Employing HPC for Heterogeneous HEP Data Processing

AUTHOR:

Marco
Barbone

CERN IT-DI-OPL
DEEP-EST

SUPERVISORS:

Viktor Khristenko
Felice Pantaleo
Maria Girone

Project Specification

project specification

Abstract

THIS IS MY ABSTRACT

Contents

List of Figures

List of Tables

Listings

1.   From physics to... Physics

Modern high energy physics (HEP) requires analysis. To make it possible several large scale objects are needed: from accelerators, detectors, data centers to the thousands of people involved to design and run the infrastructure. Here at CERN everything starts with physics by colliding particles and everything ends with the physics performed by analyzing the data acquired. But, to produce the necessary data, in the right amount, a long and complicated process, showed in figure 1.1, is involved. It is worth to briefly describe it to understand the reason of our work and where is it place inside it.

Data generation   The process starts with **particle collisions** this lead to particle interactions that create some **intermediate product**. This intermediate product can not be directly observed, bit it decays in **particles** that go through the detectors. The intermediate product is divided in **X** and **Y**, X is what physicists are trying to study while Y is something that produces similar particles as Y but is not what they are looking for.

Data aquisition   Detectors are split in two levels: **physics detector level** and **electronics level**. The physics level takes in input sensor readouts and produces an analog signal. This analog signal is the digitalized by the electronics level. This level also decides if the event is interesting or not, based on this the event is discarded or recorded. The event that survive this ends up dumped into **disks** and send to the **High level trigger**.
It is important to notice that these decision are taken in real time, to meet the throughput and timing requirements everything is built with **asic**s and **fpga**s boards.

Data processing   Data processing is performed both online and offline. The first step, called **local reconstruction**, in the offline data processing is to transform charges in physical quantities such as **energy**, **time**, and **position**. This operation is done channel by channel independently form each other. Then, information coming from different channel of the same detector are combined by the **cross channel clustering** into **local detector cluster**s. The final step needed to obtain **particle object**s is the **cross detector clustering** in which data coming from different detector is combined. The particle object forms the dataset used by theoretical physicists to do physics.

High level trigger (HLT)   The **HLT** belongs both to data acquisition and data processing, since it would not be correct to include it in one of this categories, it deserves a separate discussion.
The HLT main purpose is to select interesting events before writing them to disk. In order to accomplish this, it runs the same code used for the offline processing, but **online** and with less features because of strict time constraints.
The main difference between **L1** and HLT is that L1 is implemented in hardware with no host while HLT is software based, it runs on hosts with accelerators used to speed-up the processing.
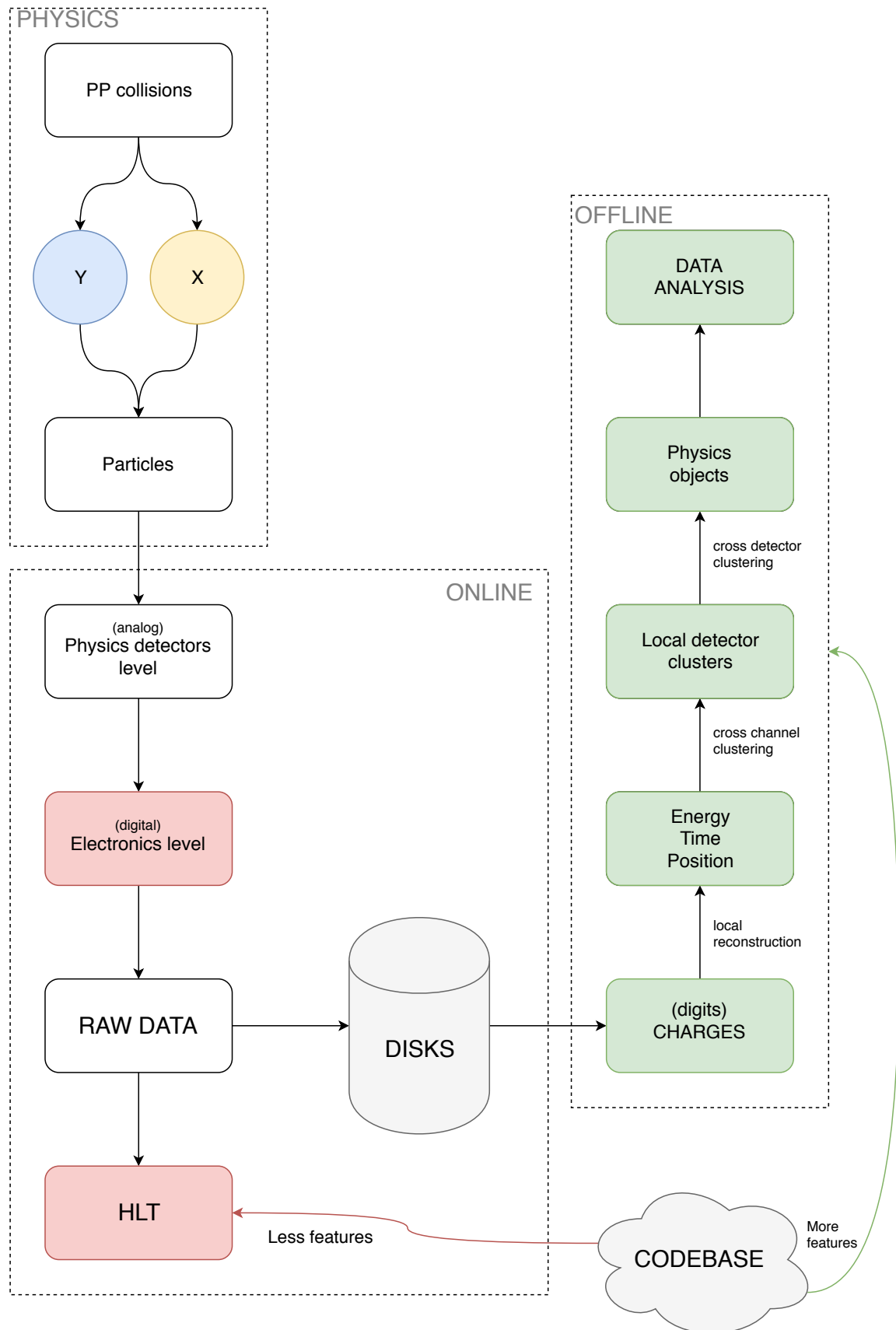
Figure 1.1: Cern data flow from collisions to analysis

