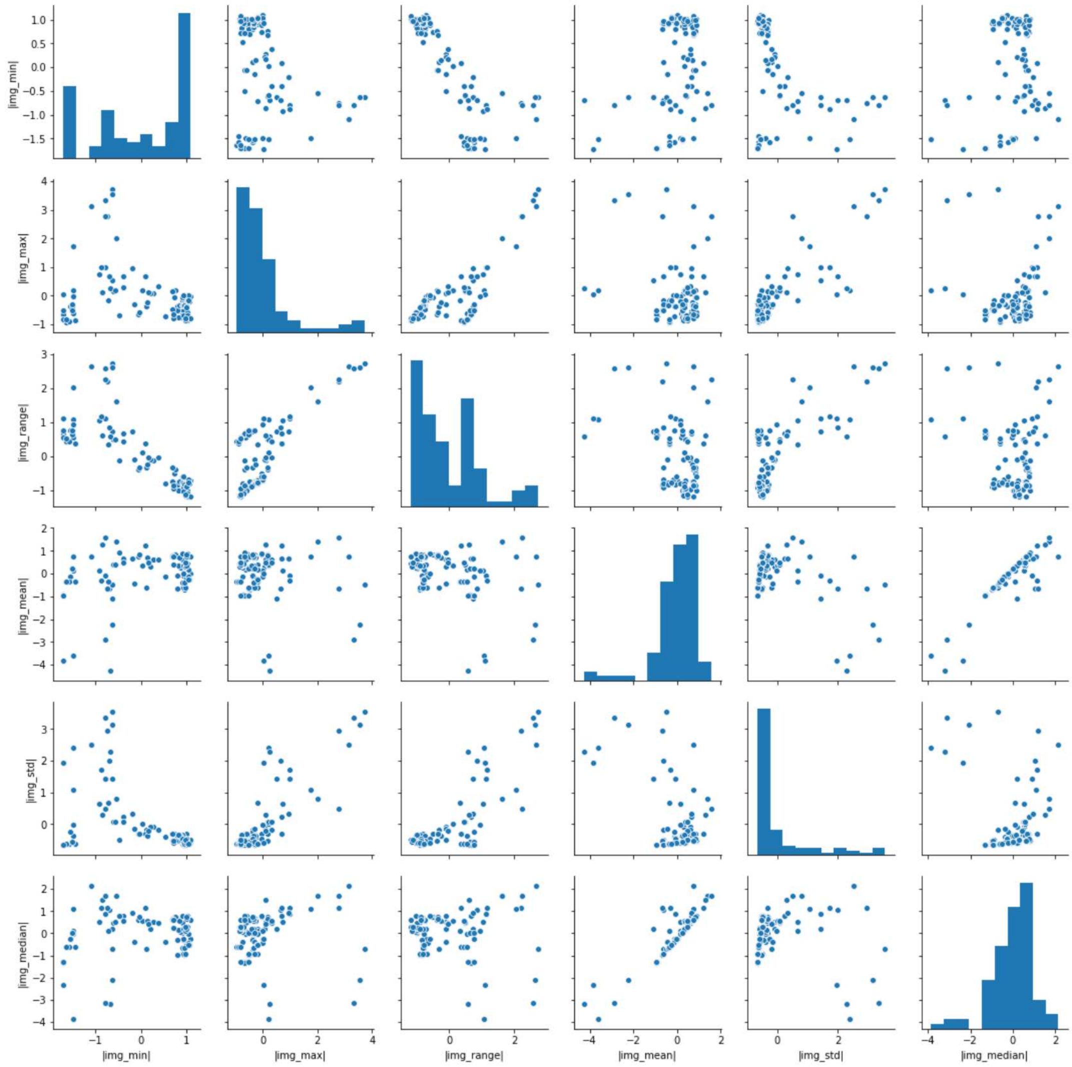
```
['|img_min|', '|img_max|', '|img_range|', '|img_mean|', '|img_std|', '|img_median|']
```

## 3. Check some combinations for patterns

(using the seaborn pairplot)

In [9]:
```
import seaborn as sb
```

In [10]:
```
%matplotlib inline
sb.pairplot(df, vars=stat_normnames)
plt.show()
```

