Computational time reconstruction code

## Summary

$\square$ Study computational time on reconstruction code:

- Computational time test on CLOUD and LNGS
$\square$ Added to the reco file the time consumption of some pieces of the code:
$\square \quad$ Clustering time per image;
$\square$ Variables calculation time per image;
- Total time of the run.
- Close look at the Variables calculation:
- Grouping the variables in 13 categories;
$\square$ Adding category by category to measure the time of execution;
$\square$ Deeper study on the most time-consuming category.
$\square \quad$ Evaluate reconstruction computational time for Run2 e Run3.
$\square$ Conclusions


## Computational time test on CLOUD and LNGS

We have tested the reconstruction algorithm in terms of computational time using the HTCondor queues on the so-called CLOUD and also on the LNGS batch system (cygno-custom), both of them using SingleCore mode:

- Run1-4320 (Fe55) and 400 images;
- Using Autumn22 tag;

And as you can see the computational time is comparable.

All the analysis in the next slides were done using both environments.


## Added to the reco file the time consumption of some pieces of the code:

- Clustering time per image;
$\square$ Variables calculation time per image;
$\square$ Fill Camera variables time per image;
- Fill Cluster variables time per image;Total time of the run.



## Example:

Using the following configuration:

- Run1 LIME underground number: 4320 (Fe 25 cm far from GEMs)
- Reconstruction branch: Autumn22
- Processed at: HTCondor Cloud
- Number of Threads: 1 (Single core)

The resulted computational time is:

- Average computational time per image:

| $\circ$ | DBSCAN: | c.a. 16 s |
| :--- | :--- | :--- |
| $\circ$ | Variables: | c.a 25 s |
| $\circ$ | Total time: | c.a 42 s |

- Average computational time entire run (~400 images):

Total time:
$292.86 \pm 5.6$ minutes

## Close look at the variables calculation

The reconstruction algorithm was tested (using the same run) for all the different kind of categories listed in Table. The categories were being added one by one to study the trend of the computational time.

The result can be seen below:


| variable | description | category |
| :---: | :---: | :---: |
| run |  | 0 |
| event | event number |  |
| pedestal_run | run number used for pedestal subtraction |  |
| t_DBSCAN |  |  |
| t variables |  |  |
| cmos_integral | integral counts of the full CMOS sensor | 1 |
| cmos_mean | average counts of the full CMOS sensor |  |
| cmos_rms | RMS of the counts of the full CMOS sensor |  |
| nSc | Number of clusters found in the image | 2 |
| sc_integral | uncalibrated integral of counts of all the pixels in the cluster |  |
| sc_size | number of pixels of the cluster, without zero-suppression | 3 |
| sc_nhits | number of pixels of the cluster above zero-suppression threshold |  |
| sc_rms |  | 4 |
| sc_length | length of the major axis of the cluster | 5 |
| sc_width | length of the minor axis of the cluster | 6 |
| sc_xmax | x position of the rightmost pixel of the cluster | 7 |
| sc_xmin | x position of the leftmost pixel of the cluster |  |
| sc_y max | y position of the topmost pixel of the cluster |  |
| sc ymin | y position of the bottommost pixel of the cluster |  |
| sc_xmean | x position of the cluster energy baricenter | 8 |
| sc ymean | position of the cluster energy baricenter |  |
| sc_theta | polar angle inclination of the major-axis of the cluster | 9 |
| sc_Ifullirms | full RMS of the cluster along the major axis | 10 |
| sc_tfullrms | full RMS of the cluster along the minor axis |  |
| sc_longrms | truncated RMS of the cluster along the major axis | 11 |
| sc_latrms | truncated RMS of the cluster along the minor axis |  |
| sc_tgaussamp | amplitude of the Gaussian transverse profile | 12 |
| sc_tgaussmean | mean position of the Gaussian transverse profile |  |
| sc_tgausssigma | standard deviation of the Gaussian transverse profile |  |
| sc_tchi2 | chi-squared of the Gaussian fit to the transverse profile |  |
| Sc_tstatus | status of the Gaussian fit to the transverse profile |  |
| sc_lgaussamp | amplitude of the Gaussian longitudinal profile |  |
| sc_lgaussmean | mean position of the Gaussian longitudinal profile |  |
| sc_lgausssigma | standard deviation of the Gaussian longitudinal profile |  |
| sc_lchi2 | chi-squared of the Gaussian fit to the longitudinal profile |  |
| sc_lstatus | status of the Gaussian fit to the longitudinal profile |  |
| sc_lp0amplitude | mplitude of the main peak of the longitudinal cluster profile | 13 |
| sc_lp0prominence | prominence main peak wrt the baseline along the long. cluster profile |  |
| sc_lp 0 fwhm | FWHM main peak of the long. cluster profile |  |
| sc_lp0mean | mean position main peak wrt the start of the cluster of long. cluster profile |  |
| sc_tp0fwhm | FWHM main peak of the transverse cluster profile |  |
| Table 5.1: Variables calculated in the full reconstruction code grouped in different categories. |  |  |

## Deeper study on the most time-consuming category

Having a close look at the algorithm we saw that the function "DynamicsProfileBins" was taking most of the time.

