Neural Triggering System Operating on High Resolution Calorimetry Information

A. dos Anjos, R.C. Torres, J.M. Seixas, B.C. Ferreira, T.C. Xavier

Signal Processing Laboratory/COPPE/Federal University of Rio de Janeiro

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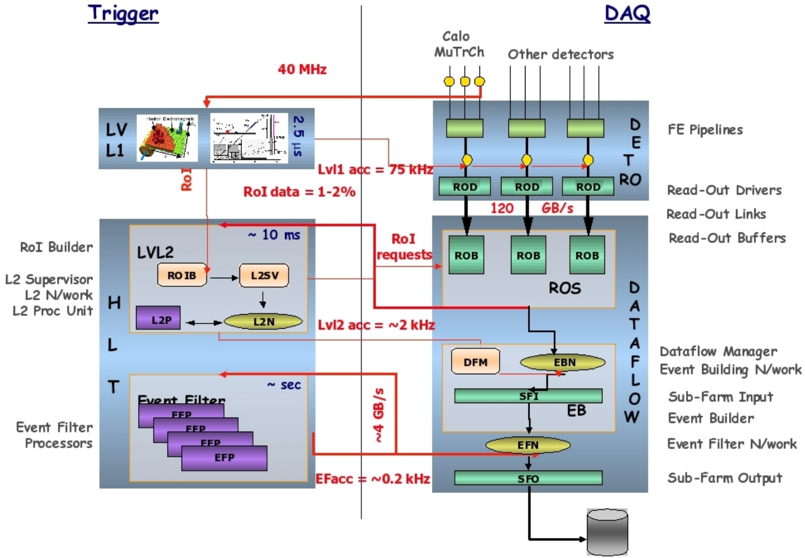
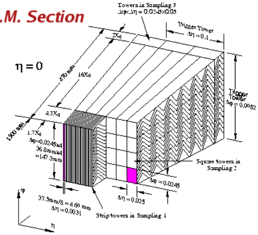
An ATLAS Trigger Overview

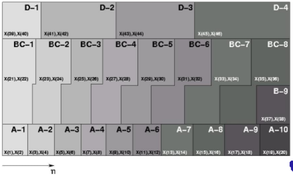


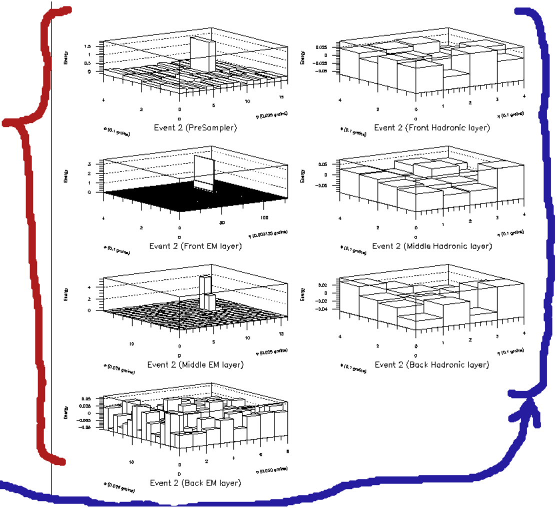
ATLAS Calorimetry for LVL2 (Region of Interest)

E.M. Section



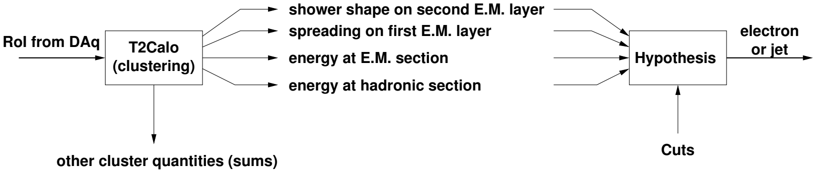
Hadronic Section (Tilecal)





T2Calo

- The input is (normally) a 0.4×0.4 region in the $\eta \times \phi$ plane, which encompasses (in the order of) 1,000 cells;
- It is a clustering algorithm;
- Evaluates 4 discriminating quantities and other properties of the candidate RoI;
- It is followed by a hypothesis algorithm that applies cuts on the 4 quantities.