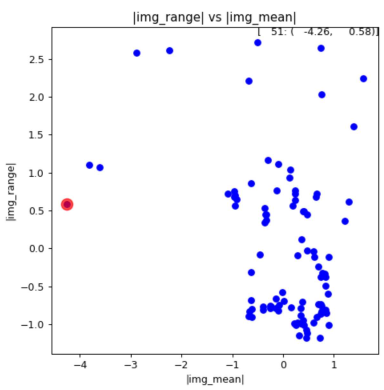


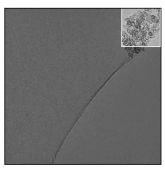

## 4. Inspect interactively

Let's inspect some combinations that have 'signs of clustering' in the interactive graph

In [261]:
```
%matplotlib notebook
```

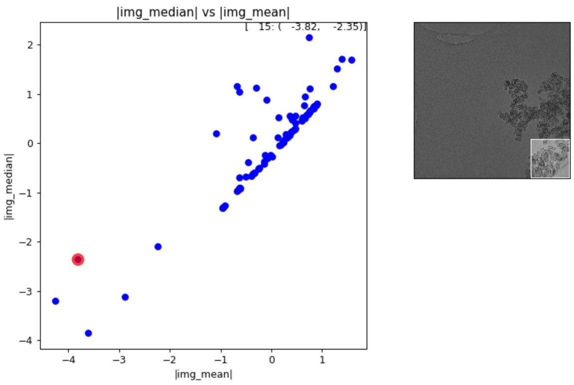
In [262]:
```
imgutils.plotwithimg(df, '|img_mean|', '|img_range|', imgutils.highlightimgslice)
```



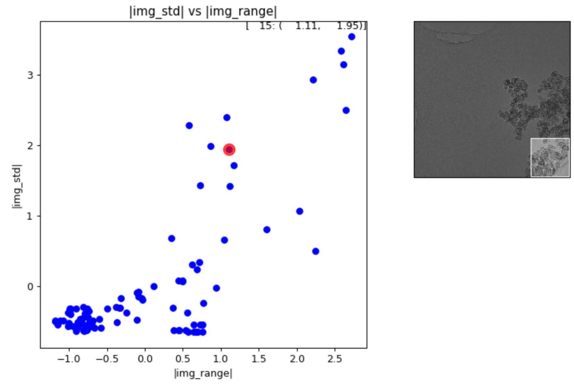
Looks likt the sort-of cluster in lower right are points without a crystal

In [263]:
```
imgutils.plotwithimg(df, '|img_mean|', '|img_median|', imgutils.highlightimgslice)
```




The separation is not representative, the group at top-left contains both with and without micro crystals

In [264]:
```
imgutils.plotwithimg(df, '|img_range|', '|img_std|', imgutils.highlightimgslice)
```




This looks better, bottom left are empty regions, top-left have crystals.

## 5. Heatmaps

Let's do an attempt to create a score for a heatmap. Looks like |img_std| is most infromative

In [15]:
```
df['dummy']=0
```

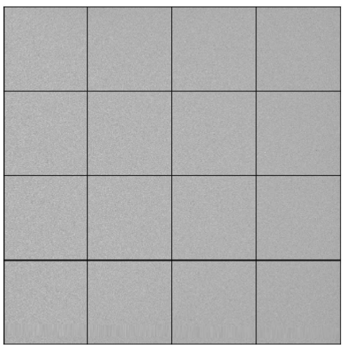
In [16]:
```
imgname = df_imgfiles.iloc[3]['filename']
print(imgname)
```

```
..\data\Crystals_Apr_12\Tileset7\Tile_002-001-000_0-000.tif
```

In [17]:
```
imgs, heats = imgutils.getimgslices_fromdf(df, imgname, '|img_std|')
```

In [18]:
```
%matplotlib inline
```

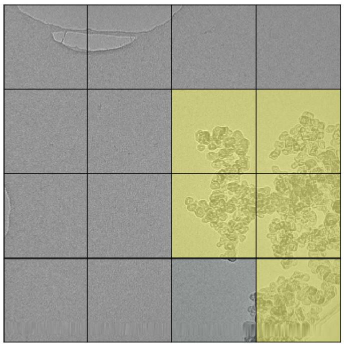
In [237]:
```
imgutils.showheatmap(imgs, heats)
print(heats)
```



```
[[-0.5007574  -0.55362623 -0.60028822 -0.64122158]
 [-0.48290759 -0.53099997 -0.57905287 -0.63107007]
 [-0.47531551 -0.52509339 -0.58101869 -0.63091528]
 [-0.49651996 -0.55462781 -0.61553092 -0.6530468 ]]
```