In an attempt to improve the computational time we have optimized the function using numpy arrays. The output of the "DynamicsProfileBins" function was not changed!

Case with a big track (Run 4320 Image 9):

| Function | Computational Time [s] |
| :---: | :---: |
| DynamicsProfileBins "Original" | 86,1864 |
| DynamicsProfileBins "Arrays" | 0,4801 |
| Factor | 179,53 |

With this new function we could almost zeroed the variable calculation contribution.

# Evaluate reconstruction computational time for <br> Run1 $_{(4320)}$ Run2 $_{(9877)}$ e Run3 $_{(17408)}$ <br> Run1 using Autumn22e Run2 e 3 using Winter23 

Comparison between Run 1, 2 and 3


Comparison between Run 1, 2 and 3


## Evaluating Run3 ${ }_{(17408)}$ with and without the optimization



> As we can see in this new implementation is capable of decrease the computational time even for the Run3.

## Conclusions

We have two main contributions for the computational time: DDBSCAN + Variables Calculation:

- The first increase with the amount of clusters found per image;
- And the second with the size of the clusters, but with the 'numpyrized' function we could almost zeroed this contribution.

Apart from that we saw that even for Run3 (the last populated one by now) the reconstruction algorithm is in average over 7 seconds per image (but some images could take up to 40 seconds).

BACKUP

## Evaluate reconstruction computational time for <br> Run1 $_{(4320)}$ Run2 $_{(9877)}$ e Run3 $_{(17408)}$ <br> Run1 using Autumn22e Run2 e 3 using Winter23

Comparison between Run 1, 2 and 3


Comparison between Run 1, 2 and 3


## Dynamics Profile

```
def dynamicProfileBins(hits,coord='x',relError=0.1):
    minPixels = max(1,1/relError/relError)
    print('minPixels: %f' % minPixels)
    index = 0 if coord=='x' else 1
    xmin=min([h[index] for h in hits])
    print('xmin: %f' % xmin)
    xmax=max([h[index] for h in hits])
    print('xmax: %f' % xmax)
    x=int(xmin)
    print('x: %f' % x)
    xedges=[x]
    integral=0
    while x<int(xmax):
        if integral<minPixels:
            somma = sum([int(h[index])==int(x) for h in hits])
            integral += somma
            print('x: %f' % int(x))
            print('counts: %f' % somma)
            print('integral: %f' % integral)
        else:
            print('Saved x: %f' % x)
            xedges.append(x)
            integral=0
        x+=1
    xedges.append(int(xmax))
    return xedges
```

def dynamicProfileBins_v2(hits,coord='x',relError=0.1): import numpy as $n p$
$\operatorname{minPixels}=\max (1,1 /$ relError/relError $)$
index = 0 if coord=='x' else 1
h = hits.T[index].astype(int)
xmin=min(h)
$x \max =\max (\mathrm{h})$
$x=x$ in
xedges=[ x ]
integral=0
xunique, xcounts $=n p$.unique(h,return_counts=True) if xmin>=0:
xrange $=$ list(range( $0, x m a x+1)$ )
$c \quad=n p . z e r o s(l e n(x r a n g e), d t y p e=i n t)$
$c$ [xunique] = xcounts
$c=c[x \min :-1]$
else:
xrange $=$ list $($ range $(0,(x m a x+1)-x m i n))$
$c \quad=n p . z e r o s(l e n(x r a n g e)$, dtype $=i n t)$
$c[$ xunique-xmin] $=$ xcounts
for ind, $x$ in enumerate(range(xmin, xmax)):
if integral<minPixels:
integral += c[ind]
else:
\#print('Saved x: \%f' \% x)
xedges.append ( $x$ )
integral=0
xedges.append (xmax)
return xedges

## Tempo Dynamics V1 x Dynamics V2 in one image

| Dynamics V1 Total | 86,1864 |
| :--- | ---: |
| seconds |  |
| Dynamics V2 Total | 0,4801 seconds |
| Factor | 179,53 times |

## Number of clusters vs computational time




