'Fake' micro crystals - checking if they are revealed in the statistics

Creation Date: May 2018
Last Update: 28 Oct 2018

Author: Michael Janus

Description:
The goal of this notebook was to test one of the initial assumptions: is the presence of a particle in an image visible in the basic statistics (like mean, std, ...). To this purpose, a number of images was collected, roughly half of them containing a small particle, and the other half did not. These are real microscope images, but the particles are not micro-crystals, just some dust or whatever. The images have been pre-categorized into two folders: with and without particle.

(this work was done in May 2018 in two short notebooks. This notebook was created later to merge the two and add more comments)

1. Import Packages

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import seaborn as sns
sns.set_style('whitegrid')
import pandas as pd
import pathlib as path
import skimage.io

import warnings
warnings.filterwarnings("ignore")
```

2. Inspect Data

Remark: if the images are not available, skip steps 2- 4 and import the csv at step 5)

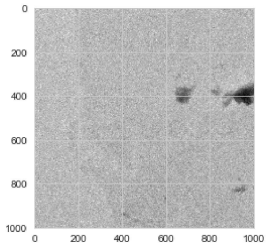
In [2]:
```
im_with = skimage.io.imread('../data/Fake-Xtals/cat_true/Tile_001-002-000_0-000.tif', plugin='tifffile')
im_without = skimage.io.imread('../data/Fake-Xtals/cat_false/Tile_001-002-000_0-000.tif', plugin='tifffile')
```

In [3]:
```
im_with.dtype, im_with.shape
```

Out[3]: (dtype('uint16'), (1000, 1000))

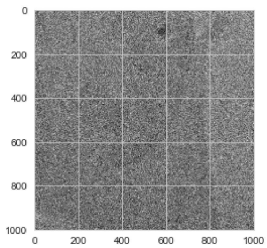
In [4]:
```
print("Image WITH particle")
imgplot = plt.imshow(im_with, cmap='gray')
```

```
Image WITH particle
```



In [5]:
```
print("Image WITHOUT particle")
imgplot = plt.imshow(im_without, cmap='gray')
```

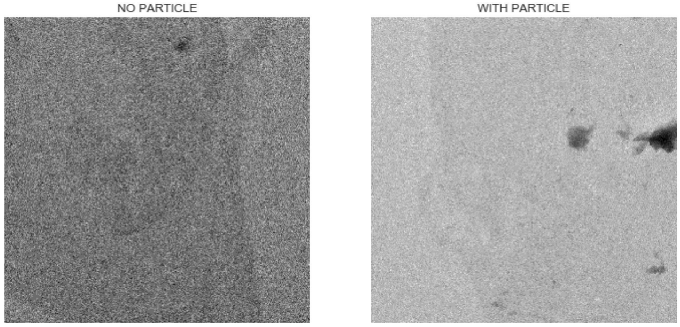
```
Image WITHOUT particle
```



let's put them side by side

In [6]:
```
f, (ax1,ax2) = plt.subplots(1,2, figsize=(12,6))
ax1.imshow(im_without, cmap='gray')
ax2.imshow(im_with, cmap='gray')
ax1.set_title("NO PARTICLE")
ax2.set_title("WITH PARTICLE")
ax1.axis('off')
ax2.axis('off')
```

Out[6]: (-0.5, 999.5, 999.5, -0.5)



3. Label all images and store in data frame

In [7]:
```
# import files into dataframe
df = pd.DataFrame([['dummy', False]], columns=['filename','has_particle'])
df = df.drop(df.index[[0]])
pathlist1 = path.Path('../data/Fake-Xtals/cat_false')
pathlist2 = path.Path('../data/Fake-Xtals/cat_true')

for item in pathlist1.iterdir():
    filename = str(item)
    df.loc[len(df)] = [filename, False]
for item in pathlist2.iterdir():
    filename = str(item)
    df.loc[len(df)] = [filename, True]
```

4. Calculate basic image statistics

In [8]:
```
# Read images and determine statistics
import skimage.io
import sys


df['mean'] = 0
df['median'] = 0
df['std'] = 0
df['max'] = 0
df['min'] = 0
n = len(df)
for index, row in df.iterrows():
    imfn = row['filename']
    im = skimage.io.imread(imfn, plugin='tifffile')
    df.at[index, 'mean'] = np.mean(im)
    df.at[index, 'median']= np.median(im)
    df.at[index, 'std'] = np.std(im)
    df.at[index, 'min'] = np.min(im)
    df.at[index, 'max'] = np.max(im)