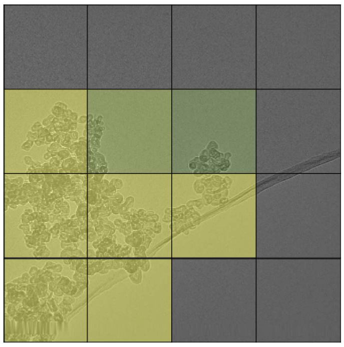
Yes, looks great!. Let's check for some other images as well

In [238]:
```
imgname = df_imgfiles.iloc[0]['filename']
imgs, heats = imgutils.getimgslices_fromdf(df, imgname, '|img_std|')
imgutils.showheatmap(imgs, heats, opacity=0.5)
print(heats)
```



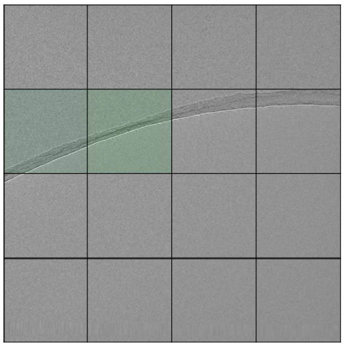
```
[[-0.10099756 -0.07945079 -0.39267662 -0.4894673 ]
 [-0.29757537 -0.3273344   1.4246215   1.43493234]
 [-0.18030138 -0.32036146  1.99383811  2.39706397]
 [-0.32505447 -0.38569278  0.06486636  1.95016713]]
```

In [239]:
```
imgname = df_imgfiles.iloc[1]['filename']
imgs, heats = imgutils.getimgslices_fromdf(df, imgname, '|img_std|')
imgutils.showheatmap(imgs, heats, opacity=0.5)
print(heats)
```



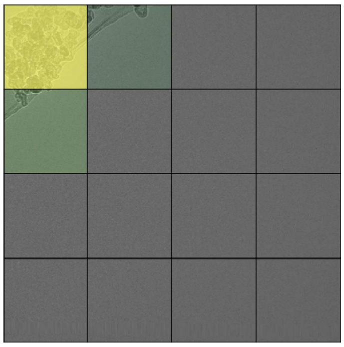
```
[[-0.30616301 -0.3702352  -0.44774946 -0.51603165]
 [ 2.50175087  0.80320234  0.65300243 -0.180137  ]
 [ 3.55004565  2.94066527  1.71852491 -0.2448691 ]
 [ 3.1514378   1.07195892 -0.5602243  -0.65242612]]
```

In [240]:
```
imgname = df_imgfiles.iloc[2]['filename']
imgs, heats = imgutils.getimgslices_fromdf(df, imgname, '|img_std|')
imgutils.showheatmap(imgs, heats, opacity=0.7)
print(heats)
```



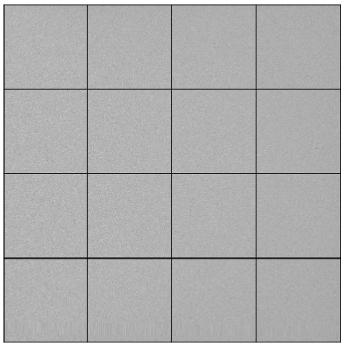
```
[[-3.25663596e-01 -3.98403099e-01 -4.54799075e-01 -5.20120403e-01]
 [ 2.32004465e-01  3.33913520e-01 -4.85345650e-04 -1.48112655e-01]
 [-3.12944453e-01 -5.22354114e-01 -5.79775101e-01 -6.29787851e-01]
 [-4.94901820e-01 -5.52180410e-01 -6.15687209e-01 -6.54574240e-01]]
```

In [241]:
```
imgname = df_imgfiles.iloc[4]['filename']
imgs, heats = imgutils.getimgslices_fromdf(df, imgname, '|img_std|')
imgutils.showheatmap(imgs, heats, opacity=0.7)
print(heats)
```



```
[[ 3.34714189  0.30222308 -0.60226899 -0.64055911]
 [ 0.49391915 -0.52329529 -0.57912635 -0.62971287]
 [-0.47261207 -0.52582949 -0.579462   -0.63034999]
 [-0.49885962 -0.55231449 -0.61765429 -0.65437469]]
```