Trigger Facts

- The ATLAS Trigger is predominantly inclusive (searches for high-pT representative objects and accepts events based on those);
- Important objects to be identified in this system are high-pT electrons;
- In average, for every 25,000 high-pT electrons accepted by LVL1, it is expected that only 1 is a true electron;
- Today's algorithms for electron identification @ LVL2 (T2Calo) use basic clustering strategies and apply cuts to identify electrons and reject jets;
- This algorithm depends on the input object energy.
- If approved by the cuts applied after T2Calo, Inner Detector (tracker) algorithms are applied to the object. These algorithms take longer processing times;
- The average processing time per event (**not** per RoI) should be in the order of 10 ms.

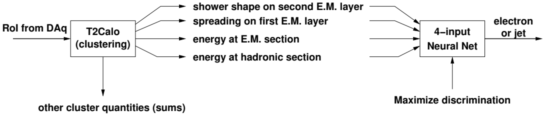
Things we have tried to address...

- Try to devise a discriminator that is more resilient to noise and independent of the input object energy;
- Have a system that can be re-calibrated without a specialist help;
- Try to improve jet detection efficiencies so the system looses **less** time on uninteresting objects;
- Try to keep ourselves within the time budget defined by LVL2;
- Find a handle to control algorithm timing (by minimizing efficiency losses).

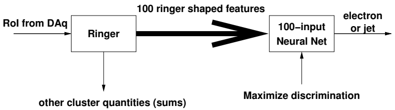
Places where Neural Networks could be used

Neural Networks make sense at hypothesis making, where the user has to "guess" the particle type from a summary of the RoI data.

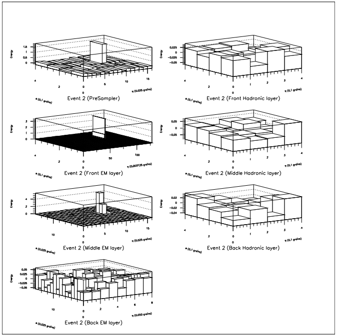
1. **At the output of T2Calo (T2Calo-Neural)** Substituting the current hypothesis algorithm

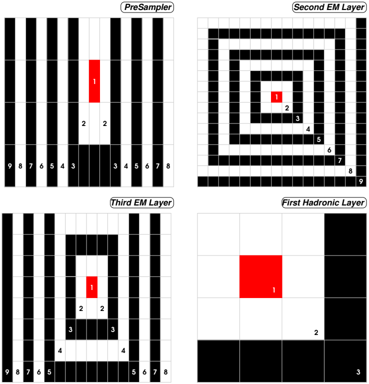


2. **Replacing T2Calo (Ringer-Neural)** With a feature extraction algorithm that better preserves the shower shapes and could achieve better discrimination



The Ringer



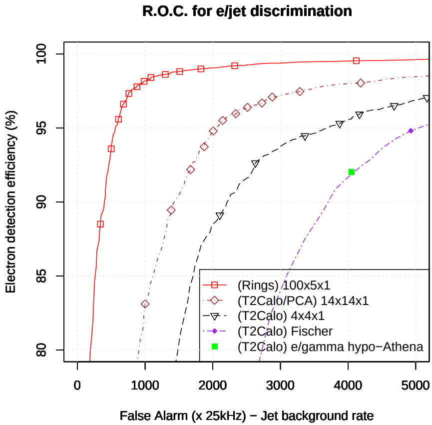


The ring sum strategy is adapted to every layer granularity and leads to 100 values, using full RoI data;

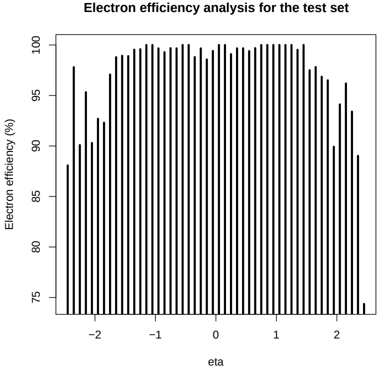
Energy-based normalization can use the energy per layer, section (E.M. and Hadronic) or of the whole object to normalize the input previously to hypothesis making.