    # show progress
    prline = "{0} / {1} - {2}".format(index, n, imfn)
    sys.stdout.write("\r" + prline)
    sys.stdout.flush()
```

```
87 / 88 - ..\data\Fake-Xtals\cat_true\Tile_011-011-000_0-000.tifff
```

In [9]:
```
df.head(3)
```

Out[9]:

	filename	has_particle	mean	median	std	max	min
0	..\data\Fake-Xtals\cat_false\Tile_001-002-000_...	False	4191	4112	186	5140	3341
1	..\data\Fake-Xtals\cat_false\Tile_001-003-000_...	False	4189	4112	186	5140	3084
2	..\data\Fake-Xtals\cat_false\Tile_001-005-000_...	False	4193	4112	182	5140	3341

In [10]:
```
df.tail(3)
```

Out[10]:

	filename	has_particle	mean	median	std	max	min
85	..\data\Fake-Xtals\cat_true\Tile_011-006-000_0...	True	4192	4112	259	5397	2056
86	..\data\Fake-Xtals\cat_true\Tile_011-007-000_0...	True	4223	4112	208	5140	2313
87	..\data\Fake-Xtals\cat_true\Tile_011-011-000_0...	True	4221	4112	190	5397	2827

export to csv

In [11]:
```
# export to csv:
df.to_csv('../data/Fake-Xtals/image_stats.csv', index=False )
```

5. (Re)Load the labelled data

In [12]:
```
file = "../data/Fake-Xtals/image_stats.csv"
img_df = pd.read_csv(file, sep=',')
img_df.head(3)
```

Out[12]:

	filename	has_particle	mean	median	std	max	min
0	..\data\Fake-Xtals\cat_false\Tile_001-002-000_...	False	4191	4112	186	5140	3341
1	..\data\Fake-Xtals\cat_false\Tile_001-003-000_...	False	4189	4112	186	5140	3084
2	..\data\Fake-Xtals\cat_false\Tile_001-005-000_...	False	4193	4112	182	5140	3341

6. EDA on the labelled data

In [13]:
```
img_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 88 entries, 0 to 87
Data columns (total 7 columns):
filename        88 non-null object
has_particle    88 non-null bool
mean            88 non-null int64
median          88 non-null int64
std             88 non-null int64
max             88 non-null int64
min             88 non-null int64
dtypes: bool(1), int64(5), object(1)
memory usage: 4.3+ KB
```

In [14]:
```
part_true = img_df[img_df['has_particle']==True].count()['has_particle']
part_false = img_df[img_df['has_particle']==False].count()['has_particle']
```

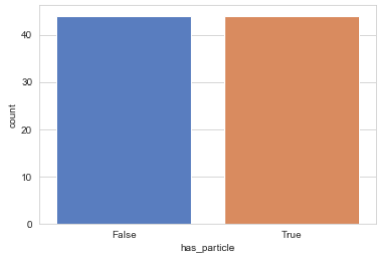
6a. Look at distributions

In [15]:
```
print (part_true, part_false)
```

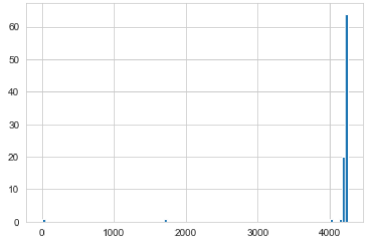
```
44 44
```

data is well balanced between WITH and WITHOUT

In [16]:
```
ax = sns.countplot(x="has_particle", data=img_df,palette="muted")
```

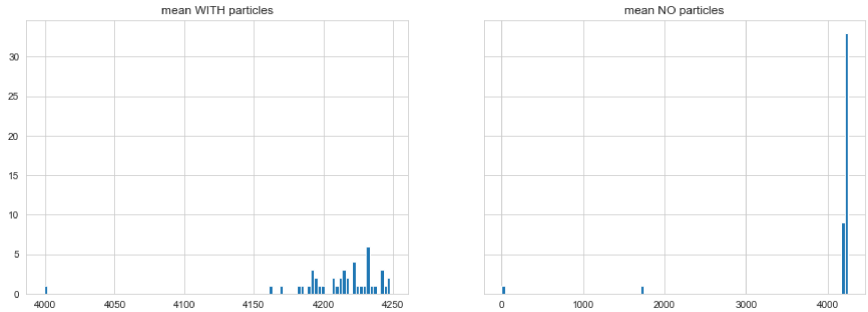


In [17]:
```
hplt = plt.hist(img_df['mean'], bins=100)
```

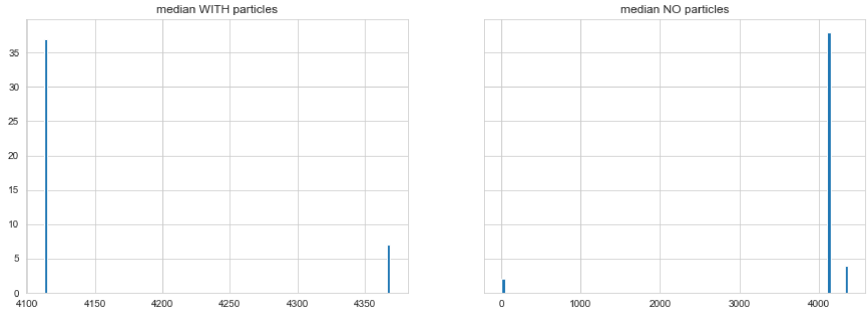


In [18]:
```
def plot_hist(statname):
    x_part = img_df[img_df['has_particle']==True][statname]
    x_nopart = img_df[img_df['has_particle']==False][statname]
    f, (ax1, ax2) = plt.subplots(1, 2, sharey=True)
    ax1.hist(x_part, bins=100)
    ax1.set_title(statname + ' WITH particles')
    ax2.hist(x_nopart, bins=100)
    ax2.set_title(statname + ' NO particles')
    f.set_figwidth(15)
    f.set_figheight(5)
```

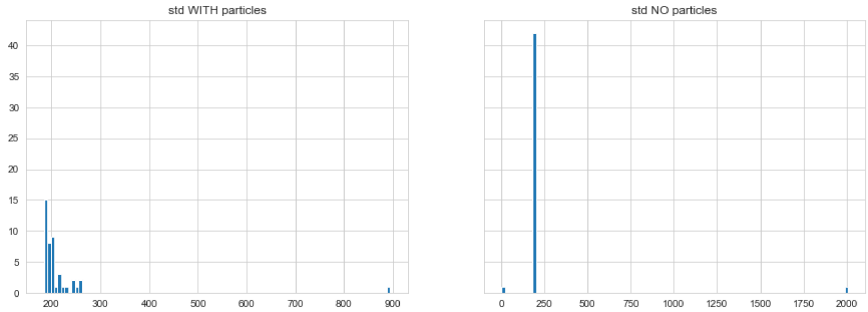
In [19]:
```
plot_hist('mean')
```



In [20]:
```
plot_hist('median')
```



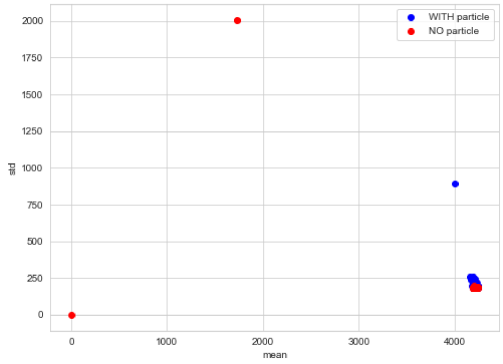
In [21]:
```
plot_hist('std')
```



6b. Look at scatter plots

In [22]:
```
def plot_scatter(stat1, stat2):
    x1 = img_df[img_df['has_particle']==True][stat1]
    y1 = img_df[img_df['has_particle']==True][stat2]
    x2 = img_df[img_df['has_particle']==False][stat1]
    y2 = img_df[img_df['has_particle']==False][stat2]

