tma_analysis_sacla

September 6, 2018

In [28]:
```
%matplotlib inline

import glob
from collections import Counter

import h5py
import pandas
import numpy as np

import pylab as plt
```

In [100]:
```
run = 656748
h5 = h5py.File('r%d/radials.h5'%run, 'r')
print( h5.keys())
```

```
[u'dark', u'pumped']
```

In [30]:
```
print(h5["pumped"].keys())
```

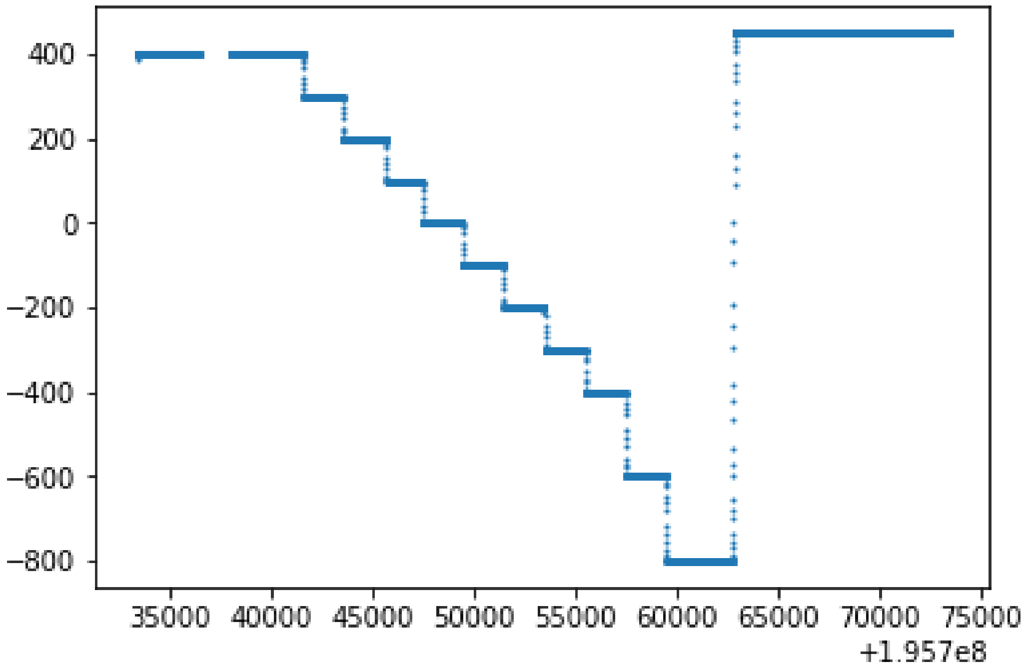
```
[u'Qrads', u'olaser_delay', u'olaser_volt', u'photon_energy', u'pulse_energy', u'radials', u'tag
```

In [31]:
```
# nominal delay values
# Each unit corresponds to roughly 6.6 femtoseconds
# and time 0 is roughly olaser_delay=0
delay_vals = h5['pumped']['olaser_delay'].value # optical laser delay stage value
```

In [32]:
```
pumped_tag = h5['pumped/tag'].value
order = np.argsort( pumped_tag)
print pumped_tag.shape, delay_vals.shape
plt.plot( pumped_tag[order], delay_vals[order], '.', ms=2)
# watch how we changed the delay during this run
# negative stage olser_delay means
```

```
(14423,) (14423,)
```