In [242]:
```
imgname = df_imgfiles.iloc[5]['filename']
imgs, heats = imgutils.getimgslices_fromdf(df, imgname, '|img_std|')
imgutils.showheatmap(imgs, heats, opacity=0.7)
print(heats)
```



```
[[-0.5007574  -0.55362623 -0.60028822 -0.64122158]
 [-0.48290759 -0.53099997 -0.57905287 -0.63107007]
 [-0.47531551 -0.52509339 -0.58101869 -0.63091528]
 [-0.49651996 -0.55462781 -0.61553092 -0.6530468 ]]
```

## 6. Conclusions & Remarks

- The visualization and heatmap concept looks nice.
- Did not use real clustering, but from data exploration just used normalized standard deviation as indicator
- For larger or different sets (with outliers), I guess a combination of statistics is needed (which was the idea in the first place and let ML figure out what)

## 7. Next steps

- Export this data set and label it based on std-dev (e.g. 3 cats: none, some, full)
- Export this data set for unsupervised learning
- Repeat on bigger and more versatile set

Michael Janus, 15 June 2018

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# Update 5 July 2018

## 8. Assign labels

inspecting the heats, define 3 cats:

- |img_std|<0 = A (no particle);
- 0<|img_std|<1 = B (partly)
- |img_std|>1 = C (fully)

In [25]:
```
def assign_label(score):
    if score<0: return 'A'
    if score>=1: return 'C'
    return 'B'

df['class'] = df.apply(lambda r: assign_label(r['|img_std|']), axis=1)
```

In [26]:
```
df.head()
```

Out[26]:

| | filename | s_y | s_x | n_y | n_x | alias | img_min | img_max | img_range | img_mean | img_std | img_median | \|img_min\| | \|img_max\| | \|img_range\| | \|img_mean\| |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 0 | 4 | 4 | img0_0-0 | 5419.0 | 12927.0 | 7508.0 | 8955.557637 | 489.754848 | 8960.0 | 0.272467 | 0.099593 | -0.110160 | 0.615795 |
| **1** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 1 | 4 | 4 | img0_0-1 | 5248.0 | 12854.0 | 7606.0 | 8883.137305 | 501.739963 | 8893.0 | 0.208221 | 0.071800 | -0.086875 | 0.289248 |
| **2** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 2 | 4 | 4 | img0_0-2 | 6084.0 | 10737.0 | 4653.0 | 8786.996070 | 327.512136 | 8786.0 | 0.522312 | -0.734208 | -0.788528 | -0.144258 |
| **3** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 0 | 3 | 4 | 4 | img0_0-3 | 7105.0 | 12208.0 | 5103.0 | 8679.430512 | 273.673569 | 8679.0 | 0.905910 | -0.174153 | -0.681605 | -0.629277 |
| **4** | ..\data\Crystals_Apr_12\Tileset7\Tile_001-001-... | 1 | 0 | 4 | 4 | img0_1-0 | 4534.0 | 10926.0 | 6392.0 | 8982.867158 | 380.410977 | 8980.0 | -0.060035 | -0.662250 | -0.375329 | 0.738935 |

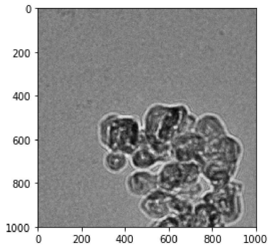
In [27]:
```
df2 = df[df['class']=='C']
```

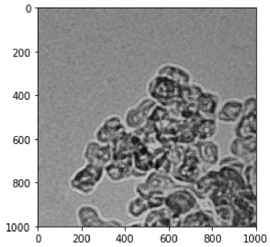
In [28]:
```
print(len(df2))
```

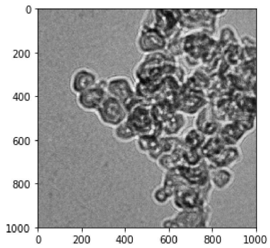
```
13
```

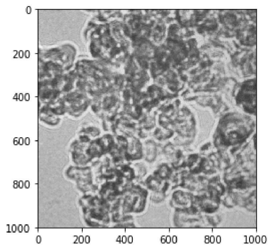
In [29]:

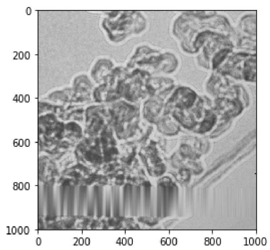
```
%matplotlib inline
# check class C images
for i in range(0,len(df2)):
    img = imgutils.getimgslice(df2, i)
    imgutils.showimg(img)
```

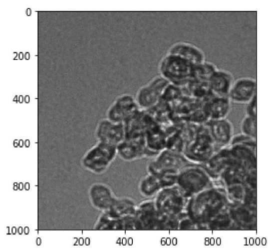

0 200 400 600 800 1000
0 200 400 600 800 1000

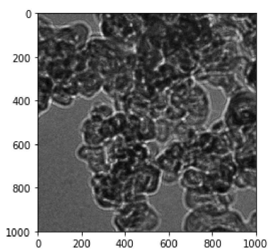

0 200 400 600 800 1000
0 200 400 600 800 1000

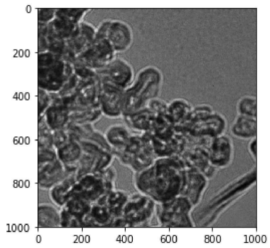

0 200 400 600 800 1000
0 200 400 600 800 1000

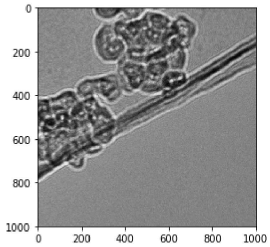

0 200 400 600 800 1000
0 200 400 600 800 1000

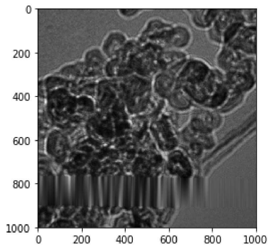

0 200 400 600 800 1000
0 200 400 600 800 1000

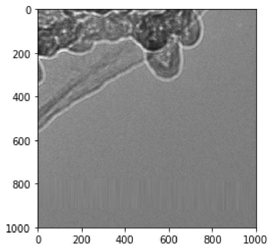

0 200 400 600 800 1000
0 200 400 600 800 1000

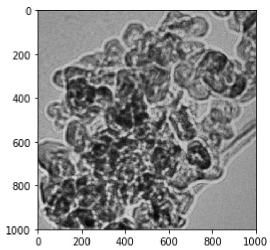

0 200 400 600 800 1000
0 200 400 600 800 1000

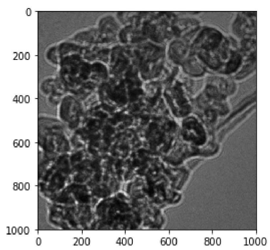


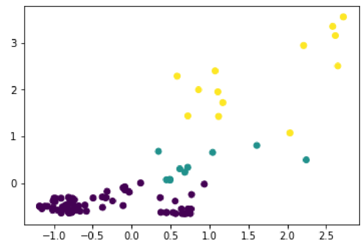



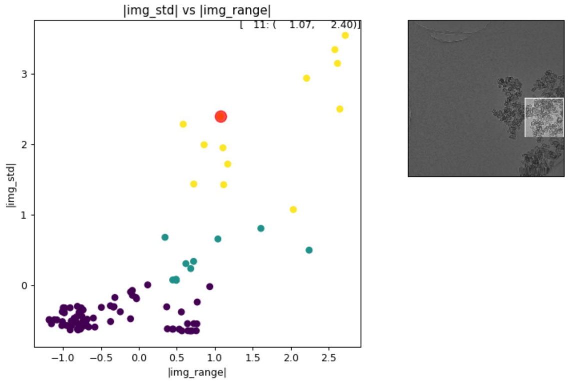




In [30]:
```
# also plot them the img_std vs img_range with the labels
labels = df['class'].tolist()
colors = [(0 if (l=='A') else (1 if (l=='B') else 2))  for l in labels]
plt.scatter(df['|img_range|'], df['|img_std|'], c=colors)
plt.show()
```




ideally we should have this interactive with the images, so extend the infrastructure (done, had to change to interactive scatter plot instead of line plot)