    f = plt.figure(figsize=(8,6))
    f1 = plt.scatter(x1,y1, color='blue')
    f2 = plt.scatter(x2,y2, color='red')

    plt.xlabel(stat1)
    plt.ylabel(stat2)
    plt.legend((f1,f2),('WITH particle', 'NO particle'), frameon=True)
    plt.show()
```

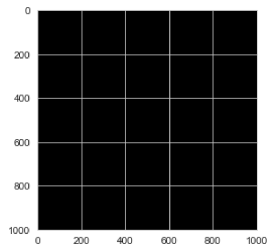
In [23]:
```
plot_scatter('mean','std')
```



let's look at the datapoint at 0,0

In [24]:
```
# This is a completely black image
print(img_df[img_df['mean']==0])
fn = img_df[img_df['mean']==0].iloc[0,0]
im = skimage.io.imread(fn, plugin='tifffile')
imgplot = plt.imshow(im, cmap='gray')
```

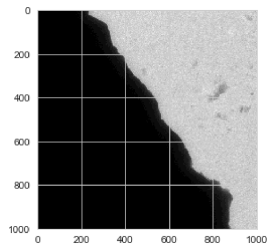
```
                                             filename  has_particle  mean  \
37  ..\data\Fake-Xtals\cat_false\Tile_011-002-000_...         False     0

    median  std  max  min
37       0    0    0    0
```



Ah, it's completely black !

In [25]:
```
# This is also an outlier
print(img_df[img_df['std']>2000])
fn = img_df[img_df['std']>2000].iloc[0,0]
im = skimage.io.imread(fn, plugin='tifffile')
imgplot = plt.imshow(im, cmap='gray')
```