Out[32]:
```
[<matplotlib.lines.Line2D at 0x1161e8510>]
```




```
In [33]: # Now those are the nominal delay values

         # We wish to make the time delay more precise by using the
         # sub picosecond time-tool at SACLA

         # This data is in the TMA results.CSV file(s) provided by SACLA
         results = glob.glob("TMA/*/results.csv") # there are multiple files for different parts

In [34]: # this is the title row in each results.CSV
         cols = 'tagNumber,time_of_getting_image[msec/tag],time_of_detection[msec/tag],time_of_w
             ',')
         print(cols)

['tagNumber', 'time_of_getting_image[msec/tag]', 'time_of_detection[msec/tag]', 'time_of_writing

In [35]: # load the data from each results.CSV file and store in a large array
         data = np.vstack(
                 [np.loadtxt(r, skiprows=1, delimiter=',') for r in results ])

In [118]: # convert the array data to a pandas dataframe
          df = pandas.DataFrame(columns=cols, data=data) # this is the tma data for the entire e

In [119]: # lets query the tma data for the particular run
```

```
# first, we find the minimum and maximum tag number in our experimental data h5 file
tags = np.hstack( (h5['dark']['tag'].value, h5['pumped']['tag'].value))
tmin, tmax = tags.min(), tags.max()

# then we query the time-tool dataframe
df_run = df.query("tagNumber >= %d and tagNumber <= %d" % (tmin, tmax))
print ("%d shots in run %s"%(len( df_run), h5.filename) )
```

```
20000 shots in run r656748/radials.h5
```

In [120]:
```
# Now , we should merge this TMA data frame with the experimental data in the hdf5 fil

pumped = h5['pumped']
dark = h5['dark']

# These are the relevant bits of the files, in particular the energy, radials and tag
df_pumped_h5data = pandas.DataFrame({'radials': list(pumped['radials'].value),
                        'tagNumber': pumped['tag'].value, # note we keep same name tag
                        'olaser_delay': pumped['olaser_delay'].value,
                        'pulse_energy': pumped['pulse_energy'].value,
                        'photon_energy': pumped['photon_energy'].value,
                        'olaser_volt': pumped['olaser_volt'].value,
                        'xlaser_joule_bm_1': pumped['xlaser_joule_bm_1'].value})

# the dame for the dark data
df_dark_h5data = pandas.DataFrame({'radials': list(dark['radials'].value),
                        'tagNumber': dark['tag'].value, # note we keep same name tagNu
                        'olaser_delay': dark['olaser_delay'].value,
                        'pulse_energy': dark['pulse_energy'].value,
                        'photon_energy': dark['photon_energy'].value,
                        'olaser_volt': dark['olaser_volt'].value,
                        'xlaser_joule_bm_1': dark['xlaser_joule_bm_1'].value})

#NOTE: we made pumped[radials] a list, this is slightly abusing the pandas philosophy
# but it is quite convenient because we can keep all the parameters aligned
# when we analyze the radials

# NOTE: if radials is left as a numpy array pandas will raise an exception
```

In [121]:
```
# We can join the pumped and dark dataframes into one

# To do so, we first create a boolean column called pumped
df_pumped_h5data['pumped'] = True
df_dark_h5data['pumped'] = False

# then we can concatenate
df_h5 = pandas.concat( (df_pumped_h5data, df_dark_h5data))
```

In [122]:
```
print (list(df_h5), len(df_h5))
```

```
(['olaser_delay', 'olaser_volt', 'photon_energy', 'pulse_energy', 'radials', 'tagNumber', 'xlase
```

In [132]:
```
# Now we can merge the hdf5 dataframe with the SACLA time tool dataframe
df_main = pandas.merge(df_run, df_h5, on='tagNumber') # NOTE: pandas does an inner mer
print( list(df_main), len( df_main))
```

```
(['tagNumber', 'time_of_getting_image[msec/tag]', 'time_of_detection[msec/tag]', 'time_of_writin
```

In [133]:
```
# During the experiment, as the optical laser delay stage was translated,
# the olaser_delay values being read out changed continuously.

# This was because the time to jump from one delay stage value to another
# was much longer than the time between shots.

# Therefore, we need to isolate the fixed values of olaser_delay in order
# to query the nominal delay values.

# Usually, if a value is read out 10+ times in a row,  it's considered a fixed value
all_olaser_vals = Counter( df_main.olaser_delay.values)
print (all_olaser_vals.items() )  # (olaser_value, frequency) pairs
```