In [265]:
```
%matplotlib notebook
imgutils.plotwithimg(df, '|img_range|', '|img_std|', imgutils.highlightimgslice, 'class')
```




## 9. Export as csv

In [32]:
```
df.to_csv('../data/Crystals_Apr_12/Tileset7.csv', sep=';')
```

## 10. Also other stats

In [33]:
```
statfuncs = [imgutils.img_mean, imgutils.img_std, imgutils.img_kurtosis, imgutils.img_skewness, imgutils.img_mode]
df2 = imgutils.slicestats(list(df_imgfiles['filename']), 4, 4, statfuncs)
print("records: ", df2.shape[0])
```

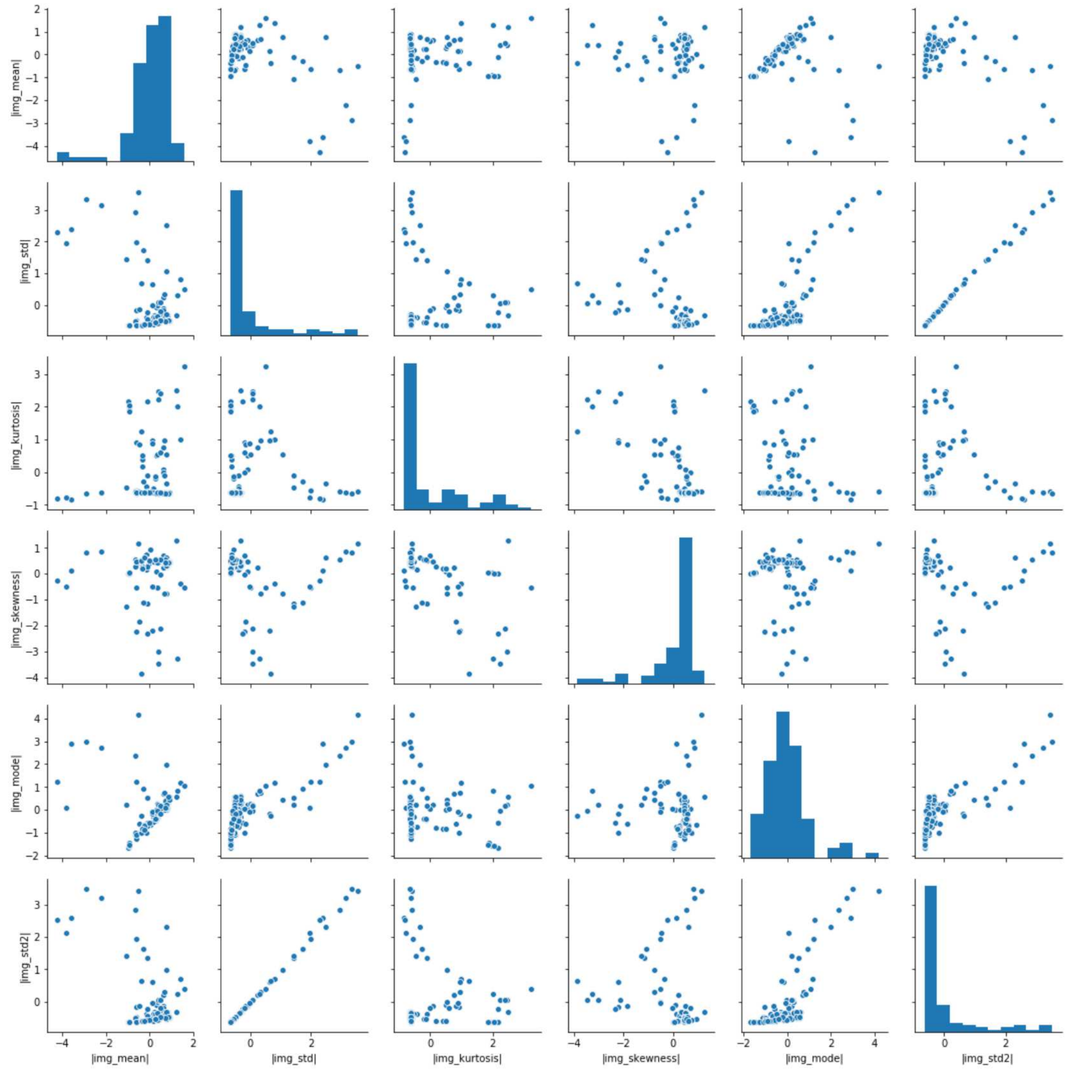
```
records:  96
```

In [34]:
```
df2['img_std2']=df2['img_std']/df['img_mean']
```

In [35]:
```
stat_names = imgutils.stat_names(statfuncs) + ['img_std2']
imgutils.normalize(df2, stat_names)
```