```
                                             filename  has_particle  mean  \
36  ..\data\Fake-Xtals\cat_false\Tile_011-002-000_...         False  1729

    median   std   max  min
36       0  2008  5140    0
```



Other outliers are the partial blacks

6c. Check with pair plots if any combination is clearly separatable

In [26]:
```
sns.pairplot(img_df,vars=['mean','median','std','min','max'],hue='has_particle')
```

Out[26]: <seaborn.axisgrid.PairGrid at 0xd079278>

Hard to see, but graph of median and std could work if outliers are excluded

7. Train a model

In [27]:
```
print(img_df.count())
```

```
filename        88
has_particle    88
mean            88
median          88
std             88
max             88
min             88
dtype: int64
```

In [28]:
```
# Create train and test set
from sklearn.model_selection import train_test_split

X = img_df[['mean','std','min','max']].astype(float).values
y = img_df[['has_particle']].astype(dtype=np.float).values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.6, random_state=42)
```

In [29]:
```
print(X_train[:5], y_train[:5])
```

```
[[4221.  190. 2827. 5397.]
 [4228.  195. 3084. 5140.]
 [4222.  186. 3084. 5140.]
 [4189.  196. 2056. 5140.]
 [4181.  198. 2313. 5140.]] [[1.]
 [1.]
 [0.]
 [1.]
 [1.]]
```

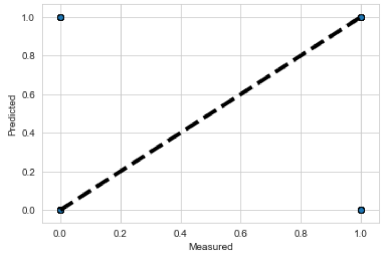
In [30]:
```
# import the classifier
from sklearn.neighbors import KNeighborsClassifier

# instantiate the model (with the default parameters)
knn = KNeighborsClassifier()

# fit the model with data (occurs in-place)
knn.fit(X_train, y_train)
```

Out[30]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
           metric_params=None, n_jobs=1, n_neighbors=5, p=2,
           weights='uniform')
```

Show model accuracy

In [31]:
```
y_pred = knn.predict(X_test)
fig, ax = plt.subplots()
ax.scatter(y_test, y_pred, edgecolors=(0, 0, 0))
ax.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=4)
ax.set_xlabel('Measured')
ax.set_ylabel('Predicted')
```

Out[31]: Text(0,0.5,'Predicted')

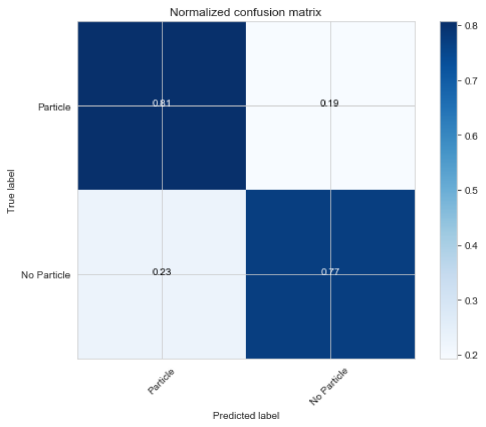


hmm, not ideal. let's use a confusion matrix (code from sklearn)

In [32]:
```
import itertools
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    f = plt.figure(figsize=(8,6))
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
```

In [33]:
```
# Compute confusion matrix
from sklearn.metrics import confusion_matrix

cnf_matrix = confusion_matrix(y_test, y_pred)
np.set_printoptions(precision=2)

class_names = ['Particle','No Particle']

# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,title='Normalized confusion matrix')

plt.show()
```

```
Normalized confusion matrix
[[0.81 0.19]
 [0.23 0.77]]

<Figure size 432x288 with 0 Axes>
```



Not perfect, but without removing any outliers there is about 80% prediction accurracy

8. Conclusions

- It looks viable to detect a particle in an image just from statistics
- Outliers due to (partly) black images obscure the statistics
- To inspect data points, you need to see underlying image. This is cumbersome and needs more assistance with scripts