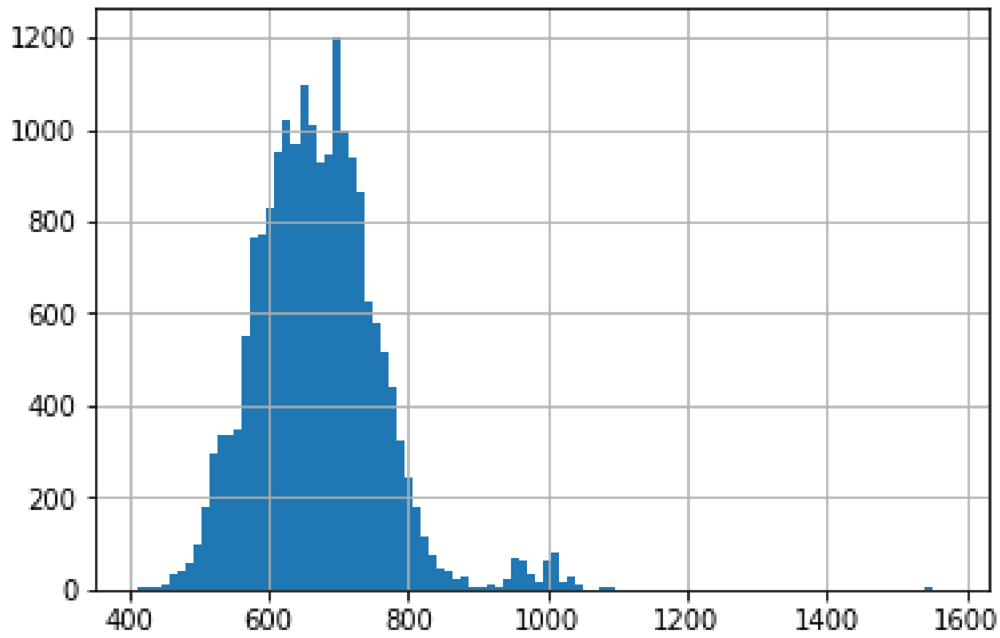
```
[(0, 971), (1, 1), (3, 1), (-508, 1), (5, 1), (-502, 1), (11, 1), (-424, 1), (19, 1), (-488, 1),
```

In [142]:
```
good_delays = [k for k, v in all_olaser_vals.items() if v > 10]
print ( good_delays) # store these numbers for later use in analysis queries
```

```
[0, -800, 100, -400, 200, -300, 300, -200, 400, -100, -600, 450]
```

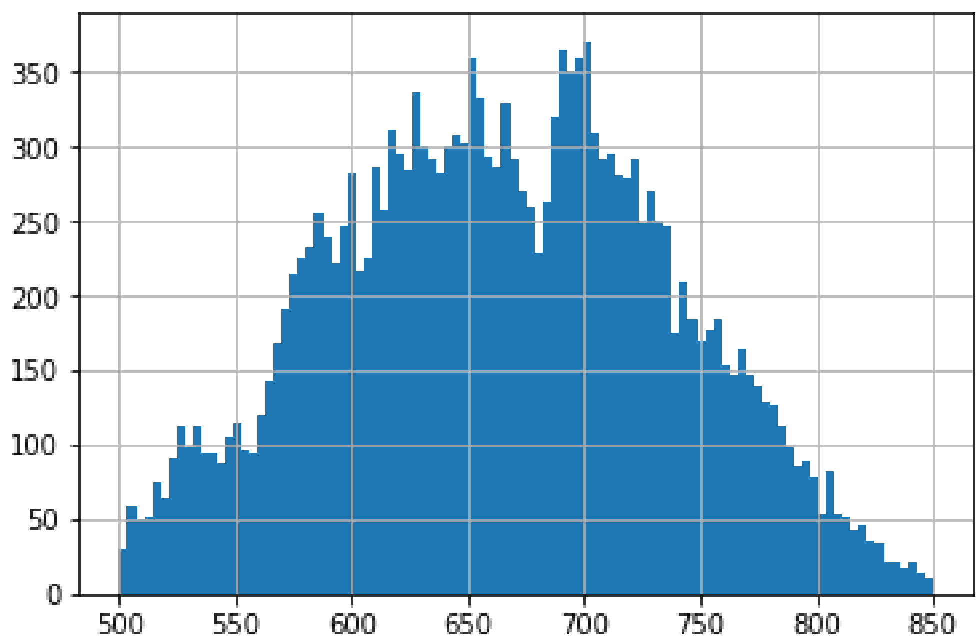
In [135]:
```
# Above are the nominal delay values that were set during this run
# (remember, the units correspond to roughly 6.6 picoseconds of delay)

# We can calculate the time-delay per shot using the fit_edge from the time-tool data

# Lets look at the time tool fit_edge position across the run
df_main.fit_edge.hist(bins=100)
```