In [36]:
```
stat_normnames = imgutils.normalized_names(stat_names)

%matplotlib inline
sb.pairplot(df2, vars=stat_normnames)
plt.show()
```




In [37]:
```
#Label them based on std (first experiment)
df2['class'] = df.apply(lambda r: assign_label(r['|img_std|']), axis=1)
```

In [38]:
```
df2.to_csv('../data/Crystals_Apr_12/Tileset7-2.csv', sep=';')
```

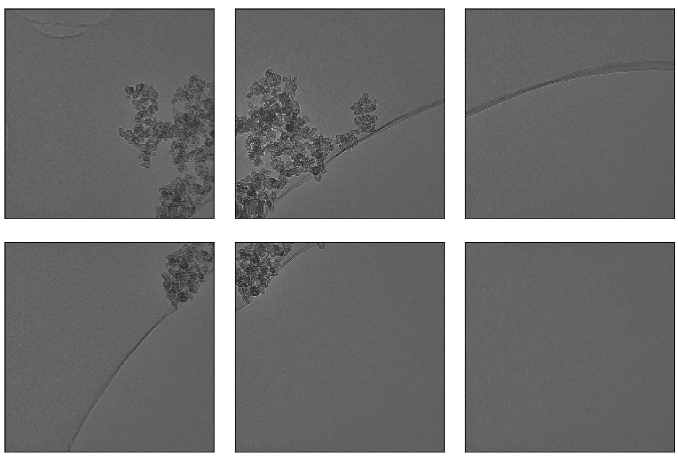
## Update October 30 - Improved visualization (for report)

In [223]:
```
# Re-run this cell if you altered imgutils or imgutils_test
import importlib
importlib.reload(imgutils)
```

Out[223]:
```
<module 'imgutils' from 'C:\\JADS\\SW\\Grad Proj\\sources\\imgutils.py'>
```

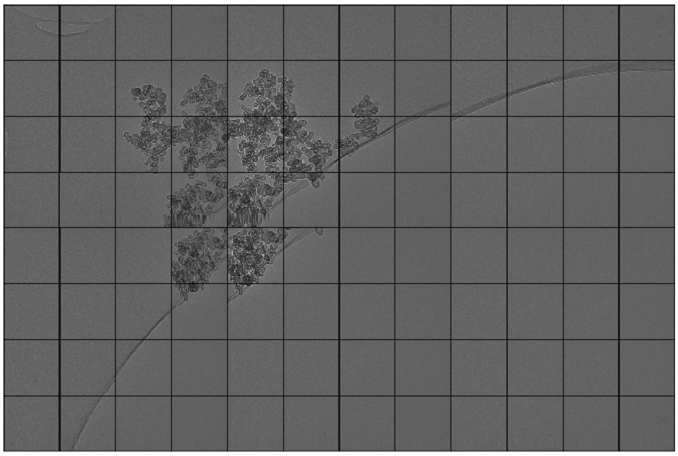
In [145]:
```
imgfiles = df_imgfiles['filename'].tolist()
```

In [249]:
```
# this is a set of 2 x 3 images covering a larger area (a so called 'tile set')
imgutils.showimgset(imgfiles, 2,3, fig_size=(12, 8), relspacing=(0.1,0.1))
```



In [243]:
```
imgutils.show_large_heatmap(df, 'dummy', imgfiles, 2, 3, opacity=0.8, cmapname='summer', no_borders=False, fig_size=(10,8))
```

Heats from: dummy



In [253]:
```
imgutils.show_large_heatmap(df, '|img_std|', imgfiles, 2, 3, opacity=0.8, cmapname='summer', no_borders=False, heatdependent_opacity=True, fig_size=(12,8.2))
```

Heats from: |img_std|