2. Local energy reconstruction

The HLT shares the same code used for offline data processing, thus the processing pipeline is more or less the same. The fundamental difference is that the output is used to perform event classification instead of data analysis. The table 2.1 shows how much time is spent in every

Figure 2.1: HLT processing pipeline
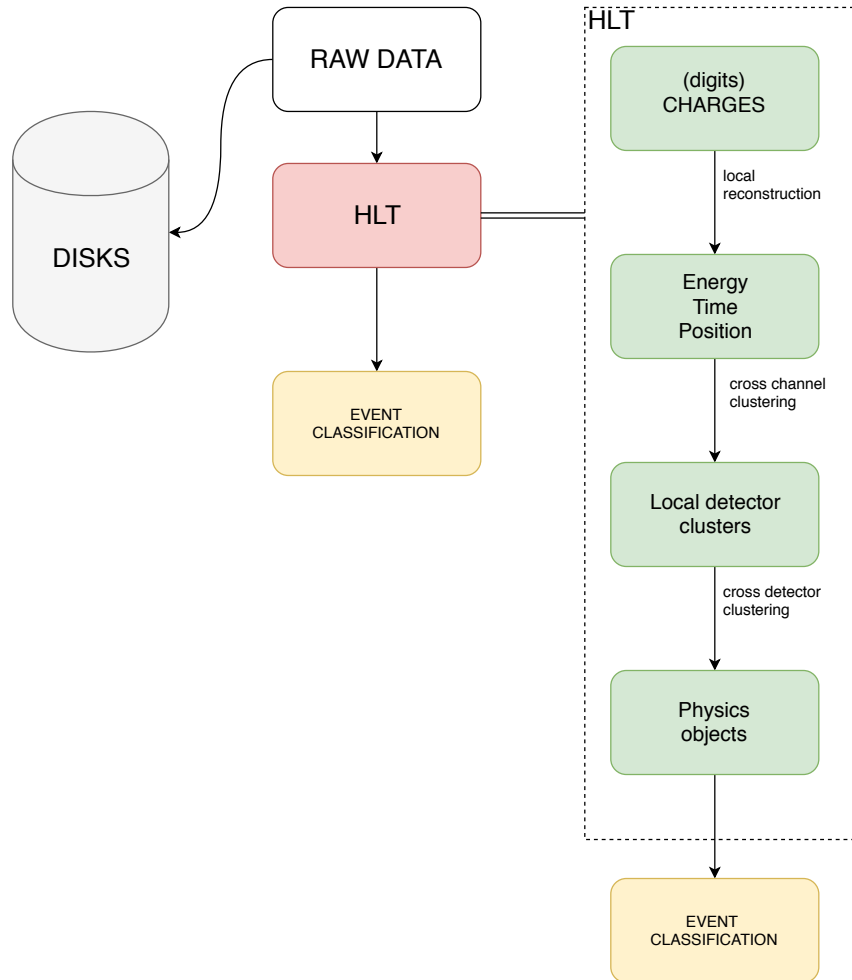
single step of the reconstruction process. Most of it is spent into tracking but after it, the second more time consuming step is HCAL+ECAL local reconstruction that takes $113ms$ corresponding to 24% of the total time. Given the time needed to perform this reconstruction even achieving a speedup of two would reduce the total processing time of more than 10%. This is my focus in this project try to reduce it as much as possible.
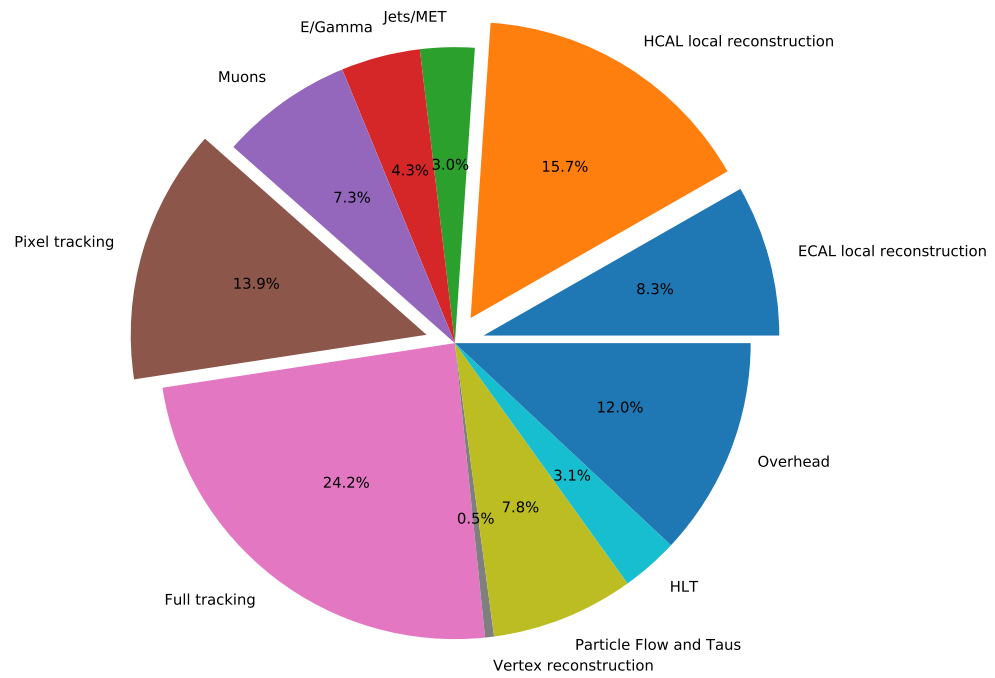
Figure 2.2: Data processing time share

Table 2.1: Time spent into the various HLT reconstruction steps

Step	Real-Time	Percentage
ECAL local reconstruction	38.9 ms	8.25%
HCAL local reconstruction	73.9 ms	15.67%
Jets/MET	14 ms	2.97%
E/Gamma	20.4 ms	4.33%
Muons	34.2 ms	7.25%
Pixel tracking	65.7 ms	13.93%
Full tracking	114.2 ms	24.22%