Out[135]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11aba7390>
```



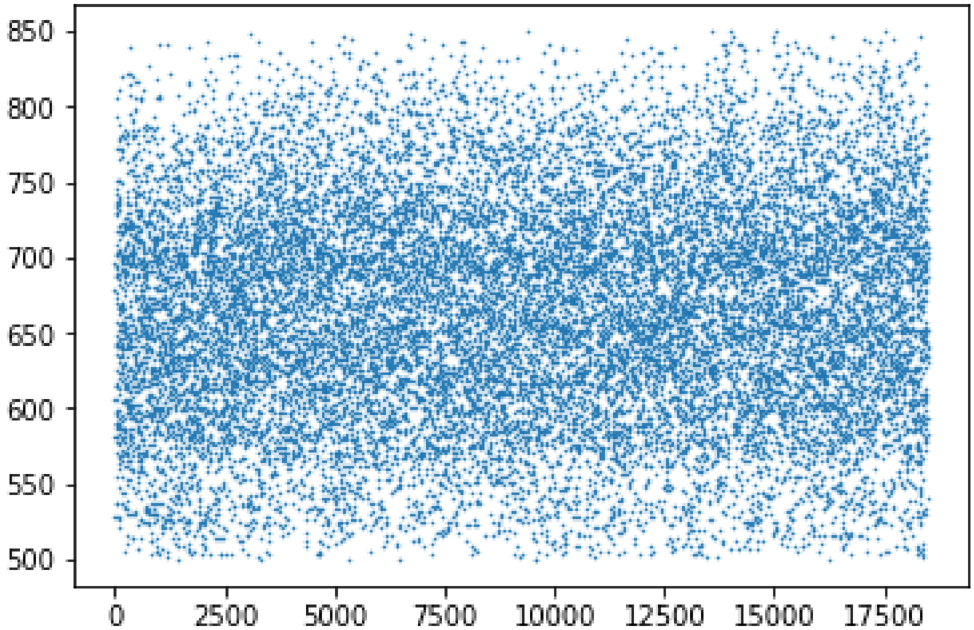

```
In [136]: # Looks like some outliers near edge positions 1000, so lets give a modest crop to the
          df_main = df_main.query('fit_edge > %d and fit_edge < %d' % (500, 850))
          df_main.fit_edge.hist( bins=100)
```

```
Out[136]: <matplotlib.axes._subplots.AxesSubplot at 0x11c61ae50>
```



In [137]:
```
# lets watch how this fit_edge is changing in time by sorting according to tagNumber
plt.plot( df_main.fit_edge[np.argsort(df_main.tagNumber)], '.', ms=1)
```

Out[137]:
```
[<matplotlib.lines.Line2D at 0x11ccba3d0>]
```



In [138]:
```
# It looks like the fit_edge is pretty uniform across this sun,

# Therefore, we can assume the average fit_edge is the nominal time delay.

# The correction to the time delay is ~3 femtosecond per fit_edge
# and arrival timing increases with fit_edge
df_main['time_adjust'] = (df_main.fit_edge - df_main.fit_edge.mean()) * 0.003
```

In [139]:
```
# now , we commpute the per-shot time delay: (olaser_delay unit is roughly 6.6 femtose
df_main['delay_time'] = df_main.olaser_delay * 0.0066 + df_main.time_adjust
```

In [140]:
```
# lets save this dataframe
df_main.to_pickle("run%d_main.pkl"%run)
```

In [141]:
```
# the dataframe is quite useful
# e.g. to plot the average pumped radial profile
plt.plot( df_main.query("pumped==True").radials.mean(0) )
# The next notebook explains how to do detailed analysis
```

Out[141]: [<matplotlib.lines.Line2D at 0x11ab54410>]