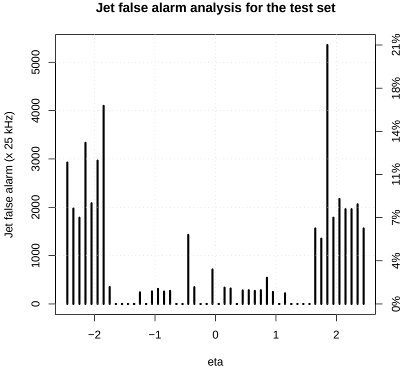
Comparative discrimination efficiencies

Data sets: $H \rightarrow 4e$, $H \rightarrow 2e2mu$, single electrons and dijets, prefiltered by a realistic (Athena) LVL1 trigger simulation.



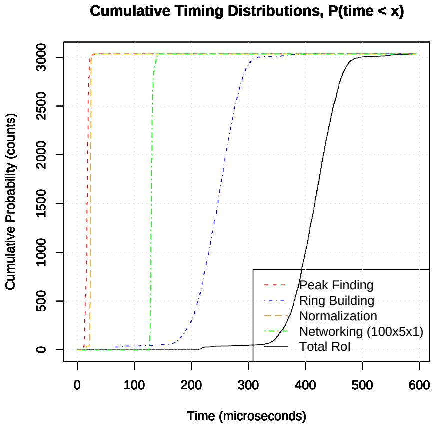
η Scan Analysis



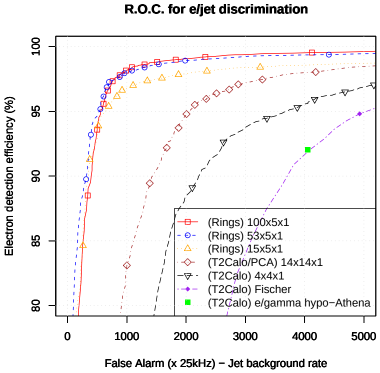


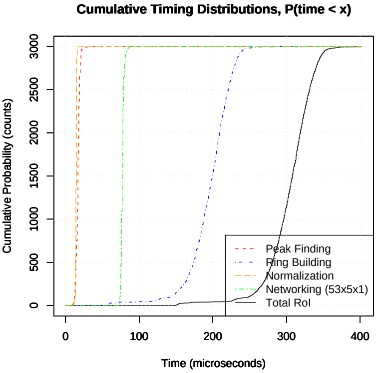
Timings

The machine is a Pentium-4 @ 2.8 MHz with 512 Mb RAM, the system is fully implemented in C++ and optimized for speed. The inputs represent a realistic sample of RoI's which would be approved by ATLAS LVL1 Trigger.