Vertex reconstruction	2.3 ms	0.49%
Particle Flow and Taus	36.8 ms	7.8%
HLT	14.7 ms	3.12%
Overhead	56.4 ms	11.96%
Total	471.5 ms	100%

2.1 Problem statement

As the name says the goal of this step is:

<u>Claim:</u> For each channel {given n charge readouts $\rightarrow$ reconstruct the energy}.
Where in this case n is fixed to 10.
Translated into mathematical terms this means:

$$\min(\chi^2) = \arg min_x(\|Px - b\|)$$
$$\forall x : x \geq 0$$

where: (2.1)

$$x = \text{energy vector}$$
$$P : CHARGE \rightarrow ENERGY = \text{feature matrix}$$
$$b = \text{charge vector}$$

Which is a minχ^2 problem with additional positivity constraints. This constraint is present because physically speaking negative energy does not make sense.
As shown in [1] the statement above is incomplete. A perfect mapping from charges to energy does not exist because signal from the shower does not dissipate within one time slice ($25ns$). Adding the correlation term this problem becomes:

$$\arg min_x(\|(Px - b)^T \Sigma(x)^{-1}(Px - b)\|)$$
$$\forall x : x \geq 0$$
             (2.2)

It is worth pointing out that Σ depends on x, meaning also Σ is unknown.
To compute Σ an iterative procedure is used:

1. Compute Σ.

2. Minimize χ^2.

3. If not convergence goto 1.

More precisely Σ is the covariance matrix representing the noise correlation between time samples i and j, obtained from data where no signal is present, and the single sample noise.
To solve the problem stated in 2.1 several algorithms exists, for example **lsqnonneg** illustrated in [4] and the **ffnls** illustrated in [2]. The one implemented is fnnls since as measured in [3] it is faster.
The problem presented in 2.2 is not a χ^2 problem but to solve it with nnls needs to be reduced into the canonical form. The redution exploits the Cholesky decomposition and is illustrated in 2.3.

$$(Px - b)^T \Sigma(x)^{-}1(Px - b)$$
$$\equiv \quad \Sigma = LL^T, (AB)^{-1} = B^{-1}A^{-1}$$
$$(Px - b)^T L^{-T} L^{-1}(Px - b)$$
$$\equiv \quad (AB)^T = B^T A^T$$
$$(L^{-1}Px - L^{-1}b)^T L^{-1}(Px - b)$$
$$\equiv$$
             (2.3)
$$(L^{-1}Px - L^{-1}b)^T (L^{-1}Px - L^{-1}b)$$
$$\equiv \quad L^{-1}P = P', L^{-1}b = b'$$
$$(P'x - b')^T (P'x - b')$$
$$\equiv$$
$$min(\chi^2)$$

2.2 Fast non negative least square algorithm (FNNLS)

Algorithm 1 NNLS

Input:
  A real valued matrix of dimension $m \times n$
  b real valued vector of dimension m
  ϵ the maximum accepted error
  K the maximum number of iterations
Output:
  x the solution vector

 1: **function** NNLS(A, b, ϵ, K)
 2:     $x \leftarrow 0$
 3:     $P = \varnothing$
 4:     $R = \{1, 2, ..., m\}$
 5:     $w = A^T(b - Ax)$ ▷ compute the gradient
 6:     **while** $R \neq \varnothing \wedge max(w) < \epsilon \wedge k < K$ **do**
 7:         $j \leftarrow max(w^P)$ ▷ $w^P \leftarrow \{w_j : j \in P\}$
 8:         Add j to P
 9:         Remove j from R
10:         $A^P \leftarrow \{a_{ij} \in A : i \in P \wedge j \in P\}$
11:         $s \leftarrow ((A^P)^T A^P)^{-1} A^P b^P$ ▷ s is a vector of the same dimension of P
12:         **while** $min(s) \leq 0$ **do**
13:             $\alpha = min_i\{\frac{x_i}{x_i - s_i} : i \in P \wedge s_i \leq 0\}$
14:             $\forall i \in P : x_i \leftarrow x_i + \alpha(s_i - x_i)$
15:             move to R all $i \in P : x_i \leftarrow 0$
16:             $s \leftarrow ((A^P)^T A^P)^{-1} A^P b^P$ ▷ recompute s for the next iteration
17:         $\forall i \in P : x_i \leftarrow s_i$
18:         $w \leftarrow A^T(b - Ax)$
19:         $k \leftarrow k + 1$

Algorithm 2 FNNLS

 1: $w \leftarrow (A^T b)(A^T A)x$
 2: $s \leftarrow ((A^T A)^P)^{-1}(A^T b)^P$
---

3. Conclusions

Write your conclusions here.

Bibliography

[1] P Adzic, R Alemany-Fernandez, Carlos Almeida, N Almeida, Georgios Anagnostou, M.G. Anfreville, Ivan Anicin, Zeljko Antunovic, Etiennette Auffray, S Baccaro, S Baffioni, D Barney, L.M. Barone, Pierre Barrillon, Alessandro Bartoloni, S Beauceron, F Beaudette, K.W. Bell, R Benetta, and The CMS Electromagnetic Calorimeter Group. Reconstruction of the signal amplitude of the cms electromagnetic calorimeter. 46:23–35, 07 2006. 5

[2] R. Bro and S. d. Jong. A fast non-negativity- constrained least squares algorithm. *Journal of Chemometrics*, 11:393–401, 1997. 5

[3] Donghui Chen and Robert J. Plemmons. Nonnegativity constraints in numerical analysis. In *in A. Bultheel and R. Cools (Eds.), Symposium on the Birth of Numerical Analysis, World Scientific*. Press, 2009. 5

[4] Charles L Lawson, 1938 Hanson, Richard J., Society for Industrial, and Applied Mathematics. *Solving least squares problems*. Philadelphia : SIAM, [rev. ed.] edition, 1995. "This SIAM edition is an unabridged, revised republication of the work first published by Prentice-Hall, Inc., Englewood Cliffs, New Jersey, 1974"–T.p. verso. 5

A. My First Appendix

In this file (appendices/main.tex) you can add appendix chapters, just as you did in the thesis.tex file for the 'normal' chapters. You can also choose to include everything in this single file, whatever you prefer.