Relevance and “controlled” input compaction

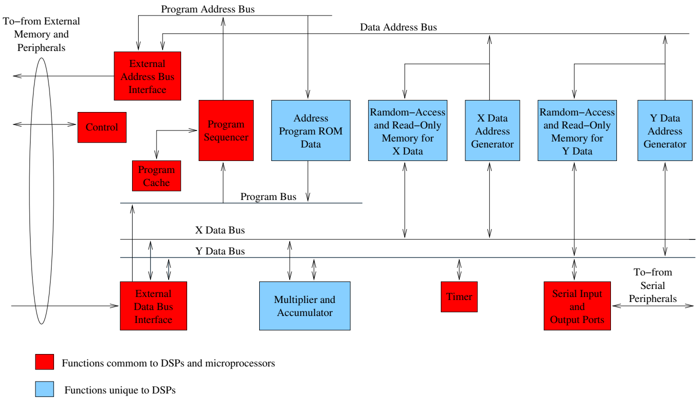




The DSP Alternative

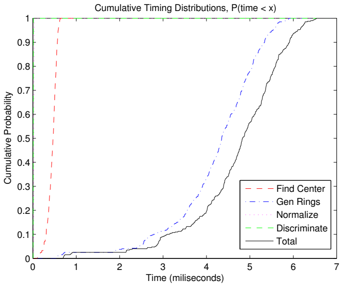
- Digital signal processors (DSPs) may be used in order to optimize the overall system performance.
- The inner structure of a DSP exploits inherent features of digital signal processing algorithms, like MAC, loops and modular operations.
- With a multi-bus architecture, together with a set of internal devices working in parallel, a DSP can achieve higher execution rates with lower clock frequencies.
- Benefits:
  - Fast execution speed.
  - Low power consumption.
  - Reduced size.
  - Reduced costs.

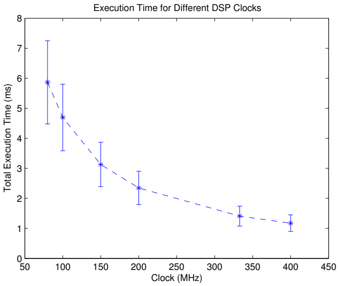
DSP Inner Structure



Results Using DSP

- The DSP used was a floating point, 32-bit ADSP-21160N @ 100 MHz with SIMD capabilities and 4 Mbits of internal memory.
- An average time of 4.692 ± 1.108 ms per RoI was achieved.
- The performance suffered from the fact that the ring generation is a hard to optimize process.
- The average time of 10.429 ± 0.465 μs for the discrimination part, however, proved the DSP efficiency for numerical operations.

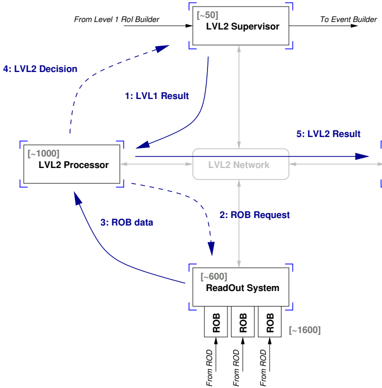


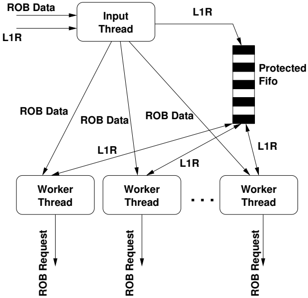


Conclusions

- Neural networks improve considerably hypothesis making for LVL2 e/jet discrimination, either using T2Calo's original output or with new feature extraction methods, by a factor of 2, approx.;
- Ring analysis outperforms T2Calo, sometimes cutting the background rate by a factor of 3 or 4 of T2Calo's capacity for the same electron detection efficiency;
- Ring feature extraction married to relevance analysis provides a flexible and controllable way to exchange robustness and efficiency in a optimal manner, providing a knob to control execution speed and background rejection;
- The C++ algorithm implementation proves this is a feasible ATLAS LVL2 option (with an average of $\sim$**420** μ**s** execution time for **100 rings** and $\sim$**320** μ**s** for 53 rings), with timings better than today's T2Calo implementation (latest known timings point to 4 ms) for the same computer architecture) in ATLAS's Athena;
- DSP may be an alternative due to its efficiency in digital signal processing algorithms.

The Second Level Trigger (Back-up)





η Scan comparison T2Calo (PCA + 14-14-1) *versus* Rings (Back-up)